Measuring the Spatial Heterogeneity in Environmental Externalities from Driving: A Comparison of Gasoline and Electric Vehicles*

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Abstract

Electric vehicles offer the promise of reduced environmental externalities relative to their gasoline counterparts. We determine the spatial heterogeneity in these externalities and evaluate several spatially-differentiated policies to correct them. To do this, we combine a discrete-choice model of new vehicle purchases, an econometric analysis of the electric power industry, and the AP2 air pollution model. We find three main insights. First, there is considerable spatial variation in the environmental benefit of electric cars, ranging from a positive $2144 in California to a negative $2607 in North Dakota. Second, the vast majority of environmental externalities from driving an electric car in one place are exported to other places, implying that electric cars may be subsidized locally, even though they may lead to negative environmental benefits overall. Third, spatially differentiated policies can raise welfare, but the effect is much stronger for taxes on miles driven than for subsidies on vehicle purchases.

JEL Codes: Q48, Q53

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1 Introduction

Due to a combination of factors, including technological advances, environmental concerns, and entrepreneurial audacity, the market for electric vehicles, which was moribund for more than a century, is poised for a dramatic revival. Several models are already selling in considerable volumes, the portfolio of electric vehicles is beginning to span the consumer vehicle choice set, and almost all major manufacturers are bringing new models to the market. The Federal Government is encouraging these developments by providing a significant subsidy for the purchase of an electric vehicle, and some states augment the Federal subsidy with their own additional subsidy. One of the main motivating reasons for these subsidies is the belief that electric vehicles provide an environmental benefit relative to gasoline vehicles by reducing externalities from air pollution.

In this paper we analyze the degree to which this environmental benefit exists, giving careful consideration to the spatial heterogeneity in the externalizes from both electric and gasoline vehicles. We also analyze the welfare implications of spatial variation in policies that target these externalities, such as subsidies on the purchase of an electric vehicle and taxes on electric and/or gasoline miles.

We first document the considerable spatial heterogeneity in the environmental benefit of an electric vehicle relative to a gasoline vehicle. Regardless of the spatial level considered (state, MSA, or county) this benefit is large and positive in some places and large and negative in other places. For example, California has relatively large damages from gasoline vehicles, a relatively clean electric grid, and a large positive environmental benefit of an electric vehicle. These conditions are reversed in North Dakota. Using the environmental benefit, we calculate the optimal spatial subsidies on electric vehicle purchases. Even in the outliers such as California, optimal subsidy values are significantly less than the current Federal subsidy. And in North Dakota the optimal subsidy actually implies a tax on the purchase an electric vehicle.

Our second set of results shows the remarkable degree to which electric vehicles driven in one place lead to environmental externalities in other places. For example, at the state level, over ninety one percent of non-greenhouse damages from driving an electric vehicle are exported to other states, i.e. accrue to states other than the state in which the vehicle is driven. In contrast, only nineteen percent of non-greenhouse damages from driving a gasoline vehicle are exported to other states. This discrepancy has interesting political economy implications. Suppose that a given state is considering whether or not to implement a subsidy on the purchase of an electric vehicle. It is not obvious whether the state will consider total damages, or only native damages (those damages which actually occur in the given state) when setting policy. The difference may be considerable. Accounting for total damages the optimal subsidy is positive in 12 states. Accounting for only native damages, the optimal subsidy is positive in 35 states.

The final set of results concerns the welfare gains from using a spatially differentiated policy relative to a uniform policy. We compare, for example, the total welfare associated with a uniform national subsidy on the purchase of an electric vehicle with the total welfare associated with of a set of state-specific subsidies. Our theoretical analysis reveals that the welfare gains from spatially differentiated subsidies depend on the second and higher order moments of the spatial distribution of environmental benefits. A companion numerical analysis shows the magnitude of these gains. Much greater gains are realized by using differentiated taxes on electric and gasoline miles rather than differentiated purchase subsidies.

To obtain these results, we extend and integrate three component models. The first component builds on discrete choice transportation models to allow for consumer choice between electric and gasoline vehicles and to analyze the benefits of spatially differentiated policy.[1] The second component builds on the econometric analysis of the relationship between electricity generation and air pollution emissions to analyze the effects of changes in electricity load due to charging electric vehicles on emissions from individual electric power plants.[2] The third component builds on air pollution integrated assessment models to describe the relationship between emissions from a given smokestack or tailpipe and damages at a given spatial location.[3] Combining the components together yields a powerful modeling framework for analyzing electric vehicle policy.

In Section 2 we develop a simple general equilibrium model that includes discrete choice over vehicle type and environmental externalities from driving. We derive several theoretical results about optimal policy choices and the welfare benefits from differentiation. In Section 3 we describe the methods by which we determine emissions and damages from electric and gasoline vehicles. Section 4 presents the results. In Section 5 we consider how the interaction with other environmental regulations such as the Corporate Average Fuel Economy (CAFE) standards may effect the optimal subsidies on electric vehicles. Section 6 concludes.

[1]Examples of discrete choice transportation models include De Borger (2001), De Borger and Mayeres (2007), and Perry and Small (2005). Spatially differentiated policy is analyzed by Weitman (1974), Mendelsohn (1986), Stavins (1996), Banzhaf and Chupp (2012), Muller and Mendelsohn (2009), and Fowlie and Muller (2013).

[2] Babaee et al (2014), Graff Zivin et al (2014), Michalek et al (2011) analyze the benefits of electric vehicles at the aggregate level, ours is the first to consider the spatial variation in these benefits at the state and county level.

[3]Previous works includes Mendelsohn (1980), Burtraw et al. (1998), Mauzerall et al. (2005), Tong et al. (2006), Fann et al. (2009), Levy et al. (2009), Muller and Mendelsohn (2009), Henry et al. (2011), Mauzerall et al. (2005), and Tong et al. (2006). In our application of integrated assessment, we model both ground level-emissions and power plant emissions throughout the contiguous U.S., and we and report damages within the county of emission, within the state of emission, and in total (across all receptors).

2 Theoretical Model

Consider a general equilibrium discrete choice model with five goods. There are two transportation options: a gasoline vehicle and an electric vehicle.[4] The vehicles are used to consume transportation miles. Both vehicles and miles are produced from labor with a constant returns to scale technology, so that producer prices are fixed in the model. Consumers in the market for a new vehicle all have the same "universal" utility function which depends on leisure ℓ, electric miles e, and gasoline miles g. The utility function has a quasi-linear form

$$U(\ell, g, e) = \ell + f(g) + h(e),$$

where f and h are strictly concave functions. Because the marginal utility of income is constant, there are no income effects on the purchase of gasoline or electric miles. Consumers have an endowment of time T.

We consider several policy variables for the government. The government may place a tax t_g on gasoline miles, a tax t_e on electric miles, a subsidy s on the purchase of the electric vehicle, or use some combination of these policies. Per capita tax revenue R is returned in a lump sum manner. We normalize the units so that the wage rate is equal to one.

The indirect utility of consuming leisure and gasoline miles is given by

$$V_g = \max_{\ell, g} U(\ell, g, 0) \text{ s.t. } \ell + (p_g + t_g)g = T + R - p,$$

where p is the price of the gasoline vehicle and p_g is the price of gasoline miles. Likewise, the indirect utility of consuming leisure and electric miles is given by

$$V_e = \max_{\ell, e} U(\ell, 0, e) \text{ s.t. } \ell + (p_e + t_e)e = T + R - (p_\Omega - s),$$

where p_Ω is the price of the electric vehicle and p_e is the price of electric miles.

Following the discrete choice literature, we define the conditional utility, given that a

[4] In supplementary Appendix B, we extend the model to include several gasoline vehicles and several electric vehicles.

consumer elects the gasoline vehicle, as

$$\mathcal{U}_g = V_g + \epsilon_g,$$

and the conditional utility, given that a consumer elects the electric vehicle, as

$$\mathcal{U}_e = V_e + \epsilon_e,$$

where the ϵ's are i.i.d. random variables that follow the extreme value distribution.[5] A consumer selects the gasoline vehicle if $\mathcal{U}_g > \mathcal{U}_e$. The probability of the consumer selecting the gasoline vehicle is given by

$$\pi = \text{Probability}(\mathcal{U}_g > \mathcal{U}_e) = \frac{\exp(V_g/\mu)}{\exp(V_g/\mu) + \exp(V_e/\mu)},$$

where μ is a measure of the variance of the extreme value random variables. The expected utility of a new vehicle purchase is given by[6]

$$\mathbb{E}\left[\max[\mathcal{U}_e, \mathcal{U}_g]\right] = \mu \ln\left(\exp(V_e/\mu) + \exp(V_g/\mu)\right).$$

Consumers create an environmental externality when they consume transportation miles due to damages from air pollution. They ignore this externality when making choices about the type of vehicle and number of miles. Gasoline vehicles cause damages through tailpipe emissions and electric vehicles cause damages though smokestack emissions from the electric power plants that charge them. We assume that the damage functions are linear. The marginal damage (in dollars) of an electric vehicle mile is given by δ_e and the marginal damage (in dollars) of an gasoline vehicle mile is given by δ_g. Following Alcott et al. (2012),

[5]For examples of discrete choice models, see Anderson et al. 1992, Small and Rosen 1981, de Borger 2001, de Borger and Mayeres 2007. The extreme value distribution (or double exponential distribution) has two parameters, η and μ. The expected value is $\mu\gamma + \eta$ where γ is Euler's constant (0.577). The variance is $\mu^2\pi^2/6$. We assume that the expected value is zero.

[6]There are two ways to think about non-externality welfare in a discrete choice model. First, just define welfare as the expected value of the maximum over the utility choices (i.e. de Borger 2001.) Second, use the standard notion of compensating variation. In our model, there are no income effects. Under this condition, Small and Rosen 1981 show that these two methods are equivalent.

we assume that the regulator's objective is to maximize the expected welfare associated with a consumer's purchase of a new vehicle, defined as the difference between expected utility and expected pollution damage

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

We now determine the optimal policy choices for the government. Resuls for a subsidy on electric vehicle purchases are in the main text. Results for taxes on miles are in the Appendix.

2.1 Single region: Subsidy on the purchase of an electric vehicle

In the most basic form of our model, there is a single region. The optimal subsidy on the purchase of an electric vehicle is described in the following Proposition (all proofs are in the Appendix).

subsidy **Proposition 1.** *The optimal subsidy on the purchase of the electric vehicle is given by* s^* *where*

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

The term $\delta_g g - \delta_e e$ is simply the difference between the damages when a consumer drives a gasoline vehicle and the damages when a consumer drives an electric vehicle. Even if the electric vehicle emits less pollution per mile than the gasoline vehicle, the sign of the optimal subsidy is ambiguous, because the number of miles driven may be different. If the miles driven are indeed the same, and the electric vehicle emits less pollution per mile than the gasoline vehicle, then the optimal subsidy is positive. We refer to the difference $\delta_g - \delta_e$ as the environmental benefit of the electric vehicle. Keep in mind, though, that this concept really only makes sense when the number miles driven by the two types of vehicles is the same (an assumption we will maintain throughout the empirical section below).

2.2 Multiple regions: Uniform vs. differentiated regulation

Next we analyze a simple spatial model in which there are m regions. The utility functions and (pre-policy) prices are the same across regions but both the marginal damages from the consumption of miles and the population of new vehicle buyers varies across regions. The marginal damage of gasoline miles consumed in region i is denoted by δ_{gi}. It is important to stress that this number includes the native damages that accrue to region i as well as external damages that accrue to other regions. Marginal damages from electric miles δ_{ei} are defined analogously. Let α_i be the proportion of the total population of new vehicle buyers that resides in region i. It follows that $\bar{\delta}_g = \sum \alpha_i \delta_{gi}$ and $\bar{\delta}_e = \sum \alpha_i \delta_{ei}$ are the weighted average marginal damages from gasoline and electric miles.

Under differentiated regulation, each regional government selects a region-specific subsidy on the purchase of the electric vehicle. Revenue is also region specific. If the subsidy in region j increases, this decreases the revenue in region j, but does not effect the revenue in other regions. For the moment, we assume that each regional government cares about both native and external damages. We will relax this assumption below. Regional government i selects the subsidy s_i to maximize the welfare associated with the purchase of a new vehicle within the region

$$\mathcal{W}_i = \mu \left(\ln(\exp(V_{ei}/\mu) + \exp(V_{gi}/\mu)) \right) - (\delta_{gi}\pi_i g + \delta_{ei}(1 - \pi_i)e).$$

Because there are no income effects, the subsidy does not effect the purchase of miles e and g. Hence the values of e and g do not vary across regions. From Proposition 1, it follows that that the optimal differentiated subsidy in region i is given by

$$s_i^* = (\delta_{gi} g - \delta_{ei} e).$$

Under uniform regulation, the same subsidy applies to all m regions. The central government sets the subsidy and all revenue is returned equally across all regions in a lump sum manner. The government's objective is to maximize the weighted average of welfare across regions. The next proposition delineates the optimal uniform subsidy. It also describes an approximate formula for the welfare gain in moving from the uniform policy to the differentiated policy.

spatial **Proposition 2.** *The optimal uniform subsidy on the purchase of an electric vehicle is given by*

$$\tilde{s} = \left(\bar{\delta}_g g - \bar{\delta}_e e\right).$$

Furthermore, let $\mathcal{W}(S^*)$ *be the weighted average of welfare from using the optimal differentiated subsidy* s_i^* *in each region and let* $\mathcal{W}(\tilde{S})$ *be the weighted average of welfare from using the optimal uniform subsidy* $\tilde{s}$ *in each region. To a second-order approximation, we have*

$$\mathcal{W}(S^*) - \mathcal{W}(\tilde{S}) \approx \frac{1}{2}\pi(1-\pi)\left(\frac{1}{\mu}\sum \alpha_i(s_i^* - \tilde{s})^2 + \frac{1}{\mu^2}(1-2\pi)\sum \alpha_i(s_i^* - \tilde{s})^3\right).$$

In both formulas, π *is evaluated at the optimal uniform subsidy.*

This result has a nice interpretation in the special case in which $g = e$ and the population of new vehicle buyers is the same in each region. Consider the distribution of the environmental benefits of an electric vehicle, i.e. the distribution of the *difference* between δ_{ei} and δ_{gi}. Using the second-order approximation formula, we see that the welfare gain from using the optimal differentiated subsidies rather than the optimal uniform subsidy depends on both the second and third moments for the distribution of the environmental benefits of an electric vehicle.

The formula in Proposition 2 provide useful intuition for the factors that influence the welfare gains from using differentiated subsidies. And it provides an interesting point of comparison to previous work on differentiation. For example, Mendelsohn (1986) finds the exact welfare improvement from differentiation to be a function of the second moment of the distribution of the relevant environmental parameter (intercept of marginal abatement costs) across regions. In contrast, we find that the second-order approximation to the welfare improvement depends on both the second and third moment of the distribution of the relevant environmental parameter (the benefits of an electric vehicle). The reasons for this difference are discussed in Additional Appendix C. But the practical applicability of the formula is limited it depends on the value of μ. Recall that this parameter is a measure of the variance of the random variables in the utility function. If we determine a value for μ, either by an econometric procedure (Dubin and McFadden 1984) or by a calibration procedure (De

Borger and Mayeres 2007), then we will generally be able to determine the exact numerical value of the welfare gain, which eliminates the need for an approximation.

2.3 Political economy considerations

It may be the case that a given region only cares about native damages. In this case, the objective of region i is to maximize

$$\mu\left(\ln(\exp(V_{ei}/\mu) + \exp(V_{gi}/\mu))\right) - (\beta_{gi}\delta_{gi}\pi_i g + \beta_{ei}\delta_{ei}(1-\pi_i)e),$$

where β_{gi} and β_{ei} are the proportion of marginal damages that are occur solely in region i. It follows that the political economy subsidy $\hat{s}_i^*$ is

$$\hat{s}_i^* = \left(\beta_{gi}\delta_{gi}g - \beta_{ei}\delta_{ei}e\right).$$

We would expect considerable heterogeneity in the β's due to the various chemical and physical process that govern the flow of emissions across regions. In general, however, we would expect β_{gi} to be greater than β_{ei} due to the distributed nature of most grid-tied electricity consumption. This implies that the political economy subsidy is likely to be larger than the optimal differentiated subsidy. The greater the extent to which the electric emissions are exported to other regions, the greater the extent to which the given region may want to subsidize the purchase of an electric vehicle.

These issues suggest it may be interesting to compare between a differentiated policy in which each regional government selects their own subsidies but ignores the external effects of their own emissions on other regions, and a uniform policy in which a central government accounts for all effects of emissions. The first-order welfare comparison between these systems can be stated as a simple Corollary to Propostition 2.

political **Corollary 1.** *Let $\mathcal{W}(\hat{S}^*)$ be the weighted average of welfare from using the optimal political economy subsidies $\hat{s}_i^*$ in each region and let $\mathcal{W}(\tilde{S})$ be the weighted average of welfare from* *using the optimal uniform subsidy $\tilde{s}$ in each region. To a first-order approximation, we have*

$$\mathcal{W}(\hat{S}^*) - \mathcal{W}(\tilde{S}) \approx \frac{1}{\mu}\pi(1-\pi)\left(\sum \alpha_i (s_i^* - \tilde{s})(\hat{s}_i^* - \tilde{s})\right).$$

We now turn to the task of determining empirical values for the marginal damages from driving gasoline and electric vehicles.

3 Damages from emissions of gasoline and electric vehicles

We consider the damages from air-pollution emissions of five pollutants: CO_2, SO_2, NO_X, $PM_{2.5}$, and VOCs. These pollutants account for the majority of air pollution damages and have been a major focus of public policy.[7]

Estimating the marginal damages of emissions of these pollutants (in dollars per mile) requires different procedures for gasoline and electric vehicles. For gasoline vehicles, our first step is to calculate the emissions rates (in grams per mile) of the five pollutants. As in our theoretical model, the marginal damages from these emissions may vary spatially according to the location of the vehicle. So our second step is to use the AP2 model (for example, see Muller and Mendelsohn 2009) to map emissions from a given region into a spatially distributed plume of concentrations of pollutants across many regions and then determine the overall damages (in dollars per mile) associated with the plume. For electric vehicles, the procedure is more complicated, even though electric vehicles have no tailpipe emissions. Our first step is to calculate the electricity required (kWh) per mile for electric vehicles. Our second step is to use an econometric model to estimate the marginal emissions from additional electricity usage in a given region at a given time across all power plants. Combining these first two steps with a charging-time profile gives us the emissions rates (in grams per mile) from power plants that result from charging an electric vehicle in a given

[7] A more complete analysis would also include assessment of emissions from CO and toxics as well as a "cradle-to-grave" life-cycle assessment (damages from construction, use, and wear of vehicles, roads, and refineries). See for example, the analysis by Michalek et al. (2011) of the life-cycle damages from hybrid electric vehicles.

region. Our third step is to use the AP2 model map these emissions from power plants into a spatially distributed plume and then into overall damages (in dollars per mile).

We now describe these steps in turn.

3.1 Emissions per mile for gasoline vehicles

Data for gasoline vehicle emissions comes from EPA's Tier 2 emission standards and the GREET model developed by Argonne National Laboratory.[8] Our set of gasoline vehicles is meant to capture the closest substitutes to existing electric vehicles. For each of the eleven 2014 pure electric vehicle models in the EPA fuel efficiency database, we identify the gasoline vehicle which is the closest substitute to the electric vehicle in terms of non-price attributes. In many cases, we are able to simply use the gasoline powered version of the identical vehicle, e.g., the gasoline-powered Ford Focus is the closest substitute for the electric Ford Focus. However, in other cases, we identify a make and model which is a close substitute, e.g., we identify the BMW 750i as the closest substitute for a Tesla Model S. The resulting emissions rates for these vehicles are reported in Appendix Table 1.

3.2 Emissions from Electric Vehicles

Electricity usage per mile varies across vehicles but is straightforward to calculate. For each electric vehicle, we use the EPA estimates of MPG equivalent (i.e., the estimated kWh per mile).

The increase in emissions due to an increase in electricity use to charge electric vehicles depends on both the time of day and the specific location at which the vehicle is charged. To account for the time of day, we hypothesize eight charging profiles: one profile based on Electric Power Research Institute (EPRI) estimates, a second profile based on a flat profile, and six profiles based on non-overlapping four-hour charging blocks (See Appendix Figure 1 for the EPRI profile.)

To account for the location of charging, we must model the electricity grid because an increase in electricity usage at a specific location causes a responses from many power plants.

[8]See the Appendix for additional details.

Some plants may increase generation even if they are not in the same state, while others may even have to decrease generation in order to keep electricity flows continuously balanced on the power grid. A broad view of the U.S. electric power grid starts with three "interconnects": Eastern, Western, and Texas. In theory, any area within an interconnect is completely connected to any other area within the same interconnect. But in practice, transmission constraints and losses can prevent electricity from flowing costlessly throughout an interconnect. Given this, we follow the North American Electric Reliability Corporation (NERC) classification system in which the contiguous U.S. is divided into 9 distinct regions.[9] We use these 9 NERC regions to define the spatial scale for measuring electric vehicle emissions. We assume that an electric vehicle charged at any place within a given region will generate the same marginal emissions as an electric vehicle charged at any other place within the same region. (In practice, there is some variation in marginal emissions within a given NERC region due to local transmission congestion, but the variation across regions is more consistent and substantial.)

To estimate the response of each power plant to increases in electricity usage, we collect data from 2010 to 2012 on hourly emissions of CO_2, SO_2, NO_X, and $PM_{2.5}$ at 1486 power plants. We also collect data on hourly electricity consumption (i.e., electricity load) for each of the nine NERC regions.[10] We estimate the marginal emissions using methods similar to Graff Zivin et al. (2014). We allow for an integrated market where electricity consumed within an interconnection may be provided by any power plant within that interconnection. In contrast to Graff Zivin et al. (2014), we estimate the effect of changes in electricity load *separately* for each power plant in the interconnection. The dependent variable, y_{it}, is power plant i's hourly emissions (CO_2, SO_2, NO_X, or $PM_{2.5}$) at time t. For each power plant, we regress the dependent variable on the contemporaneous electricity load in each of the regions within the power plant's interconnection. In order to examine charging times, the coefficients on load vary by hour of the day. The regression includes fixed effects for each hour of the day interacted with the month of the sample. For power plant i and time t, we

[9] See http://www.nerc.com/AboutNERC/Documents/NERC%20Overview%20AUG13.pdf for a description of NERC regions. We model the Eastern interconnection as the six NERC regions FRCC, MRO, NPCC, RFC, SERC, and SPP, the Western interconnection as California and the rest of the WECC, and the Texas interconnection is simply the coterminous ERCOT.

[10] More details about this data are given in the Appendix.

regress:

$$y_{it} = \sum_{h=1}^{24} \sum_{j=1}^{J(i)} \beta_{ijh} HOUR_h REGION_j LOAD_{jt} + \sum_{h=1}^{24} \sum_{m=1}^{12} \alpha_{ihm} HOUR_h MONTH_m + \varepsilon_{it}, \qquad (1)$$

where $J(i)$ equals the number of regions in the interconnection in which power plant i is located, $HOUR_h$ is an indicator variable for hour of the day h, $REGION_j$ indicates electricity region j, $MONTH_m$ indicates month of the sample m, and $LOAD_{jt}$ is the electricity consumed in region j at time t. The main coefficients of interest are β_{ijh}, which represents the marginal change in emissions at plant i from an increase in electricity usage in region j in hour h. The collection of the β_i for a given j and h captures the increase in emissions from charging an electric vehicle in region j in hour h.

3.3 Air Pollution Damages

For CO_2, we estimate damages by using the EPA social cost of carbon.[11] For the other pollutants, we estimate damages by using the AP2 model. AP2 uses an air quality module to map the emissions by sources into ambient concentrations of pollutants at receptor locations, an economic valuation module to map the ambient concentrations of pollutants into monetary damages, and finally an algorithm module to determine the marginal damages associated with emissions of any given source.[12]

With the marginal damages from AP2 in hand, we can turn to the question of calculating the marginal damages from operating gasoline and electric vehicles. In either case, the basic unit of account is the county (although we can aggregate up to the MSA or state if desired). For gasoline vehicles, we simply multiply the emissions rates (e.g., in tons of NO_X per mile) for a given vehicle in a given county by the marginal damages (e.g., in \$ per ton of NO_X) from the AP2 model (or by \$35 per ton for CO_2). We then sum the damages across pollutants to estimate the damage per mile of a vehicle in each county.

For electric vehicles, the results from estimation of the econometric model above are

[11] We use a value of \$35/ton (in year 2000 dollars), which is in the midrange of the EPA estimates. See http://www.epa.gov/climatechange/EPAactivities/economics/scc.html.

[12] See Muller, 2011; 2012; 2014. The AP2 model is an updated version of the APEEP model (Muller and Mendelsohn 2007; 2009; 2012; NAS NRC 2010; Muller, Mendelsohn, Nordhaus 2011; Henry, Muller, Mendelsohn 2011). More details of our implantation of AP2 are given in the Appendix.

coupled with the marginal damage estimates produced by AP2. Specifically, consider an electric vehicle charged in a given county. The county is located in a specific NERC region. The increase in the electric load in that region is based on the vehicle's efficiency, i.e., in kWh per mile. Our econometric model estimates the responses in terms of emissions at all the power plants in the interconnection, e.g., in terms of tons of NO_X per MWh. The AP2 model evaluates the damages resulting from the additional emissions at each of the power plants, e.g., in terms of $ per ton of NO_X. The damages from operating an electric vehicle are then the product of the marginal emissions rate and the marginal damages summed across all pollutants and all power plants in the interconnection.

We also use the AP2 model in a novel way to calculate native and external damages. Since the model calculates the damages at each receptor, we can disaggregate the plume of damages across all counties, i.e., we can calculate receptor-specific marginal damages. For example, we can calculate the marginal damages to Orange County from a vehicle in Los Angeles County. For a gasoline vehicle in Los Angeles County, the damages to Orange County are governed by the source-receptor relationship between Los Angeles County and Orange County. For an electric vehicle in Los Angeles County, the increase in electricity load causes changes at power plants throughout the Western interconnection. The damages in Orange County are then governed by the source-receptor relationships between Orange County and each of the affected power plants. The receptor-specific marginal damages allow us to estimate the percentage of emissions are exported across counties and states.

3.4 Vehicle miles travelled (VMT)

The above procedures allow us to calculate the marginal damage per mile for a specific vehicle in a specific county. To analyze any policy which affects multiple counties, we need a sense of the relative importance of the counties. In the theoretical model, we used α_i (the number of new vehicle buyers) for this purpose. In the empirical part of the paper, we use Vehicle Miles Travelled (VMT).[13] We collect VMT data by county and vehicle class

[13] These two concepts are essentially equivalent under the assumptions that vehicles are driven about the same number of miles per year in each county, and vehicles last the same number of years in each county as well.

estimated by the USEPA for their Motor Vehicle Emission Simulator (MOVES) model.

4 Results

All of our results are in terms of year 2000 dollars.

4.1 Damages from electric vehicles

Table 1 shows the damages per mile across the 9 NERC regions for a 2014 Ford Focus EV as a function of various charing profiles. There is roughly an order of magnitude difference between the NERC regions with the largest and smallest marginal damages. This difference is generally robust across the various charging profiles. The lowest marginal damages tend to occur during normal business hours. This is unfortunate as it is widely assumed (for example in the EPRI charging profile) that the vast majority of electric vehicles will be charged at night. We use the EPRI charging profile for all subsequent calculations. Table 2 shows the damages per mile NERC region level level corresponding to each of the 2014 model year electric vehicles that have been given an EPA fuel economy sticker. The electric vehicle with the highest average damages (BYD e6) is 100 percent dirtier than the electric vehicle with the lowest average damages (Chevy Spark EV). For subsequent calculations, the damages from driving and electric vehicle in a given county are assigned the value for damages from the NERC region in which that county is located.

4.2 Electric vehicles vs. gasoline vehicles

Assuming both vehicles are driven the same distance in their lifetime, the environmental benefit of an electric vehicle is simply the difference between the damages caused by the electric vehicle and the damages caused by the forgone gasoline vehicle. Table 3 shows the county level results by vehicle. (As described above, for each electric vehicle we selected a companion gasoline vehicle to serve as the forgone vehicle.) Many of the averages in this table are negative. In the average county, most electric vehicles lead to greater damages than the forgone gasoline vehicle. The distributions are skewed however, as in each case the median is less than the mean. In a small number of places, electric vehicles are a very good idea.

Data at the MSA further illustrate this point, as shown Table 4. In this table, and all subsequent tables, we use the Ford Focus as the standard vehicle of comparison. The value for a given MSA is determined by the weighted average of environmental benefits across counties in the MSA, with the weights given by VMT. Communities in California are generally characterized as having large damages from gasoline vehicles and a clean electric grid. Hence electric vehicles generate considerable environmental benefit. In contrast, in the Upper Midwest these conditions are reversed, and electric vehicles impose significant environmental costs.

It is also interesting to consider states as the jurisdictional unit. Indeed, many states have implemented subsidies for the adoption of electric vehicles, above and beyond the federal subsidy.[14] Table 5 present the environmental benefit of an electric vehicle across states. The value for a given state is determined by the weighted average of environmental benefits across counties in the state, with the weights given by VMT. Generally speaking, the environmental benefit of an electric vehicle is large and positive in many western states, and large and negative in the Midwest. The overall average for the entire United States is slightly negative.

Using Proposition 2, we can convert the environmental benefit per mile of an electric vehicle into the optimal subsidy on the purchase of an electric vehicle. Figure 1 shows the optimal subsidy for each county in the contiguous U.S. for the Ford Focus. Except for a few counties around New York City, Chicago, and Atlanta, the optimal subsidy is negative throughout the eastern part of the country. It is large and negative in the Upper Midwest. It is positive in most places in the west, and, consistent with the MSA data described above, large and positive in many counties in California. The optimal subsidies as the state level are given in the last column in Table 5. The values range from $2144 in California to -$2607 in North Dakota. There are only 12 states in which the optimal subsidy is positive.

[14]Six states offer a purchase subsidy: California ($2500), Colorado ($6000), Georgia ($5000), Illinois ($4000), Maryland ($3000), and Massachusetts ($2500). States also offer a variety of other subsides such as carpool lane access, electricity discounts, and parking benefits. A small number of states impose a special registration fee for electric vehicles.

The optimal uniform subsidy for the entire United States is -$424. In the average state, a 2014 Ford Focus electric causes $424 more environmental damages over its lifetime than the equivalent gas powered Ford Focus. With these results in mind, it is interesting to note that the current Federal subsidy for electric vehicles is $7500 (or $5440 in year 2000 dollars).

4.3 Exporting pollution: Full and native damages

As discussed in Section 2, using a vehicle in a given region may lead to damages within that region as well as surrounding region. So we found it useful to break up full damages (the sum of all the damages across all regions from driving a vehicle) into native damages (only damages within the given region) and exported damages (only damages to other regions).

Although both gasoline and electric vehicles export pollution to other regions, this occurs to a remarkable degree for electric vehicles. Before discussing numerical results, it is useful to make this point visually. Panel 1 in Figure 2 shows the change in $PM_{2.5}$ associated with driving a gasoline-powered Ford Focus for 150 million miles in Fulton County, Georgia. (Or equivalently, a fleet of 10,000 vehicles driven 15,000 miles each.) Most of the increase in $PM_{2.5}$ is centered within a few nearby counties, although there are small increases several states away. Panel 2 in Figure 2 shows the change in $PM_{2.5}$ associated with same number of miles driven by an electric powered Ford Focus that is charged in Fulton County, thereby increasing the production of electricity in the SERC region. Clearly the spatial footprint of the environmental externalities from driving is much greater with the electric vehicles than it is with the gasoline vehicle. As shown in Figure 3 (Cook County Illinois) and Figure 4 (Los Angeles County California) this relationship holds throughout the country.

A corresponding numerical analysis is given in Tables 6-7. Table 6 shows that, at the county level, almost all of the damages due to driving an electric vehicle in a given county are exported to other counties. Even at the state level, ninety one percent of damages are exported to other states. In contrast, only fifty seven percent of gasoline damages are exported at the county level and only nineteen percent at the state level. So it is not surprising, when we account only for native damages, that electric vehicles now appear to provide positive environmental benefits in many more states and counties. As shown in Table 7, the state benefit for an electric vehicle, using native damages, is positive in 35 out of 49 states. This suggests that, insofar as politicians only care about damages within their jurisdiction, there will be motivation to subsidize electric vehicles in these places.

4.4 Welfare gains from differentiation

In Supplementary Appendix D, we describe our calibration procedure. With the calibrated model, we can analyze welfare gains from differentiated policies. Table 8 shows the results for a variety of policies and also shows the sensitivity of these results to the value of μ. (These are exact welfare calculations, not first or second order approximations.) For example, the "Welfare gain state specific vs uniform national" row shows benefit from adopting a state specific subsidy on the purchase of an electric vehicle rather than adopting a uniform federal subsidy. The overall message is that the benefits of differentiated policies are in the order of \$2-\$10 per new vehicle sold. To put this in context, annual vehicle sales in the United States are approximately 15 million. In addition, using the county as the jurisdiction rather than the state leads to about a fifteen percent improvement in welfare. Table 8 also includes considerations of native damages. As discussed above in conjunction with Corollary 1, a natural comparison is between state regulation with native damages and federal regulation with full damages. As shown in the "Welfare gain state specific (native) vs uniform" row, these two regulatory structures lead to roughly the same welfare. Notice that there is a non-monotonic relationship between the benefits of differentiation and the value of μ, but the model results do no appear to be very sensitive to the value of μ.

Differentiation can also be done by state governments. Here we compare the benefits of differentiation between the state and the county level, so we have 49 sets of results, one for each state. As can be seen in Table 9, these benefit are generally small, with the exception of states like California, NY, and South Dakota.[15] From Proposition 2, we know that the gains from differentiation will depend on the variance and skewness of the distribution for the difference between environmental damages across counties. Indeed, the reason that South Dakota generates relatively large benefits from differentiation is that, although most

[15]For a few states, the welfare gains from differentiation under native damages are slightly negative. This is due to the fact that the subsidy is determined using native damages but welfare is determined using full damages.

of the counties are connected to a relatively dirty electric grid, there are three counties in the southwest corner of the state that are connected to a much cleaner grid. Table 9 also lists the optimal state specific subsidy for the purchase of electric vehicles accounting for full damages, and the political economy subsidy (which accounts only for native damages). Consistent with previous results, the optimal state specific subsidy is positive in 12 states, but the political economy subsidy is positive in 34 states.

We also computed welfare calculations for taxes on miles. First consider a policy in which there are taxes on both gasoline miles and electric miles and these taxes are set at the Pigovian level (i.e. $t_e = \delta_e$ and $t_g = \delta_g$.) The results are shown in Table 10 and Table 11. Comparing Tables 8 to 10, as well as Tables 9 to 11, reveals that the welfare gains from differentiated taxes on miles are generally much greater than the welfare gains from differentiated taxes on the purchase of an electric vehicle. The benefits of differentiated tax policies are in the order of \$10-\$40 per new vehicle sold. Also of interest are the results in the "Welfare gain state specific (native) vs uniform" row in Table 10. Recall that we found very little differences between these two policies under purchase subsidies. In contrast, under taxes on fuel, the state specific policy performs significantly worse than the uniform policy. Table 10 also shows that the optimal federal tax on gasoline miles (1.535 cents per mile) is slightly less than the optimal federal tax on electric miles (1.819 cents per mile). This relationship does not hold as the state level, however, as shown in Table 11. For example, for California, the optimal tax on gasoline miles is 1.983 cents/mile, and the optimal tax on electric miles is 0.554 cents/mile. If California implemented county specific taxes rather than a uniform state wide tax, the welfare gain per vehicle would be over \$36. Again, this is much greater than the corresponding gain in California from implementing county specific purchase subsidies.

Next consider single tax policies. For a policy in which there is tax on gasoline miles only (electric miles are untaxed) and the baseline value for $\mu = 396.8$, the optimal federal tax on gasoline miles (1.426 cents per mile) is less than the optimal Pigovian tax on gasoline miles (1.535 cents per mile), as predicted by Proposition 3 in the Appendix. The welfare cost of using only a gasoline tax at the federal level instead of the Pigovian taxes on gasoline and electric miles is \$84 per vehicle. The welfare gain of a differentiated taxes on gasoline miles is \$7 per vehicle at the state level and \$17 per vehicle at the county level. For a policy in which there is a tax on electric miles only (gasoline miles are untaxed) and the baseline value for $\mu = 396.8$, the optimal federal tax on electric miles (1.237 cents per mile) is less than the optimal Pigovian tax on electric miles (1.819 cents per mile). The welfare cost of using only a electric tax at the federal level instead of the Pigovian taxes on gasoline and electric miles is \$433 per vehicle. The welfare gain of a differentiated taxes on electric miles is \$5.5 per vehicle at the state level and \$5.8 per vehicle at the county level.

5 Effects of other regulations

Up to this point, we have analyzed the environmental benefit of electric vehicles in isolation from other environmental regulations. In practice, these other regulations may impact the electricity market and/or the market for vehicles, and hence have an effect of the environmental benefit of electric vehicles.

For example, electric power plants in the Northeast are subject to two regional cap-and-trade emission permit markets. Emissions of NO_X are caped by an EPA program and emissions of CO_2 are capped by the Regional Greenhouse Gas Initiative. In our model of the electricity market, we determine the marginal increase in emissions due to an increase in the load on the electricity grid. We do not model the constraint that overall emissions are capped. This implies that our calculation of the environmental benefit of an electric vehicle in the Northeast is biased downward. However, it is likely that the effect of this bias is small. During the period of our analysis, the permit prices in both markets were quite low, which suggests that the constraints due to the cap were not very severe.

Another example is the Corporate Average Fuel Economy (CAFE) standards. Under CAFE, the sales-weighted harmonic mean of MPG for a given manufacturer's fleet of vehicles must meet a certain requirement. Electric vehicles are assigned a MPG equivalent for this calculation. These values are generally much larger than any existing gasoline vehicle. Assuming that the CAFE requirement is initially binding, selling an electric vehicle enables a manufacturer to meet a lower standard for the rest of their fleet. This implies an indirect effect of selling an electric vehicle is that environmental damage from the rest of the fleet may increase. Starting in 2017, this effect will be exacerbated, as the CAFE standards will treat electric vehicles even more generously. An electric vehicle sale will receive a multiplier, starting at 2 and then lowering over time. In other words, when a manufacturer sells an electric vehicle, they will get credit in the CAFE calculation as if they have sold two electric vehicles. This will enable them to decrease the fuel economy of the rest of their fleet even more.

A thorough analysis of the interaction between CAFE standards and electric vehicle sales would require a model of both supply and demand for the entire new vehicle market, because selling an electric vehicle enables a manufacturer to change the composition of their fleet. This has welfare effects for the consumers in the market, and, in addition, a change in the fleet composition actually changes the CAFE standard itself.[16] Incorporating these elements is beyond the scope of this paper, but we can give a preliminary analysis of the effect of CAFE standards on the environmental benefit of an electric vehicle that is consistent with our model. Let the CAFE induced environmental cost of an electric vehicle be defined as the increase in environmental damage from the rest of the fleet when an electric vehicle is sold. In Supplementary Appendix E we determine a simple formula for the CAFE induced environmental cost under both the current and 2017 CAFE standards. With respect to the 2017 CAFE standards, we show that double counting the electric vehicle more than doubles its CAFE induced environmental cost. And we show that the optimal subsidy on the purchase of an electric vehicle is decreased by the amount of the CAFE induced environmental cost. Applying our baseline values for the Ford Focus and Ford Focus EV, the CAFE induced environmental cost under current CAFE standards turns out to be \$1229. The magnitude of this is significant in comparison with even the largest optimal subsidy for an electric vehicle found in our study (\$2144, in California).

[16]The CAFE standard compares the sales weighted harmonic mean of actual MPG with a sales weighted harmonic mean of targeted MPG. The targeted MPG for each vehicle is based on its footprint.

6 Conclusion

Our analysis reveals an interesting property of electric vehicles. In the vast majority of states when a consumer opts for an electric vehicle rather than a gasoline vehicle, they improve the air pollution in their state. But at the same time, in all but twelve states, this purchase makes society as a whole worse off because electric vehicles tend to export air pollution to other states more than gasoline vehicles. Thus we would not be surprised to see a proliferation of state-specific subsidies for electric vehicles, even in states in which the overall environmental benefit of an electric vehicles is negative.

Of course, given the spatial heterogeneity in the benefits of an electric vehicles, spatial differences in policy are in fact appropriate, provided they account for all externalities, not just native ones. We find that differentiated taxes on miles driven lead to greater welfare increases than differentiated subsidies on vehicle purchases. This is not surprising, as economists have long recognized the superiority of putting a direct price on externalities relative to other indirect corrective policies. Unfortunately, this insight does not seem to have had much influence on policy, as political decision makers often implement indirect policies instead. A consequence of this predilection is that multiple indirect policies may target the same externalities, as is the case with CAFE standards and purchase subsidies on electric vehicles. Our preliminary analysis suggests that the interaction of these policies may have significant unintended consequences. It seems worthwhile to devote additional study to this issue.

There are several important caveats to our results. First, they are based on a simple snapshot of the electricity grid in the year 2011. We might expect the grid to become cleaner over time by integrating new lower-emission fuels and technologies. Of course, gasoline vehicles may become cleaner over time as well. The overall effect on the environmental benefit of electric vehicles will depend on the relative rates of changes of these two factors. Second, we have focused only on the environmental externalities. To the extent that there is a geo-political externality from gasoline use, our results understate the total benefits of electric vehicles. Third, we have only considered air pollution from use of the vehicle, we have not compared life-cycle emissions from manufacture and disposal of the vehicle. Fourth, we have focused on the marginal emissions from an increase in the demand for electric power due to electric vehicles charging. This is appropriate when the electricity demand for electric vehicles is a small fraction of overall electricity use. As electric vehicles become more commonplace, it may be more appropriate to look at average rather than marginal emissions.

Although we have focused on light-duty vehicles, there is a broader trend toward electrification of a variety of forms of transportation. Our methodology, which combines discrete-choice models, distributed electricity generation, and air pollution models, may yield a useful template for further analysis of the environmental consequences of this trend.

Figure 1 Optimal Subsidy by County for Ford Focus

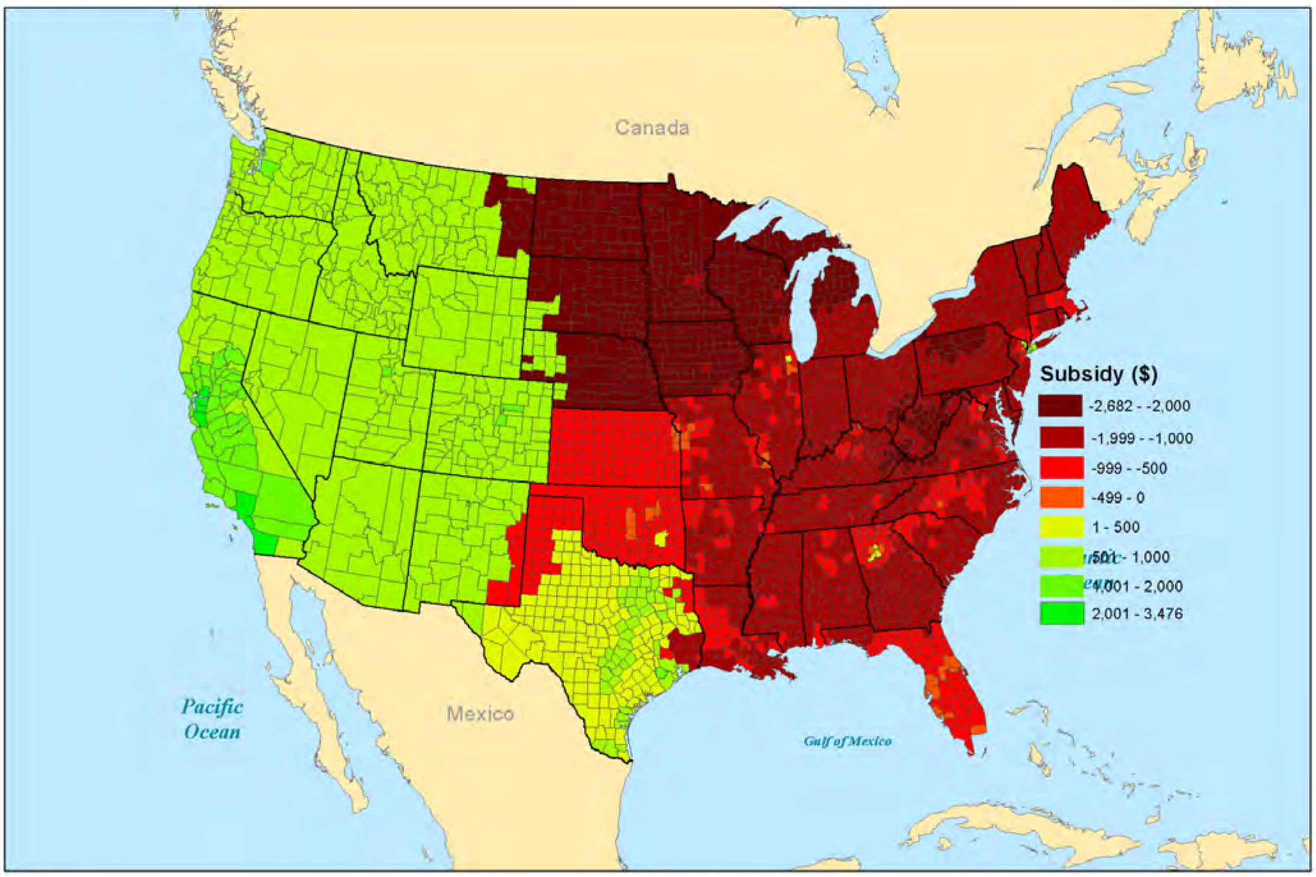

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Figure 2 Panel A: Change in $PM_{2.5}$ Preliminary Fulton County: 1000 ICE Focus

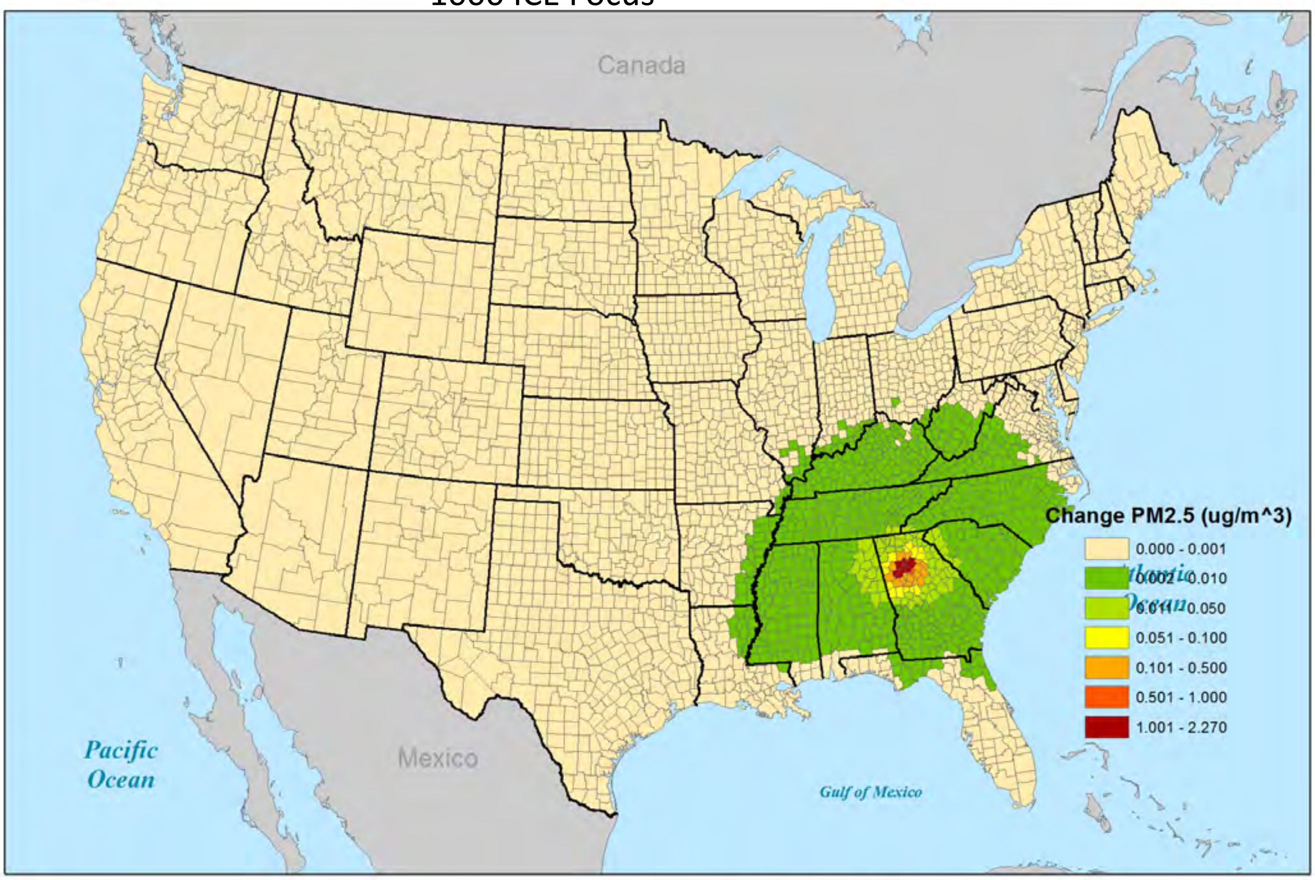

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Figure 2 Panel B: Change in $PM_{2.5}$: 1000 EV Focus in SERC Region

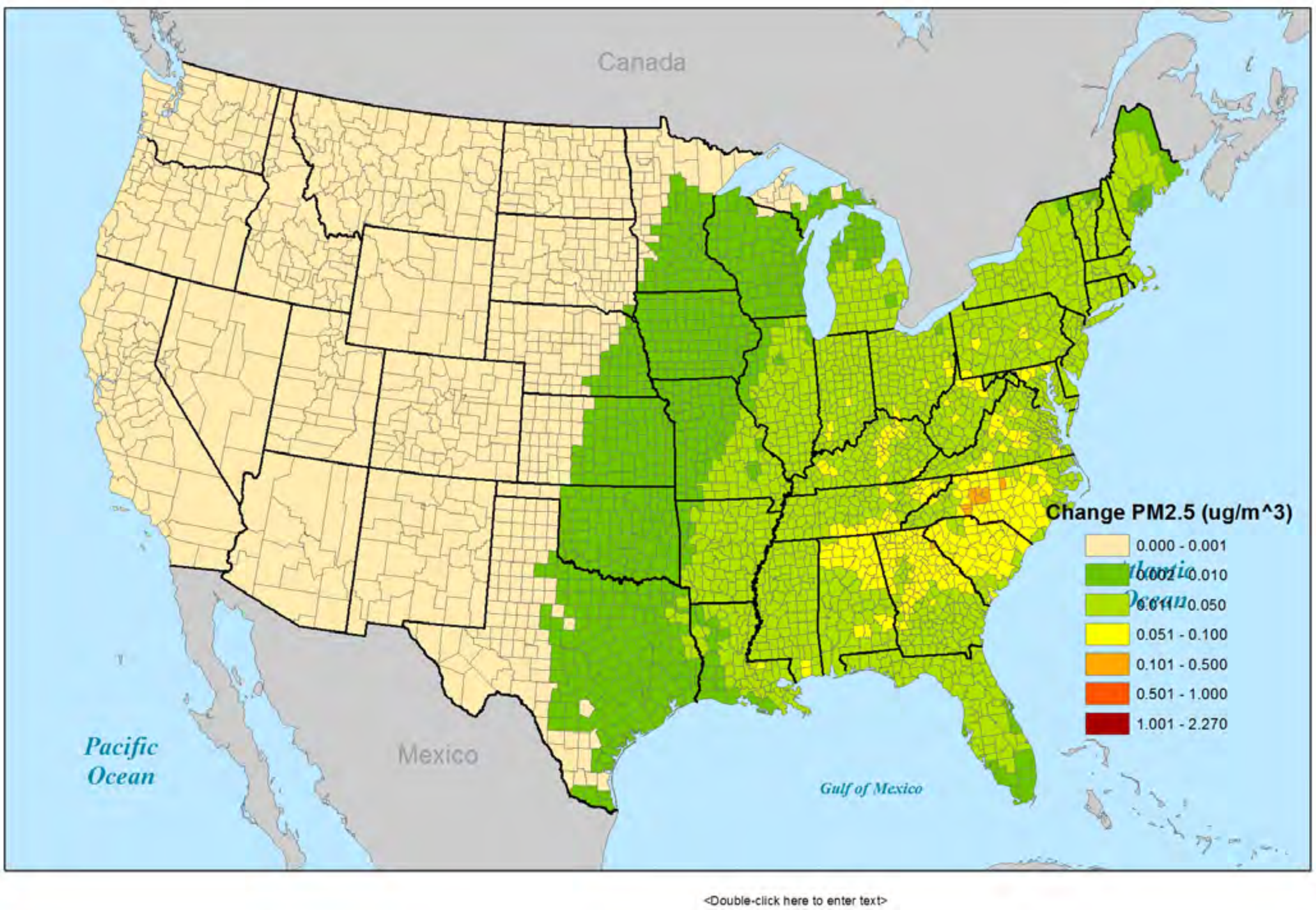

Figure 3 Panel A: Change in $PM_{2.5}$ Preliminary Cook County: 1000 ICE Focus

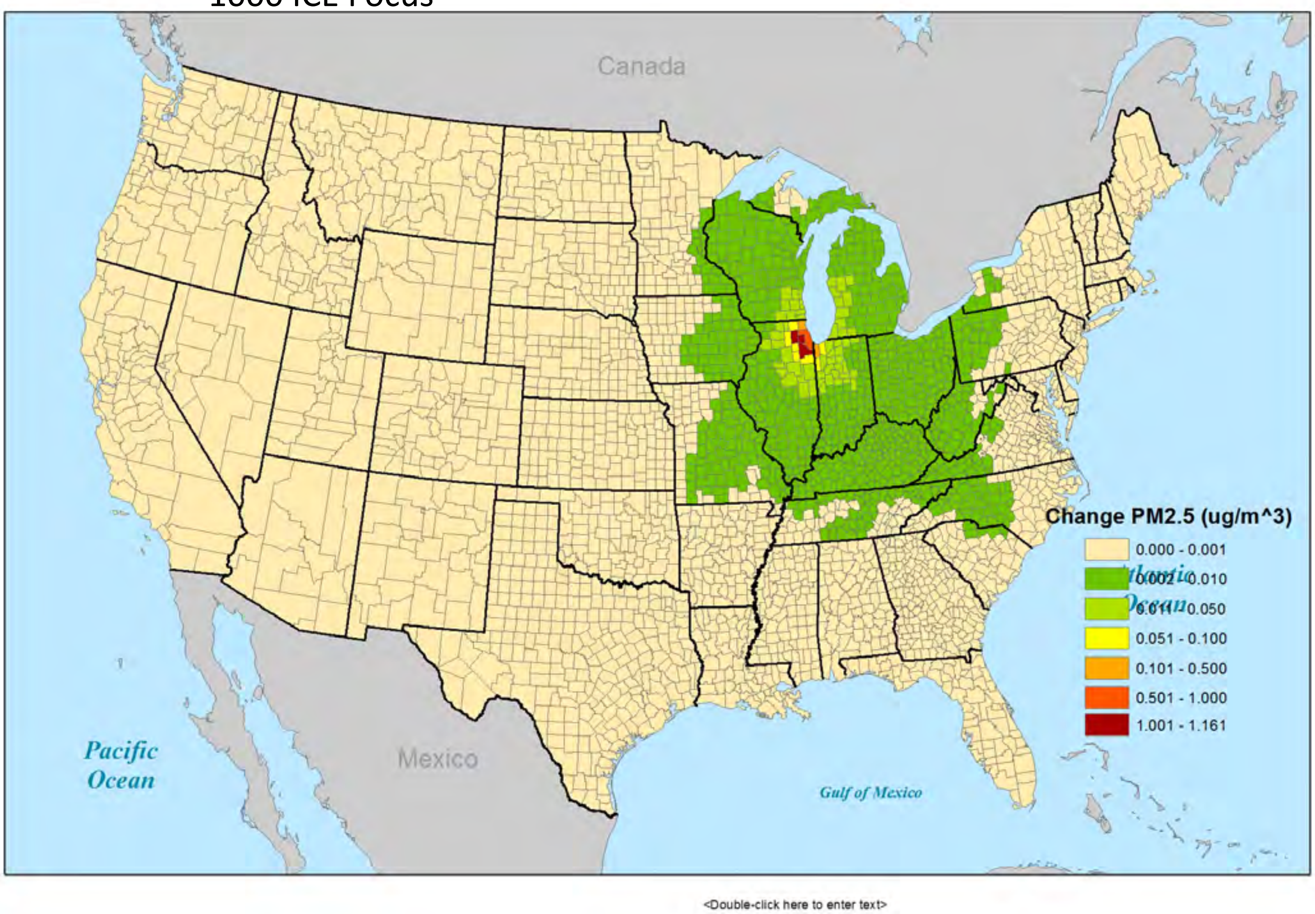

Figure 3 Panel B: Change in $PM_{2.5}$: 1000 EV Focus in RFC Region

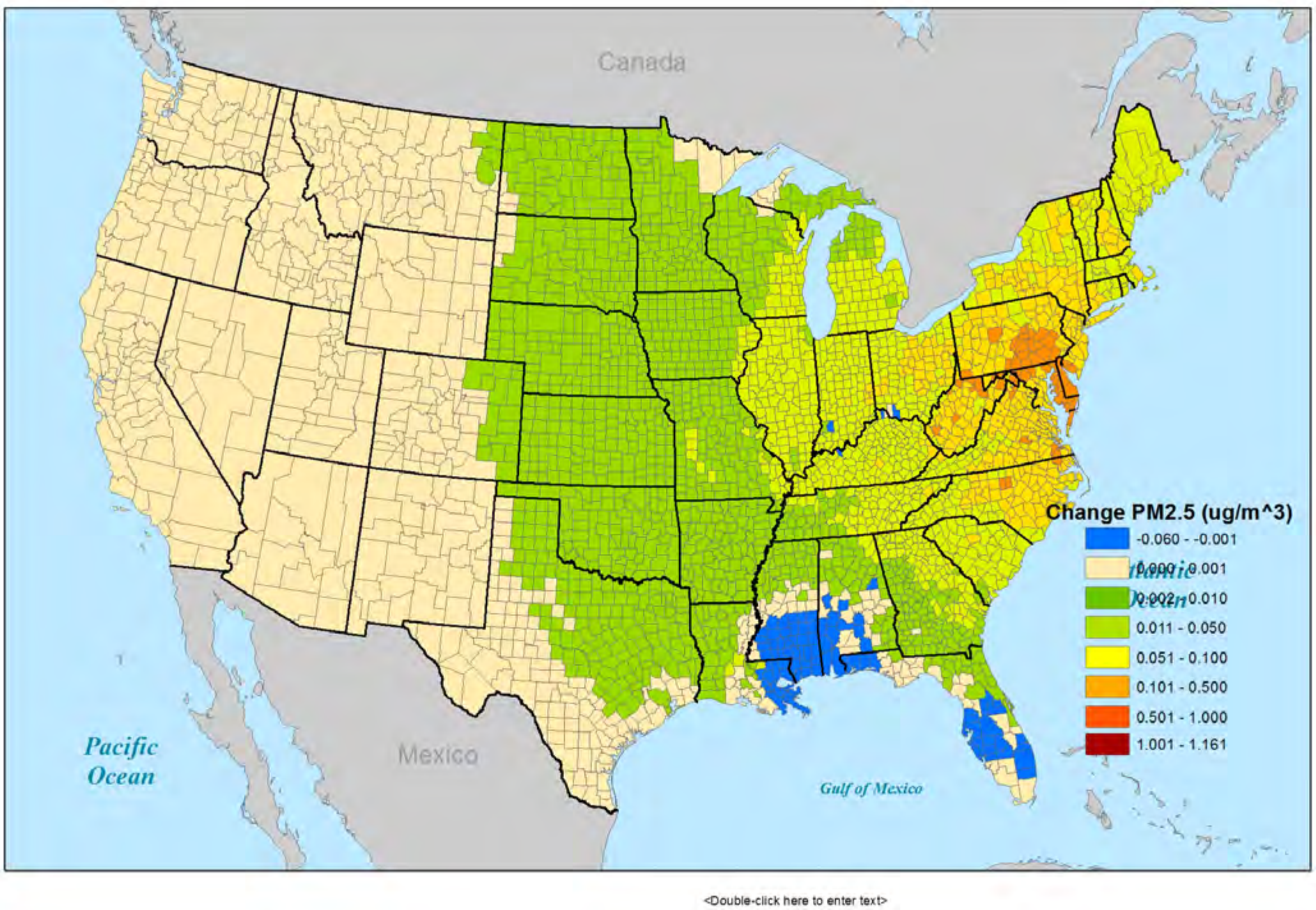

Figure 4 Panel A: Change in $PM_{2.5}$ Preliminary Los Angeles County: 1000 ICE Ford Focus

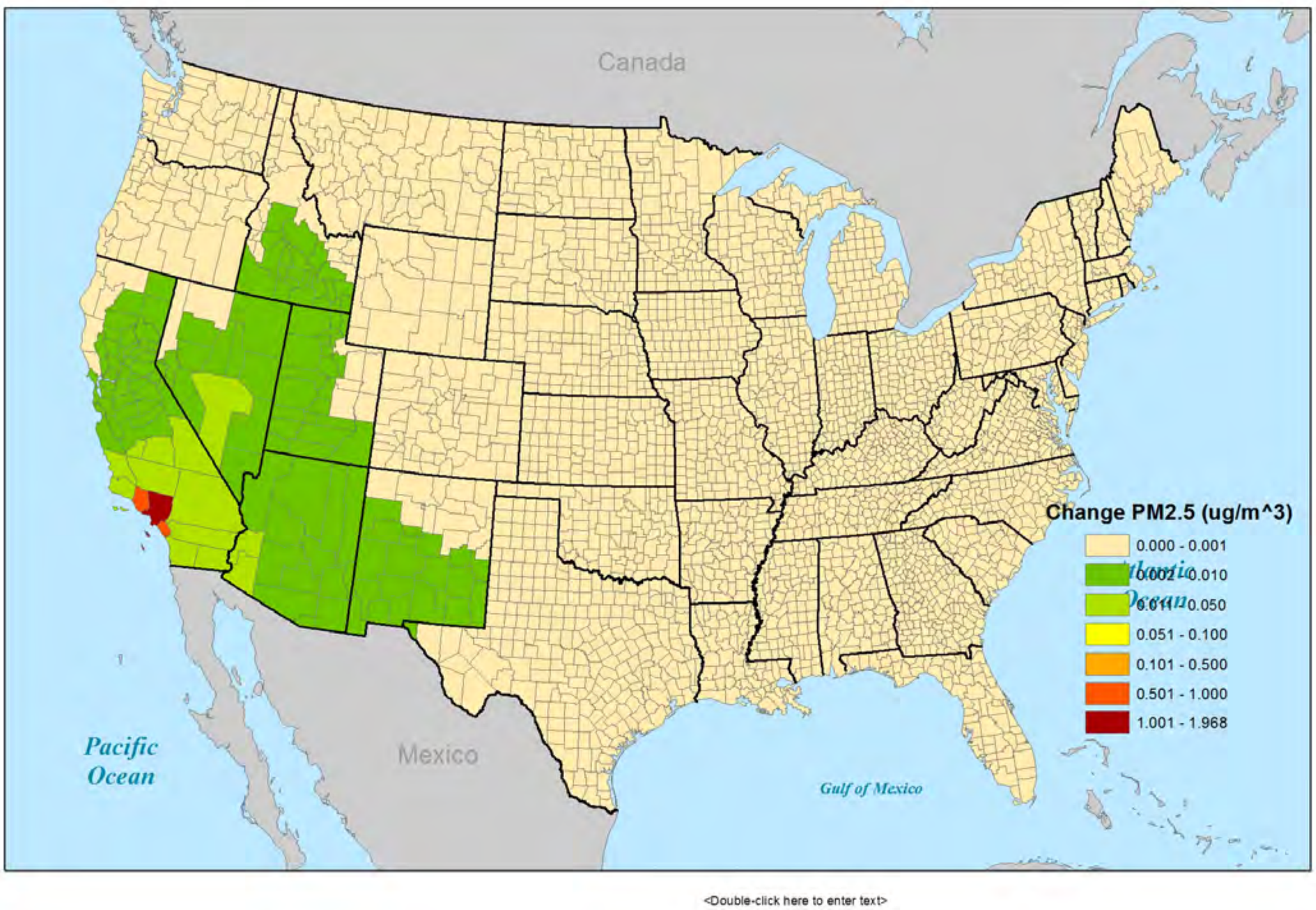

Figure 4 Panel B: Change in $PM_{2.5}$: 1000 EV Focus in CA Region

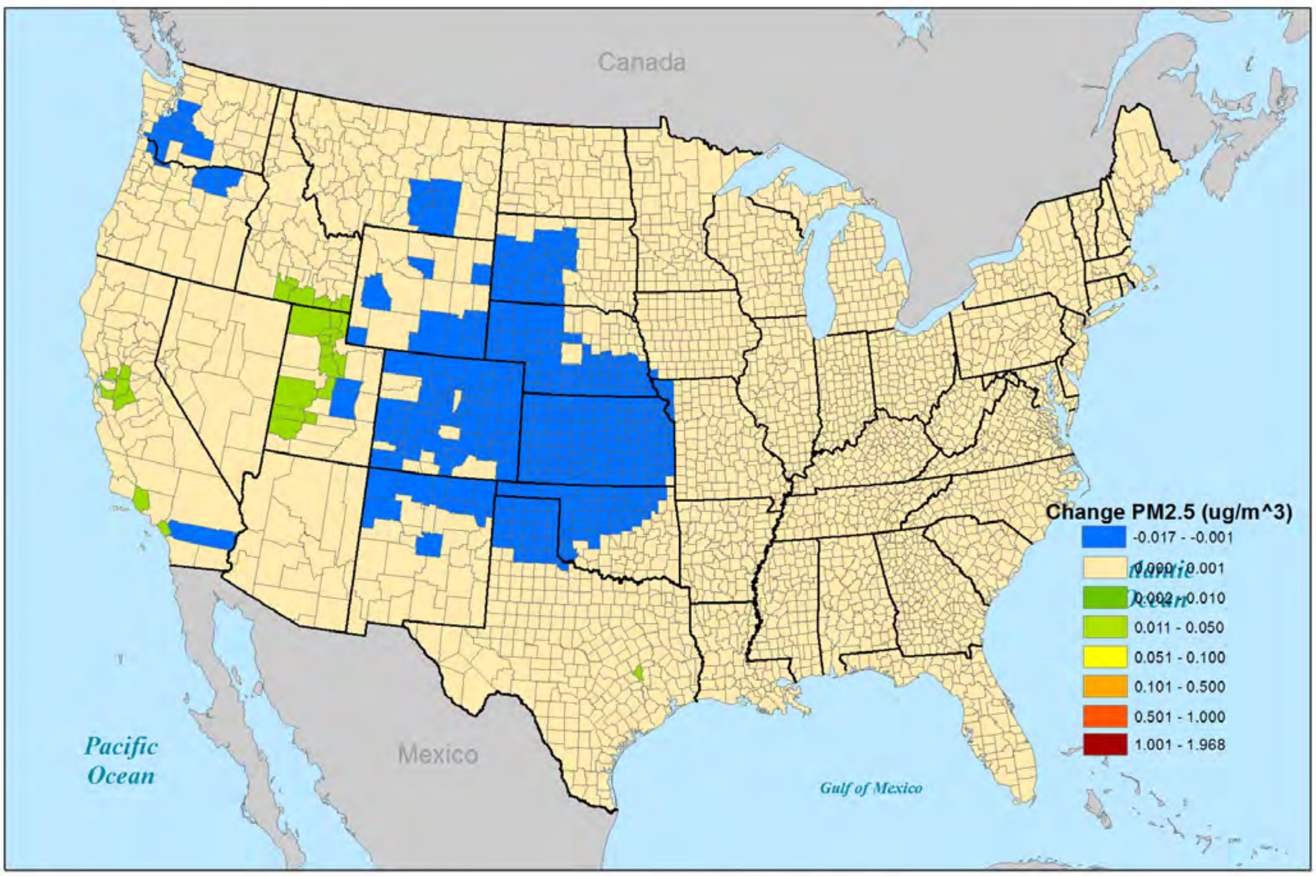

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Table 1: Damages per mile across NERC electricity regions for a 2014 Ford Focus EV for different charging profiles.

	Damage per mile								
Region	EPRI	Flat	Hr 1-4	Hr 5-8	Hr 9-12	Hr 13-16	Hr 17-20	Hr 21-24	VMT (bill)
California	\$0.006	\$0.006	\$0.005	\$0.006	\$0.006	\$0.007	\$0.007	\$0.005	182.93
WECC w/o CA	\$0.008	\$0.007	\$0.009	\$0.008	\$0.006	\$0.006	\$0.006	\$0.008	154.56
ERCOT	\$0.010	\$0.009	\$0.011	\$0.011	\$0.008	\$0.008	\$0.008	\$0.009	125.13
SPP	\$0.017	\$0.021	\$0.016	\$0.036	\$0.017	\$0.022	\$0.018	\$0.014	68.68
FRCC	\$0.018	\$0.016	\$0.024	\$0.018	\$0.017	\$0.011	\$0.012	\$0.016	102.57
SERC	\$0.020	\$0.020	\$0.020	\$0.017	\$0.020	\$0.022	\$0.020	\$0.020	375.40
NPCC	\$0.022	\$0.019	\$0.029	\$0.026	\$0.011	\$0.015	\$0.018	\$0.016	146.07
RFC	\$0.026	\$0.026	\$0.025	\$0.024	\$0.028	\$0.022	\$0.025	\$0.030	343.57
MRO	\$0.030	\$0.024	\$0.039	\$0.027	\$0.021	\$0.018	\$0.016	\$0.025	78.64
Total	\$0.018	\$0.017	\$0.020	\$0.018	\$0.017	\$0.016	\$0.016	\$0.018	1577.54

Notes: The regions are listed by the damage per mile under the "Flat" charging profile. The EPRI charging profile is illustrated in Appendix Figure 1. The flat charging profile assumes charging is equally likely across hours. Other profiles assume charging occurs only in the indicated hours. Damages are weighted by gasoline-car VMT by county.

Table 2: Distributions across NERC regions (counties) of damages per mile for 2014 electric vehicles

Vehicle	mean	med	std. dev.	min	max
Chevy Spark EV	$0.016	$0.018	$0.007	$0.005	$0.026
Honda Fit EV	$0.016	$0.018	$0.007	$0.005	$0.026
Fiat 500e	$0.016	$0.018	$0.007	$0.005	$0.027
Nissan Leaf	$0.017	$0.019	$0.007	$0.005	$0.027
Mitsubishi i-Miev	$0.017	$0.019	$0.007	$0.005	$0.028
Smart fortwo electric coupe	$0.018	$0.020	$0.007	$0.005	$0.029
Ford Focus Electric	$0.018	$0.020	$0.008	$0.006	$0.030
Tesla Model S (60 kW-hr)	$0.020	$0.022	$0.008	$0.006	$0.032
Tesla Model S (85 kW-hr)	$0.022	$0.024	$0.009	$0.007	$0.035
Toyota Rav4 EV	$0.025	$0.028	$0.011	$0.008	$0.041
BYD e6	$0.031	$0.034	$0.013	$0.009	$0.050

Notes: Damages are from power plant emissions of NOx, VOCs, PM2.5, SO2, and CO2e for electric cars assuming the EPRI charging profile. Damages are weighted by gasoline-car VMT by county.

Table 3: Distribution across counties of the environmental benefit per mile of an equivalent 2014 electric car

Vehicle	mean	med	std. dev.	min	max
Chevy Spark EV	-$0.0019	-$0.0045	$0.0082	-$0.0158	$0.0232
Honda Fit EV	$0.0003	-$0.0025	$0.0086	-$0.0141	$0.0275
Fiat 500e	-$0.0018	-$0.0046	$0.0087	-$0.0163	$0.0250
Nissan Leaf	-$0.0062	-$0.0088	$0.0082	-$0.0202	$0.0174
Mitsubishi i-Miev	-$0.0028	-$0.0056	$0.0086	-$0.0173	$0.0229
Smart fortwo electric	-$0.0037	-$0.0067	$0.0091	-$0.0191	$0.0239
Ford Focus Electric	-$0.0028	-$0.0056	$0.0089	-$0.0179	$0.0232
Tesla Model S (60 kW-hr)	$0.0005	-$0.0028	$0.0101	-$0.0163	$0.0314
Tesla Model S (85 kW-hr)	$0.0014	-$0.0022	$0.0108	-$0.0166	$0.0342
Toyota Rav4 EV	-$0.0073	-$0.0113	$0.0120	-$0.0274	$0.0266
BYD e6	-$0.0128	-$0.0176	$0.0142	-$0.0363	$0.0249

Notes: The environmental benefit is the difference in damages between a gasoline-powered car and the equivalent electric car. Equivalent cars are defined as the identical make where possible. The equivalent car for the Nissan Leaf is the Toyota Prius; for the Mitsubishi i-Miev is the Chevy Spark; for the Tesla Model S is the BMW 740 or 750; and for the BYD e6 is the Toyota Rav4. Environmental benefit is weighted by gasoline-car VMT by county.

Table 4: Top 10 and bottom 10 Metropolitan Statistical Areas by environmental benefit per mile for a 2014 Ford Focus (electric v. gasoline)

Metropolitan Statistical Area	Environmental benefit per mile	Total environmental benefit (billions)	VMT (billions)	Damage per mile (gasoline)	Damage per mile (electric)
Los Angeles-Long Beach-Santa Ana, CA	$0.023	$1.051	45.4	$0.029	$0.006
Oakland-Fremont-Hayward, CA	$0.017	$0.210	12.6	$0.022	$0.006
San Jose-Sunnyvale-Santa Clara, CA	$0.016	$0.145	9.1	$0.022	$0.006
San Francisco-San Mateo-Redwood City,CA	$0.015	$0.108	7.5	$0.020	$0.006
Santa Ana-Anaheim-Irvine, CA	$0.014	$0.220	15.7	$0.020	$0.006
San Diego-Carlsbad-San Marcos, CA	$0.014	$0.226	16.2	$0.019	$0.006
Vallejo-Fairfield, CA	$0.013	$0.036	2.7	$0.019	$0.006
Santa Cruz-Watsonville, CA	$0.012	$0.014	1.1	$0.018	$0.006
Stockton, CA	$0.011	$0.039	3.5	$0.017	$0.006
Napa, CA	$0.010	$0.005	0.5	$0.016	$0.006
Total	-$0.003	-$4.464	1577.5	$0.015	$0.018
Non-urban	-$0.007	-$2.128	301.1	$0.013	$0.020
Sheboygan, WI	-$0.017	-$0.007	0.4	$0.013	$0.030
Ames, IA	-$0.017	-$0.005	0.3	$0.013	$0.030
Wausau, WI	-$0.017	-$0.012	0.7	$0.013	$0.030
La Crosse, WI-MN	-$0.017	-$0.009	0.5	$0.013	$0.030
Sioux Falls, SD	-$0.017	-$0.017	1.0	$0.013	$0.030
Fargo, ND-MN	-$0.017	-$0.019	1.1	$0.012	$0.030
Sioux City, IA-NE-SD	-$0.017	-$0.012	0.7	$0.012	$0.030
Bismarck, ND	-$0.017	-$0.011	0.6	$0.012	$0.030
Grand Forks, ND-MN	-$0.017	-$0.009	0.5	$0.012	$0.030
Duluth, MN-WI	-$0.018	-$0.025	1.4	$0.012	$0.030

Notes: The environmental benefit is the difference in damages between the gasoline-powered Ford Focus and the electric Ford Focus. Environmental benefit is weighted by gasoline-car VMT by county within each MSA. Total environmental benefit multiplies environmental benefit by gasoline-car VMT. Non-urban includes all counties that are not part of an MSA.

Table 5: Environmental benefit per mile and Optimal Subsidy for a 2014 Ford Focus (electric v. gasoline)

State	Environmental benefit per mile	Total environmental benefit (billions)	VMT (billions)	Damage per mile (gasoline)	Damage per mile (electric)	Optimal Subsidy
California	$0.014	$2.64	184.6	$0.020	$0.006	$2,144
Utah	$0.007	$0.08	12.1	$0.015	$0.008	$1,043
Colorado	$0.006	$0.15	25.7	$0.014	$0.008	$883
Arizona	$0.006	$0.17	29.9	$0.013	$0.008	$835
Washington	$0.006	$0.13	23.0	$0.013	$0.008	$830
Nevada	$0.005	$0.07	13.1	$0.013	$0.008	$764
Oregon	$0.005	$0.08	15.7	$0.013	$0.008	$720
Idaho	$0.005	$0.03	7.2	$0.012	$0.008	$695
Wyoming	$0.004	$0.02	4.5	$0.012	$0.008	$659
New Mexico	$0.004	$0.06	12.9	$0.013	$0.009	$648
Texas	$0.004	$0.55	140.1	$0.014	$0.011	$593
Montana	$0.003	$0.02	5.9	$0.012	$0.009	$429
U.S. Average	-$0.003	-$4.46	1577.5	$0.015	$0.018	-$424
Oklahoma	-$0.003	-$0.08	24.9	$0.014	$0.017	-$482
Kansas	-$0.004	-$0.06	15.9	$0.013	$0.017	-$536
Florida	-$0.004	-$0.43	109.6	$0.015	$0.019	-$595
District of Columbia	-$0.004	-$0.01	2.3	$0.022	$0.026	-$598
New York	-$0.004	-$0.31	74.2	$0.018	$0.022	-$620
Georgia	-$0.004	-$0.25	57.5	$0.016	$0.020	-$644
Missouri	-$0.005	-$0.21	37.4	$0.014	$0.019	-$823
Illinois	-$0.006	-$0.21	36.8	$0.019	$0.024	-$856
North Carolina	-$0.006	-$0.24	38.4	$0.014	$0.020	-$930
Massachusetts	-$0.006	-$0.17	27.7	$0.015	$0.022	-$942
Arkansas	-$0.006	-$0.11	16.5	$0.013	$0.020	-$971
New Jersey	-$0.006	-$0.26	40.0	$0.020	$0.026	-$972
Louisiana	-$0.007	-$0.16	24.9	$0.013	$0.019	-$985
South Carolina	-$0.007	-$0.17	25.6	$0.014	$0.020	-$1,013
Tennessee	-$0.007	-$0.25	37.7	$0.014	$0.020	-$1,015
Kentucky	-$0.007	-$0.17	25.7	$0.014	$0.021	-$1,017
Alabama	-$0.007	-$0.23	34.2	$0.014	$0.020	-$1,031
Virginia	-$0.007	-$0.47	65.9	$0.014	$0.021	-$1,062
Mississippi	-$0.007	-$0.15	20.1	$0.013	$0.020	-$1,105
Connecticut	-$0.007	-$0.11	15.4	$0.014	$0.022	-$1,117
Rhode Island	-$0.008	-$0.04	5.5	$0.014	$0.022	-$1,151
New Hampshire	-$0.009	-$0.07	8.6	$0.013	$0.022	-$1,300
Maryland	-$0.009	-$0.27	29.1	$0.017	$0.026	-$1,386

Vermont	-$0.010	-$0.05	4.9	$0.012	$0.022	-$1,449
Maine	-$0.010	-$0.10	9.8	$0.012	$0.022	-$1,454
Ohio	-$0.011	-$0.77	72.2	$0.016	$0.026	-$1,599
Pennsylvania	-$0.011	-$0.59	53.8	$0.015	$0.026	-$1,634
Indiana	-$0.011	-$0.46	41.5	$0.015	$0.026	-$1,675
Delaware	-$0.011	-$0.04	3.8	$0.015	$0.026	-$1,686
Michigan	-$0.012	-$0.53	45.9	$0.015	$0.026	-$1,734
West Virginia	-$0.013	-$0.14	10.5	$0.013	$0.026	-$1,937
South Dakota	-$0.014	-$0.07	4.6	$0.012	$0.027	-$2,169
Wisconsin	-$0.015	-$0.39	26.1	$0.014	$0.029	-$2,218
Minnesota	-$0.015	-$0.39	26.0	$0.015	$0.030	-$2,257
Nebraska	-$0.016	-$0.16	9.8	$0.013	$0.029	-$2,388
Iowa	-$0.016	-$0.26	16.1	$0.013	$0.029	-$2,463
North Dakota	-$0.017	-$0.08	4.5	$0.012	$0.030	-$2,607

Notes: The environmental benefit is the difference in damages between the gasoline-powered Ford Focus and the electric Ford Focus. Environmental benefit is weighted by gasoline-car VMT within each state.

Table 6: Distribution across counties of native damages per mile for 2014 Ford Focus

Panel A: EPRI Load profile

Vehicle	Damages	mean	med	std. dev.	min	max
Electric	All	\$0.0182	\$0.0204	\$0.0076	\$0.0055	\$0.0297
	Non-GHG	\$0.0111	\$0.0131	\$0.0063	\$0.0011	\$0.0211
	State	\$0.0010	\$0.0011	\$0.0005	\$0.0003	\$0.0021
	Export %	91%	91%			90%
	County	\$0.0001	\$0.0001	\$0.0001	\$0.0000	\$0.0004
	Export %	99%	99%			98%
Gasoline	All	\$0.0154	\$0.0141	\$0.0038	\$0.0116	\$0.0326
	Non-GHG	\$0.0039	\$0.0026	\$0.0038	\$0.0001	\$0.0211
	State	\$0.0031	\$0.0019	\$0.0036	\$0.0000	\$0.0199
	Export %	19%	27%			5%
	County	\$0.0017	\$0.0008	\$0.0027	\$0.0000	\$0.0143
	Export %	57%	71%			32%
Env Ben	All	-\$0.0028	-\$0.0056	\$0.0089	-\$0.0179	\$0.0232
	Non-GHG	-\$0.0072	-\$0.0100	\$0.0077	-\$0.0208	\$0.0161
	State	\$0.0021	\$0.0009	\$0.0037	-\$0.0020	\$0.0179
	County	\$0.0015	\$0.0006	\$0.0026	-\$0.0004	\$0.0141

Note: “All” reports damages from all pollutants at all receptors. “Non-GHG” reports damages from local pollutants (i.e., excluding CO_2) at all receptors. “State” reports damages from local pollutants from receptors within the same state as the source. “County” reports damages from local pollutants from receptors within the same county as the source. “State Export %” reports the share of non-GHG damages which occur at receptors outside the state. “County Export %” reports the share of non-GHG damages which occur at receptors outside the county. Electric damages assume the EPRI charging profile. Damages are weighted by gasoline-car VMT.

Table 7: State benefit from electric cars for all states by environmental benefit per mile for a 2014 Ford Focus (electric v. gasoline)

State	Total benefit	Non-GHG pollutant benefit	State benefit	State gasoline damages	Gasoline export %	State electric damages	Electricity export %
California	$0.014	$0.007	$0.0074	$0.008	2%	$0.001	33%
Utah	$0.007	$0.001	$0.0027	$0.003	8%	$0.000	87%
Colorado	$0.006	$0.000	$0.0015	$0.002	18%	$0.000	88%
Arizona	$0.006	$0.000	$0.0013	$0.002	17%	$0.000	88%
Washington	$0.006	$0.000	$0.0015	$0.002	4%	$0.000	88%
Nevada	$0.005	-$0.001	$0.0007	$0.001	30%	$0.000	88%
Oregon	$0.005	-$0.001	$0.0007	$0.001	14%	$0.000	88%
Idaho	$0.005	-$0.001	$0.0002	$0.001	47%	$0.000	88%
Wyoming	$0.004	-$0.001	-$0.0001	$0.000	89%	$0.000	88%
New Mexico	$0.004	-$0.001	$0.0004	$0.001	49%	$0.000	89%
Texas	$0.004	-$0.001	$0.0019	$0.003	13%	$0.001	85%
Montana	$0.003	-$0.003	-$0.0001	$0.000	77%	$0.000	91%
Oklahoma	-$0.003	-$0.005	$0.0010	$0.002	28%	$0.000	94%
Kansas	-$0.004	-$0.006	$0.0006	$0.001	40%	$0.000	94%
Florida	-$0.004	-$0.009	$0.0014	$0.003	4%	$0.001	88%
District of Columbia	-$0.004	-$0.006	$0.0021	$0.003	69%	$0.001	93%
New York	-$0.004	-$0.010	$0.0032	$0.005	13%	$0.002	87%
Georgia	-$0.004	-$0.009	$0.0029	$0.004	12%	$0.001	91%
Missouri	-$0.005	-$0.009	$0.0006	$0.002	33%	$0.001	92%
Illinois	-$0.006	-$0.009	$0.0048	$0.006	15%	$0.001	93%
North Carolina	-$0.006	-$0.010	$0.0010	$0.002	20%	$0.001	91%
Massachusetts	-$0.006	-$0.012	$0.0012	$0.003	18%	$0.002	87%
Arkansas	-$0.006	-$0.010	-$0.0001	$0.001	47%	$0.001	92%
New Jersey	-$0.006	-$0.009	$0.0035	$0.005	44%	$0.001	93%
Louisiana	-$0.007	-$0.010	$0.0000	$0.001	24%	$0.001	92%
South Carolina	-$0.007	-$0.011	$0.0002	$0.001	35%	$0.001	91%
Tennessee	-$0.007	-$0.011	$0.0003	$0.001	31%	$0.001	91%
Kentucky	-$0.007	-$0.011	$0.0004	$0.002	41%	$0.001	92%
Alabama	-$0.007	-$0.011	$0.0002	$0.001	31%	$0.001	91%
Virginia	-$0.007	-$0.011	$0.0003	$0.002	45%	$0.001	92%
Mississippi	-$0.007	-$0.012	-$0.0002	$0.001	39%	$0.001	91%
Connecticut	-$0.007	-$0.014	-$0.0004	$0.002	44%	$0.002	87%
Rhode Island	-$0.008	-$0.014	-$0.0005	$0.002	40%	$0.002	87%
New Hampshire	-$0.009	-$0.015	-$0.0013	$0.001	57%	$0.002	87%
Maryland	-$0.009	-$0.011	$0.0022	$0.003	38%	$0.001	93%
Vermont	-$0.010	-$0.016	-$0.0018	$0.000	62%	$0.002	87%

Maine	-$0.010	-$0.016	-$0.0016	$0.000	33%	$0.002	87%
Ohio	-$0.011	-$0.013	$0.0020	$0.003	22%	$0.001	93%
Pennsylvania	-$0.011	-$0.013	$0.0016	$0.003	29%	$0.001	93%
Indiana	-$0.011	-$0.013	$0.0012	$0.002	34%	$0.001	93%
Delaware	-$0.011	-$0.013	-$0.0000	$0.001	70%	$0.001	93%
Michigan	-$0.012	-$0.014	$0.0015	$0.003	19%	$0.001	93%
West Virginia	-$0.013	-$0.015	-$0.0003	$0.001	58%	$0.001	93%
South Dakota	-$0.014	-$0.018	-$0.0007	$0.000	77%	$0.001	95%
Wisconsin	-$0.015	-$0.017	$0.0004	$0.001	35%	$0.001	95%
Minnesota	-$0.015	-$0.018	$0.0016	$0.003	17%	$0.001	95%
Nebraska	-$0.016	-$0.019	$0.0000	$0.001	36%	$0.001	95%
Iowa	-$0.016	-$0.019	-$0.0004	$0.001	57%	$0.001	95%
North Dakota	-$0.017	-$0.020	-$0.0008	$0.000	82%	$0.001	95%

Note: Benefit is the difference between gasoline and electric damages. Total benefit includes all pollutants at all receptors. Non-GHG benefit includes only local pollutants at all receptors. State gasoline damages, state electric damages, and state benefit include only local pollutants at receptors within the state. “Export %” reports the share of non-GHG damages which occur at receptors outside the state. Export % is “NA” if non-GHG damages are negative.

Table 8: Benefits of Differentiation: Federal vs. State or County, Purchase Subsidy

	μ = 254.2	μ = 396.8	μ = 531.7	μ = 842.8	μ = 1378.8	μ = 2881.4
Probability of Gas Car Adoption	0.991	0.953	0.905	0.805	0.704	0.602
Welfare gain state specific vs uniform	1.966	6.032	8.539	9.608	7.728	4.233
Welfare gain county specific vs uniform	2.339	7.065	9.939	11.123	8.924	4.882
Improvement: County vs State	19%	17%	16%	16%	15%	15%
Welfare gain state specific (native) vs uniform	-0.021	-0.142	-0.251	-0.336	-0.292	-0.166
Welfare gain county specific (native) vs uniform	0.292	0.724	0.917	0.915	0.688	0.364
Welfare gain state specific vs state specific (native)	1.987	6.175	8.790	9.945	8.020	4.399
Welfare gain: county specific vs county specific (native)	2.047	6.341	9.021	10.208	8.235	4.518

Note: Welfare units are dollars per new car sale. The optimal uniform subsidy on electric car purchase Is -$424.

Table 9: Benefits of Differentiation: State vs. County, Purchase Subsidy

	Full Damages		Native Damages	
State	Optimal State Specific Purchase Subsidy	Within State Welfare Gain County Specific vs. State Specific	Political Economy Purchase Subsidy	Within State Welfare Gain County Specific vs. State Specific
Alabama	-1031	0.0341	39	0.0302
Arizona	835	0.0835	199	0.0836
Arkansas	-971	0.1755	-18	0.0487
California	2144	4.3438	1115	4.2951
Colorado	883	0.1672	236	0.1665
Connecticut	-1117	0.0420	-73	0.0148
Delaware	-1686	0.0369	-9	0.0267
District of Columbia	-598	0.0000	326	0.0000
Florida	-595	0.2327	218	0.2183
Georgia	-644	1.0121	439	0.9948
Idaho	695	0.0146	39	0.0105
Illinois	-856	1.0554	733	-0.0567
Indiana	-1675	0.1081	186	0.0622
Iowa	-2463	0.2562	-64	0.0160
Kansas	-536	0.0888	95	0.0865
Kentucky	-1017	0.4174	71	0.1938
Louisiana	-985	0.1769	8	0.0373
Maine	-1454	0.0065	-253	0.0055
Maryland	-1386	0.3683	341	0.2123
Massachusetts	-942	0.1714	180	0.1655
Michigan	-1734	0.1495	226	0.1330
Minnesota	-2257	0.2970	240	0.2654
Mississippi	-1105	0.0158	-31	0.0084
Missouri	-823	0.2916	102	0.1691
Montana	429	2.3087	-26	0.1887
Nebraska	-2388	1.0000	5	0.0486
Nevada	764	0.0405	111	0.0397
New Hampshire	-1300	0.0276	-208	0.0121
New Jersey	-972	1.7272	532	1.2428
New Mexico	648	0.6467	60	0.1234
New York	-620	3.4719	488	3.4571
North Carolina	-930	0.1056	153	0.1027
North Dakota	-2607	0.0011	-129	0.0008
Ohio	-1599	0.1394	310	0.1204
Oklahoma	-482	0.0993	156	0.0404
Oregon	720	0.0518	108	0.0506

Pennsylvania	-1634	0.2606	242	0.2539
Rhode Island	-1151	0.0451	-77	0.0423
South Carolina	-1013	0.0600	39	0.0474
South Dakota	-2169	4.0031	-110	0.3391
Tennessee	-1015	0.0419	49	0.0402
Texas	593	0.9849	290	0.4340
Utah	1043	0.9479	408	0.9375
Vermont	-1449	0.0008	-276	-0.0006
Virginia	-1062	0.7240	58	0.2748
Washington	830	0.2002	231	0.1996
West Virginia	-1937	0.0392	-55	-0.0062
Wisconsin	-2218	0.4503	67	0.3139
Wyoming	659	0.0019	-27	0.0005

Note: Welfare units are dollars per new car sale.

Table 10: Benefits of Differentiation: Federal vs. State or County, Taxes on Fuel

	μ = 254.2	μ = 396.8	μ = 531.7	μ = 842.8	μ = 1378.8	μ = 2881.4
Probability of Gas Car Adoption	0.989	0.948	0.897	0.797	0.698	0.599
Welfare gain state specific vs uniform	7.432	11.228	15.315	22.560	29.146	35.391
Welfare gain county specific vs uniform	17.339	20.999	24.795	31.292	37.019	42.348
Welfare gain state specific (native) vs uniform	-257.706	-283.380	-315.390	-379.319	-443.125	-506.891
Welfare gain county specific (native) vs uniform	-249.606	-275.483	-307.814	-372.490	-437.120	-501.756
Welfare gain state specific vs state specific (native)	265.139	294.608	330.705	401.879	472.270	542.282
Welfare gain county specific vs county specific (native)	266.945	296.483	332.608	403.782	474.139	544.105

Note: Welfare units are dollars per new car sale. Optimal uniform gas tax is \$0.015. Optimal uniform electric tax is \$0.018.

Table 11: Benefits of Differentiation: State vs. County, Taxes on Fuel

	Full Damages			Native Damages		
State	Optimal State Specific Gas Tax	Optimal State Specific Electric Tax	Within State Welfare Gain County Specific vs. State Specific	Optimal State Specific Gas Tax	Optimal State Specific Electric Tax	Within State Welfare Gain County Specific vs. State Specific
Alabama	0.0135	0.0204	0.5931	0.0014	0.0011	0.3925
Arizona	0.0134	0.0078	1.1126	0.0016	0.0003	0.7761
Arkansas	0.0131	0.0196	0.6606	0.0009	0.0010	0.1384
California	0.0198	0.0055	36.0349	0.0082	0.0008	29.9929
Colorado	0.0137	0.0078	2.1498	0.0018	0.0003	1.6605
Connecticut	0.0143	0.0218	0.7217	0.0016	0.0021	0.1797
Delaware	0.0150	0.0263	0.6763	0.0011	0.0011	0.5930
District of Columbia	0.0223	0.0263	0.0000	0.0033	0.0011	0.0000
Florida	0.0145	0.0185	2.7963	0.0029	0.0015	2.0676
Georgia	0.0161	0.0204	14.4144	0.0041	0.0011	11.5048
Idaho	0.0125	0.0078	0.2043	0.0005	0.0003	0.0549
Illinois	0.0186	0.0243	26.2631	0.0060	0.0011	18.7686
Indiana	0.0151	0.0263	1.9352	0.0024	0.0011	0.5079
Iowa	0.0129	0.0293	0.3802	0.0006	0.0010	0.1001
Kansas	0.0133	0.0169	1.4259	0.0011	0.0005	1.3491
Kentucky	0.0142	0.0210	3.2522	0.0016	0.0011	2.6375
Louisiana	0.0128	0.0194	0.5927	0.0010	0.0009	0.4268
Maine	0.0121	0.0218	0.1272	0.0004	0.0021	0.1091
Maryland	0.0170	0.0263	5.9945	0.0034	0.0011	2.7704
Massachusetts	0.0155	0.0218	2.7518	0.0033	0.0021	2.3822
Michigan	0.0147	0.0263	2.3141	0.0026	0.0011	1.7688
Minnesota	0.0147	0.0297	5.9163	0.0026	0.0010	4.5483
Mississippi	0.0130	0.0204	0.2819	0.0009	0.0011	0.0321
Missouri	0.0140	0.0194	2.3230	0.0016	0.0010	1.8777
Montana	0.0121	0.0092	2.7157	0.0001	0.0003	0.6509
Nebraska	0.0131	0.0290	2.4529	0.0010	0.0010	1.5632
Nevada	0.0129	0.0078	0.5571	0.0010	0.0003	0.4739
New Hampshire	0.0131	0.0218	0.5121	0.0007	0.0021	0.2356
New Jersey	0.0198	0.0263	21.7024	0.0047	0.0011	19.1698
New Mexico	0.0128	0.0085	1.3194	0.0007	0.0003	0.4043
New York	0.0176	0.0218	42.4079	0.0053	0.0021	36.5061
North Carolina	0.0142	0.0204	1.7536	0.0022	0.0011	1.3811
North Dakota	0.0123	0.0297	0.0258	0.0001	0.0010	0.0193
Ohio	0.0156	0.0263	2.4470	0.0032	0.0011	1.6425
Oklahoma	0.0136	0.0168	1.0523	0.0015	0.0005	0.5232

Oregon	0.0126	0.0078	0.7160	0.0010	0.0003	0.5688
Pennsylvania	0.0154	0.0263	4.5711	0.0027	0.0011	4.2299
Rhode Island	0.0141	0.0218	0.7818	0.0015	0.0021	0.5682
South Carolina	0.0136	0.0204	1.0219	0.0014	0.0011	0.6528
South Dakota	0.0122	0.0267	3.4470	0.0002	0.0009	1.2549
Tennessee	0.0136	0.0204	0.7240	0.0015	0.0011	0.5718
Texas	0.0145	0.0105	3.6032	0.0026	0.0006	2.3150
Utah	0.0148	0.0078	11.3297	0.0030	0.0003	8.9513
Vermont	0.0121	0.0218	0.0161	0.0002	0.0021	-0.0176
Virginia	0.0143	0.0214	4.0741	0.0015	0.0011	3.2825
Washington	0.0134	0.0078	2.6126	0.0018	0.0003	1.9559
West Virginia	0.0133	0.0262	0.3998	0.0008	0.0011	-0.0705
Wisconsin	0.0138	0.0286	2.1858	0.0015	0.0010	1.8108
Wyoming	0.0122	0.0078	0.0273	0.0001	0.0003	0.0091

Note: Welfare units are dollars per new car sale.

Appendix

Optimal taxes on miles

Suppose the government 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 $t_g = \delta_g$ and $t_e = \delta_e$.

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 is given by*

$$t_g^* = \left(\delta_g + \delta_e \left(\frac{e}{-g\left(\frac{p}{g(p_g+t_g^*)}\frac{\varepsilon_g}{\varepsilon_G} + 1\right)} \right) \right),$$

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

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 car and thereby avoid taxation on the externalities they generate.

The welfare gains from differentiated taxes are given in Additional Appendix A.

Proof of the Propositions

We now turn to the proofs of the propositions.

We start with a few preliminary observations. Let $G = \pi g$ and $E = (1-\pi)e$. For a generic policy variable ρ we have

$$\frac{\partial \mathcal{W}}{\partial \rho} = \mu \left(\frac{1}{\exp(V_g/\mu) + \exp(V_e/\mu)} \right) \left(\frac{1}{\mu} \exp(V_g/\mu) \frac{\partial V_g}{\partial \rho} + \frac{1}{\mu} \exp(V_e/\mu) \frac{\partial V_e}{\partial \rho} \right) - \left(\delta_g \frac{\partial G}{\partial \rho} + \delta_e \frac{\partial E}{\partial \rho} \right),$$

which simplifies to

$$\frac{\partial \mathcal{W}}{\partial \rho} = \left((1-\pi)\frac{\partial V_e}{\partial \rho} + \pi \frac{\partial V_g}{\partial \rho}\right) - \left(\delta_g \frac{\partial G}{\partial \rho} + \delta_e \frac{\partial E}{\partial \rho}\right). \tag{2}$$

focg

From the definition of π we have

$$\frac{\partial \pi}{\partial \rho} = \frac{(\exp(V_g/\mu) + \exp(V_e/\mu))\exp(V_g/\mu)\frac{1}{\mu}\frac{\partial V_g}{\partial \rho} - \exp(V_g/\mu)(\exp(V_g/\mu)\frac{1}{\mu}\frac{\partial V_g}{\partial \rho} + \exp(V_e/\mu)\frac{1}{\mu}\frac{\partial V_e}{\partial \rho})}{(\exp(V_g/\mu) + \exp(V_e/\mu))^2}.$$

which simplifies to

$$\frac{\partial \pi}{\partial \rho} = \frac{\pi(1-\pi)}{\mu}\left(\frac{\partial V_g}{\partial \rho} - \frac{\partial V_e}{\partial \rho}\right). \tag{3}$$

dpi

Using this result we can derive the following

$$\frac{\partial G}{\partial \rho} = g\frac{\partial \pi}{\partial \rho} + \pi \frac{\partial g}{\partial \rho} = g\frac{\pi(1-\pi)}{\mu}\left(\frac{\partial V_g}{\partial \rho} - \frac{\partial V_e}{\partial \rho}\right) + \pi \frac{\partial g}{\partial \rho} \tag{4}$$

theg

and

$$\frac{\partial E}{\partial \rho} = -e\frac{\partial \pi}{\partial \rho} + (1-\pi)\frac{\partial e}{\partial \rho} = -e\frac{\pi(1-\pi)}{\mu}\left(\frac{\partial V_g}{\partial \rho} - \frac{\partial V_e}{\partial \rho}\right) + (1-\pi)\frac{\partial e}{\partial \rho}. \tag{5}$$

thee

With these in hand we turn to the proof of the Propositions.

Proof of Proposition 3.

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

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

and

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

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

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

Expected per capita tax revenue is given by

$$R = t_g \pi g$$

so

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

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 gas miles is

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

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

$$\varepsilon_G = \frac{\partial \pi}{\partial p}\frac{p}{\pi} = \frac{\pi(1-\pi)}{\mu}(\frac{\partial V_g}{\partial p} - \frac{\partial V_e}{\partial p})\frac{p}{\pi} = \frac{\pi(1-\pi)}{\mu}(-1-0)\frac{p}{\pi} = -(1-\pi)p/\mu.$$

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

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

■

Proof of Proposition 1. From the Envelope Theorem, we have

$$\frac{\partial V_g}{\partial s} = \frac{\partial R}{\partial s}$$

and

$$\frac{\partial V_e}{\partial s} = \left(\frac{\partial R}{\partial s} + 1\right).$$

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

$$\left(\frac{\partial R}{\partial s} - (1-\pi)\right) - \left(\delta_g\frac{\partial G}{\partial s} + \delta_e\frac{\partial E}{\partial s}\right) = 0.$$

Expected per-capita tax revenue is

$$R = -s(1-\pi).$$

So we have

$$\frac{\partial R}{\partial s} = -(1-\pi) + s\frac{\partial \pi}{\partial s}.$$

Substituting this into the first-order condition and simplifying gives

$$\left(s\frac{\partial \pi}{\partial s}\right) - \left(\delta_g \frac{\partial G}{\partial s} + \delta_e \frac{\partial E}{\partial s}\right) = 0. \tag{6}$$

focss

So the optimal s is given by

$$s = \frac{\delta_g \frac{\partial G}{\partial s} + \delta_e \frac{\partial E}{\partial s}}{\frac{\partial \pi}{\partial s}} \tag{7}$$

opts

From (4) and (5), we have

$$\frac{\partial G}{\partial s} = \frac{\partial g}{\partial s}\pi + g\frac{\partial \pi}{\partial s} = g\frac{\partial \pi}{\partial s},$$

and

$$\frac{\partial E}{\partial s} = \frac{\partial e}{\partial s}(1-\pi) - e\frac{\partial \pi}{\partial s} = -e\frac{\partial \pi}{\partial s},$$

where the second equality in both equations follows from the fact that there are no income effects, so $\frac{\partial g}{\partial s}$ and $\frac{\partial e}{\partial s}$ are equal to zero. Substituting these into the first-order condition for s and simplifying gives

$$s = (\delta_g g - \delta_e e).$$

■

Proof of Proposition 2. First consider the optimal uniform subsidy. Except for δ_{gi}, δ_{ei}, and α_i, the regions are identical, and the government is selecting the same subsidy for each region. Therefore, the values for e, g, and π will be same across regions. It follows that the per-capital welfare in region i is

$$\tilde{\mathcal{W}}_i = \mu\left(\ln(\exp(V_e/\mu) + \exp(V_g/\mu))\right) - (\delta_{gi}G - \delta_{ei}E).$$

The government wants to pick the value for s to minimize $\tilde{\mathcal{W}}(s) = \sum \alpha_i \tilde{\mathcal{W}}_i$. There is a single per-capita revenue expression

$$R = -(1-\pi)s$$

that applies to the budget constraint for each consumer in each region. It follows from (6) that the first-order condition for s is

$$\sum s\alpha_i \frac{\partial \pi}{\partial s} - \sum \alpha_i \left(\delta_{gi} \frac{\partial G}{\partial s} + \delta e_i \frac{\partial E}{\partial s} \right) = 0.$$

Which can be written as

$$s\frac{\partial \pi}{\partial s} - \left(\frac{\partial G}{\partial s} \sum \alpha_i \delta_{gi} + \frac{\partial E}{\partial s} \sum \alpha_i \delta e_i \right) = 0.$$

Solving for s gives the optimal single subsidy $\tilde{s}$

$$\tilde{s} = \frac{1}{\frac{\partial \pi}{\partial s}} \left(\bar{\delta}_g \frac{\partial G}{\partial s} + \bar{\delta}_e \frac{\partial E}{\partial s} \right). \tag{8}$$

singles

The equation in the Proposition now follows from the same manipulations used in the proof of Proposition 1. The value for welfare is $\tilde{\mathcal{W}}(\tilde{s})$.

Next consider the case in which each region i has subsidy s_i and per capita revenue $R_i = -(1-\pi_i)s_i$. As discussed in the main text, because there are no income effects, the values for e and g will not vary across regions. Let $\mathcal{W}(S)$ denote the weighted average of per capita welfare across regions as a function of the vector of taxes $S = (s_1, s_2, \ldots, s_n)$. We have

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

where $G_i = \pi_i g$ and $E_i = (1-\pi_i)e$. We now want to take the first and second derivatives of the regulator's objective with respect to s_i. Because $\frac{\partial \mathcal{W}}{\partial s_i}$ does not depend on s_j, the cross-partial derivative terms will all be equal to zero. We have

$$\frac{\partial \mathcal{W}}{\partial s_i} = s_i \alpha_i \frac{\partial \pi_i}{\partial s_i} - \alpha_i \left(\delta_{gi} \frac{\partial G_i}{\partial s_i} + \delta_{ei} \frac{\partial E_i}{\partial s_i} \right)$$

From (3), (4), and (5) we have: $\frac{\partial \pi_i}{\partial s_i} = -\frac{\pi_i(1-\pi_i)}{\mu}$, $\frac{\partial G_i}{\partial s_i} = -\frac{\pi_i(1-\pi_i)}{\mu} g$ and $\frac{\partial E_i}{\partial s_i} = \frac{\pi_i(1-\pi_i)}{\mu} e$. With these we can write the derivative as

$$\frac{\partial \mathcal{W}}{\partial s_i} = \alpha_i \frac{\pi_i(1-\pi_i)}{\mu} \left(-s_i + \delta_{gi} g - \delta_{e_i} e\right).$$

Now take the second derivative. We have

$$\frac{\partial^2 \mathcal{W}}{\partial s_i^2} = \frac{\alpha_i}{\mu^2} \pi_i(1-\pi_i)(1-2\pi_i)\left(-s_i + \delta_{gi} g_i - \delta_{e_i} e_i\right) - \alpha_i \frac{\pi_i(1-\pi_i)}{\mu} = \frac{1}{\mu}(1-2\pi_i)\frac{\partial \mathcal{W}}{\partial s_i} - \alpha_i \frac{\pi_i(1-\pi_i)}{\mu}.$$

Now consider the point $\tilde{S} = (\tilde{s}, \tilde{s}, \ldots, \tilde{s})$ where $\tilde{s}$ is the optimal single subsidy described above. At $\tilde{S}$, all the revenue equations are the same across regions. It follows that

$$\mathcal{W}(\tilde{S}) = \tilde{\mathcal{W}}(\tilde{s}).$$

In other words, $\mathcal{W}(\tilde{S})$ describes the weighted average welfare under the optimal single subsidy. Using the definition of the optimal region-specific subsidy

$$s_i^* = (\delta_{gi} g - \delta_{ei} e),$$

the derivatives above become

$$\left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{\tilde{S}} = \frac{\alpha_i}{\mu} \pi(1-\pi)(s_i^* - \tilde{s}), \tag{9}$$

dd

and

$$\left.\frac{\partial^2 \mathcal{W}}{\partial s_i^2}\right|_{\tilde{S}} = \frac{1}{\mu}(1-2\pi) \left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{\tilde{S}} - \frac{\alpha_i}{\mu} \pi(1-\pi). \tag{10}$$

ddd

Because the cross-partial derivatives are equal to zero, the second-order Taylor series expansion of $\mathcal{W}$ at the point $\tilde{S}$ can be written as

$$\mathcal{W}(S) - \mathcal{W}(\tilde{S}) \approx \sum \left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{\tilde{S}} (s_i - \tilde{s}) + \frac{1}{2} \sum \left.\frac{\partial^2 \mathcal{W}}{\partial s_i^2}\right|_{\tilde{S}} (s_i - \tilde{s})^2.$$

We use this expansion to evaluate $\mathcal{W}(S^*) - \mathcal{W}(\tilde{S})$. From (9) and (10) we have

$$\mathcal{W}(S^*) - \mathcal{W}(\tilde{S}) \approx \frac{1}{\mu}\pi(1-\pi)\sum \alpha_i(s_i^* - \tilde{s})^2 + \frac{1}{2}\left(\frac{1}{\mu^2}\pi(1-\pi)(1-2\pi)\sum \alpha_i(s_i^* - \tilde{s})^3 - \frac{1}{\mu}\pi(1-\pi)\sum \alpha_i(s_i^* - \tilde{s})^2\right).$$

The formula for the second-order approximation follows by combining the quadratic $(s_i^* - \tilde{s})$ terms. ■

Proof of Corollary 1. From the proof of Proposition 2, first-order Taylor series approximation to $W(S)$ is

$$\mathcal{W}(S) - \mathcal{W}(\tilde{S}) \approx \sum \left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{\tilde{S}} (s_i - \tilde{s}).$$

From (9) we have

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

Evaluating this expression at the point $\hat{S}$ gives the desired result. ■

Data sources for emissions of gasoline cars

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.[17] 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 cars 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 cars. This gives a small downward bias to emissions of electric cars.

[17] 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).

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 use additional data from the EPA's eGrid database for the year 2009 to convert hourly gross generation into hourly emissions of $PM_{2.5}$ assuming a constant annual average emissions rate. 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 (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 uses an air quality module to map the emissions by sources into ambient concentrations pollutants at receptor locations, an economic valuation module to map the ambient concentrations of pollutants into monetary damages, and finally an algorithm module to determine the marginal damages associated with emissions of any given source.

The inputs to the air quality module are the emissions 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.[18]

[18]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 cars, 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.

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, 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.[19] 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.[20] This value of an incremental change in mortality risk yields a VSL of $\$6 \times 10^6 = \$600/0.0001$.

The algorithm module uses the combined air quality module and economic valuation module to determine marginal damages. First, baseline emissions data that specifies reported values for all emissions at all sources is used to compute baseline damages. (For this paper, we

[19] 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.

[20] 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 car.

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.[21] This routine is repeated for all pollutants and all sources in the model.

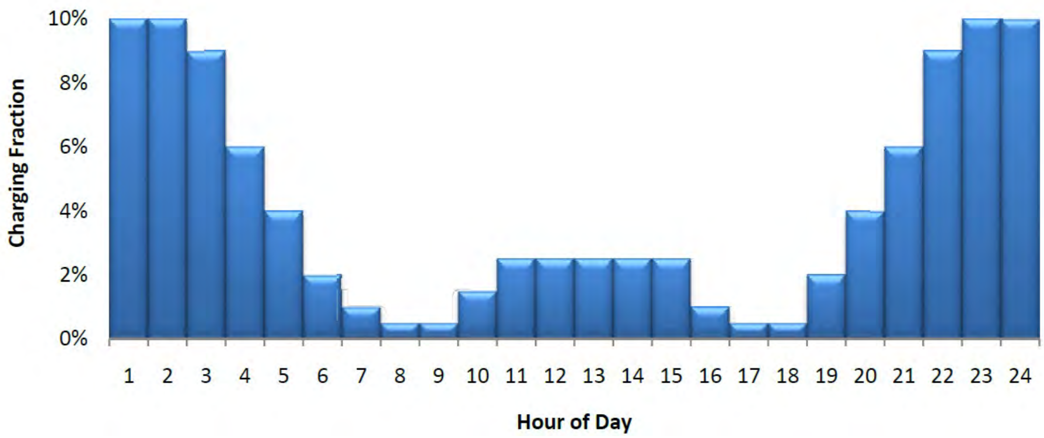
[21] We can also analyze the marginal damages at each receptor.

Appendix Table 1: 2014 Electric vehicles and gasoline equivalent vehicles

Electric Vehicle	kW-hrs/Mile	Gasoline Equivalent	MPG	NOx	VOC	PM25	SO2
Chevy Spark EV	0.283	Chevy Spark	34	0.04	0.127	0.017	0.004
Honda Fit EV	0.286	Honda Fit	29	0.07	0.147	0.017	0.005
Fiat 500e	0.291	Fiat 500e	34	0.07	0.147	0.017	0.004
Nissan Leaf	0.296	Toyota Prius	50	0.03	0.112	0.017	0.003
Mitsubishi i-Miev	0.300	Chevy Spark	34	0.04	0.127	0.017	0.004
Smart fortwo electric	0.315	Smart fortwo coupe	36	0.07	0.147	0.017	0.004
Ford Focus Electric	0.321	Ford Focus	30	0.03	0.112	0.017	0.005
Tesla Model S (60 kW-hr)	0.350	BMW 740i	22	0.07	0.147	0.017	0.007
Tesla Model S (85 kW-hr)	0.380	BMW 750i	19	0.07	0.147	0.017	0.008
Toyota Rav4 EV	0.443	Toyota Rav4	26	0.07	0.147	0.017	0.006
BYD e6	0.540	Toyota Rav4	26	0.07	0.147	0.017	0.006

Notes: NOx, VOC, PM2.5, and SO2 emissions rates for gasoline equivalent cars are in grams per mile.

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.

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Supplementary Appendix A: Welfare Gains From Differentiation: Taxation of Gasoline and Electric Miles

Here there are taxes on both gasoline and electric miles. Before turning to the analysis of multiple regions, it is first helpful to derive the result stated in the main text that Pigovain taxes are optimal. Following the proof of Proposition 3, the first-order condition for t_g is

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

We now deviate from the proof of Proposition 3, because we have taxes on both gasoline and electric miles. Per capita revenue is therefore $R = t_g \pi g + t_e (1 - \pi) e$. Taking the derivative of the revenue constraint 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

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

It follows that the optimal taxes are $t_g = \delta_g$ and $t_e = \delta_e$, as stated in the main text.

Now turn to the case in which there are m regions. It is clear that the optimal region-specific taxes are $t^*_{gi} = \delta_{gi}$ and $t^*_{ei} = \delta_{ei}$. In other words, each region implements the Pigovian solution.

Now follow similar steps as in the proof of Proposition 2. Consider m regions and determine the optimal uniform taxes. Per capita welfare in region i is

$$\tilde{\mathcal{W}}_i = \mu\left(\ln(\exp(V_e/\mu) + \exp(V_g/\mu))\right) - (\delta_{gi}G - \delta_{ei}E).$$

The government wants to pick the value for t_e and t_g to minimize $\tilde{\mathcal{W}}(t_g, t_e) = \sum \alpha_i \tilde{\mathcal{W}}_i$. There is a single per-capita revenue expression

$$R = t_g \pi g + t_e(1 - \pi)e$$

that applies to the budget constraint for each consumer in each region. The values for e and g will be the same across regions because the taxes are uniform. The first-order conditions for t_g and t_e are

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

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

The solution to these equations is $\tilde{t}_g = \bar{\delta}_g$ and $\tilde{t}_e = \bar{\delta}_e$. In other words, the optimal uniform tax on gasoline miles is equal to the weighted average of the marginal damages across regions. The value for welfare is $\tilde{\mathcal{W}}(\tilde{t}_g, \tilde{t}_e)$.

Next consider the case in which each region i has taxes t_{gi} and t_{ei} on gasoline and electric miles and per capita revenue $R_i = t_{gi}\pi_i g_i + t_{ei}(1-\pi_i)e_i$. Let $\mathcal{W}(T)$ denote the weighted average of per capita welfare across regions as a function of the vector of taxes $T = (t_{g1}, t_{g2}, \dots, t_{gm}, t_{e1}, t_{e2}, \dots, t_{em})$. We have

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

We now want to take the first derivatives of the regulator's objective with respect to the elements of T. Because the problem is separable we can simply add subscripts and α_i to the derivatives we found in the single region case. 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

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

Now consider the point $\tilde{T} = (\tilde{t}_g, \tilde{t}_g, \dots, \tilde{t}_g, \tilde{t}_e, \tilde{t}_e, \dots, \tilde{t}_e)$. At $\tilde{T}$, all the revenue equations are the same across regions It follows that

$$\mathcal{W}(\tilde{T}) = \tilde{\mathcal{W}}(\tilde{t}_g, \tilde{t}_e).$$

In other words, $\mathcal{W}(\tilde{T})$ describes the weighted average welfare under the optimal uniform taxes. Since this point has equal taxes in each region, the gasoline miles and electric miles will be the same each each region. So we can drop the subscripts from g, e, G, and E. 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

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

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

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

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 one derived in Proposition 2 for a tax on the purchase of the electric car. Using the fact that $s_i^* = -(\delta_{gi} g - \delta_{ei} e)$ and $\tilde{s} = -(\bar{\delta}_g g - \bar{\delta}_e e)$, we can write the first-order approximation formula in Proposition 2 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 region 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 B: Choice over several gasoline and electric cars

Here we expand the model to allow for a richer consumer choice set. There are m_e electric cars and m_g gasoline cars. Gasoline cars are indexed by the subscript i and electric cars are indexed by the subscript j. Each car has a different purchase price and price of a mile, and we allow for the possibility of car specific taxes on miles and purchases. The universal utility function is

$$U = \ell + \sum_i f_i(g_i) + \sum_j h_j(e_j),$$

where g_i is the consumption of miles from the i'th gasoline car and e_j is the consumption of miles from the j'th electric car. The indirect utility of consuming leisure and gasoline miles from the i'th gasoline car is given by

$$V_{gi} = \max_{\ell, g_i} U(\ell, g_i) \text{ s.t. } \ell + (p_{gi} + t_{gi})g_i = T + R - p_i.$$

The indirect utility of consuming leisure and electric miles from the j'th electric car is given by

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

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

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

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

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

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

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

And of course $\sum_i \pi_i + \sum_j \pi_j = 1$. Including the pollution externality, the expected per capita utility is given by

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

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

Differentiated taxes on purchase of electric car

Here we consider a policy in which the government selects car-specific tax on the purchase of electric cars. Let s_j be the tax on electric car j. Government revenue is $R = -\sum \pi_j s_j$. Now consider a given electric car, say car k. The optimal tax on the purchase of this car, s_k, solves the first-order condition

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

From the Envelope Theorem, we have

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

and, for $j \neq k$,

$$\frac{\partial V_{ej}}{\partial s} = \frac{\partial R}{\partial s_k}.$$

For $j = k$ we have

$$\frac{\partial V_{ej}}{\partial s_k} = \left(\frac{\partial R}{\partial s_k} + 1 \right).$$

Substituting these expressions into the first-order condition gives

$$\frac{\partial \mathcal{W}}{\partial s_k} = \sum_i \pi_i \frac{\partial R}{\partial s_k} + \sum_j \pi_j \frac{\partial R}{\partial s_k} + \pi_k - \sum_i \delta_{gi} \frac{\partial G_i}{\partial s_k} - \sum_j \delta_{ej} \frac{\partial E_j}{\partial s_k} = 0.$$

This can be simplified to

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

Now

$$\frac{\partial R}{\partial s_k} = -\pi_k - \sum_j \frac{\partial \pi_j}{\partial s_k} s_j.$$

Substituting this into the first-order condition gives

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

Now, since there are no income effects,

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

and

$$\frac{\partial E_j}{\partial s_k} = e_j \frac{\partial \pi_j}{\partial s_k}$$

Substituting the derivatives of G_i and E_j gives

$$\frac{\partial \mathcal{W}}{\partial s_k} = -\sum_j \frac{\partial \pi_j}{\partial s_k} s_j - \sum_i \delta_{gi} g_i \frac{\partial \pi_i}{\partial s_k} - \sum_j \delta_{ej} e_j \frac{\partial \pi_j}{\partial s_k} = 0. \tag{11}$$

dtec

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 car

Now suppose that the government places a uniform tax s on the purchase of any electric car. Expected per capita government revenue is given by $R = -\sum_j \pi_j s$. The optimal s can be found as a special case of the differentiated subsidy formula presented above. Let $s_k = s$ for every k. Then (11) becomes

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

Solving for s gives

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

Now since $\sum_i \pi_i + \sum_j \pi_j = 1$ it follows that

$$\sum_i \frac{\partial \pi_i}{\partial s} + \sum_j \frac{\partial \pi_j}{\partial s} = 0.$$

Using this gives

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

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

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

The optimal subsidy is a function of the weighted sum of marginal damages from each car 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.

Supplementary Appendix C: Comparison with Mendelsohn (1986)

Applying our approximation methodology to Mendelsohn's model reveals the differences in the welfare gain of 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. To see this, recall that our objective function has terms such at $\pi\delta$ where delta is the environmental parameter and π is the choice probability. Now π i is a function of the policy variable s. From (3) we have

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

and so it follows that

$$\frac{\partial^2 \pi}{\partial s^2} = -\frac{1}{\mu}(\pi(1 - \pi) - 2\pi^2(1 - \pi)),$$

and, as a consequence, the first and second derivatives are both linear in δ.

Supplementary Appendix D: Calibration

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 functional form for the utility of consuming electric miles and gasoline miles. For gasoline miles we have $f(g) = g^{\gamma_g}$ and for electric miles we have $h(e) = e^{\gamma_e}$. We determined the values for γ_g and γ_e such that the consumer would, in the absence of any policy intervention, consume 150,000 lifetime miles for each type of vehicle. As in the main text, we compared the Ford Focus with the Ford Focus Electric. The values for all of the parameters except μ are shown in Table A.[22]

For μ, we specified a range of possible values. This range was determined by considering a range of values for the probability, in the absence of any policy intervention, that the consumer would select the gasoline car. See Table B.

Table A: Calibration Parameters (2013 Dollars) : Ford Focus and Ford Focus Electric parmsa

Parameter	Value	Economic Interpretation	Source/Notes
p_ℓ	20.7	Value of time (\$ per hour)	US BLS : \$827 week
T	87600	Endowment of time	Hours in 10 year car lifetime
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 car (\$)	Ford Motors
p	16810	Price of gasoline car (\$)	Ford Motors
γ_g	0.6048	Gas miles preference parameter	Calculated so that $g = 150,000$.
γ_e	0.5272	Electric miles preference parameter	Calculated so that $e = 150,000$.

Table B: Value of μ as a function of the probability, with no policy intervention, of selecting the gasoline car

μ	Probability
254.2	0.99
396.8	0.95
531.7	0.90
842.8	0.80
1378.8	0.70
2881.4	0.60

parmsb

[22] These parameters were converted to year 2000 dollars to be consistent with the values from the AP2 model.

Supplementary Appendix E: 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, car g will play the role of the gasoline car in the main text. 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 car purchase to a low MPG car 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 car on the composition of the fleet, under the assumption that the total amount of cars sold stays the same. For CAFE purposes, the electric car is assigned it's MPG equivalent, which is typically much greater than the MPG of the most efficient gasoline car. Let this be denoted by f_e where $f_e > f_g$. Since the total amount of cars sold stays the same, the sale of an electric car leads to a reduction in sales of another type of car. 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 car sale replaces a sale of a model g car, 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:

$$\frac{\frac{n_a+1}{f_a} + \frac{n_b-1}{f_b} + \frac{n_g-1}{f_g} + \frac{1}{f_e}}{n_a + n_b + n_g} \leq \frac{1}{k}. \tag{12}$$

swap

Using the initial condition this becomes

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

and so the condition becomes

$$\frac{1}{f_a} - \frac{1}{f_b} \le \frac{1}{f_g} - \frac{1}{f_e}. \tag{13}$$

cafe

The right-hand-side of (13) 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 car. 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 cars due to the substitution of a low MPG car for a high MPG car. We can sketch a back-of-the-envelope calculation for the magnitude of this CAFE induced environmental cost and its effect on the optimal tax on electric cars as follows. Assume that car a and car b are in the same Tier 2 "bin". For cars 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 car market, we don't know which region the car 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 car a and b, respectively.[23] 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 cars. Rather we simply assume that the consumer chooses between the electric car and car g, and this choice induces a change in the composition of the rest of the fleet due to CAFE regulation considerations. The basic welfare equation becomes

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

[23]For example, $\delta_a = \frac{\$0.344}{f_a}$, where the numerator is the CO_2 damages per gallon in our model.

We see that if the consumer selects the gasoline car, then the fleet consists of this gasoline car in conjunction with car b. But if the consumer selects the electric car, then the fleet consists of the electric car in conjunction with car a. (We are ignoring the utility benefit generated by the switch from b to a.) Following similar arguments as in the 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 \$1229.[24]

Starting in 2017, CAFE regulation will make things worse, because it will allow the manufacturer to claim credit for two electric car sales for each actual sale of an electric car. Thus (12), 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 cars sold constant, but the CAFE regulation enables the manufacturer to do the calculation as if they had sold one additional electric car. 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

$$\frac{1}{f_a} - \frac{1}{f_b} \leq \left(\frac{1}{f_c} - \frac{1}{f_e}\right) + \left(\frac{1}{k} - \frac{1}{f_e}\right). \tag{14}$$

cafee

Comparing (13) with (14), we see that the effect of double counting the electric car is to

[24] The right-hand-side of (13) is given by $1/30 - 1/105 = 0.0238$. Assuming this equation holds with equality, we have $(\delta_a - \delta_b) = 0.344 * 0.0238$. Multiplying by a lifetime of 150,000 miles gives \$1229. We should also note that the EPA posted MPG number for a given car is different from the CAFE MPG number for that same car. 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 gas consumption.

more than double the CAFE induced environmental cost of the electric car, provided the gallons per mile used by car c is smaller than CAFE limit on gallons per mile $1/k$.