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

Stephen P. Holland† Erin T. Mansur‡ Nicholas Z. Muller§

Andrew J. Yates¶

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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

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†Department of Economics, University of North Carolina at Greensboro and National Bureau of Economic Research. Mailing Address: Bryan School of Business and Economics, Department of Economics, Bryan 462, PO Box 26170, Greensboro, NC 27402-6170. Phone: 336- 334-4925. Fax: 336-334-5580. Email: `sphollan@uncg.edu`

‡Department of Economics, Dartmouth College and National Bureau of Economic Research. Mailing Address: Department of Economics, Dartmouth College, 6106 Rockefeller Hall, Hanover, NH 03755-3514. Phone: 603-646-2531. Fax: 603-646-2122. Email: `erin.mansur@dartmouth.edu`

§Department of Economics, Middlebury College and National Bureau of Economic Research. Mailing Address: Department of Economics, Middlebury College, Warner Hall 305E, Middlebury, VT 05753. Phone: 802-443-2080. Fax: 802-443-2080. Email: `nmuller@middlebury.edu`

¶Department of Economics and Curriculum for the Environment and Ecology, University of North Carolina at Chapel Hill. Mailing Address: Department of Economics, University of North Carolina Chapel Hill, CB 3305 University of North Carolina Chapel Hill, NC 27599. Phone 919-966-2383. Fax: 919-966-4986. Email: `ajyates@email.unc.edu`.

electric cars, ranging from a positive $3025 in California to a negative $4773 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.

Keywords— electric vehicles, spatial heterogeneity, air pollution, subsidy policy

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. 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 greenhouse gases (GHGs) and 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 eighteen 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 34 states.

The final set of results concern the welfare analysis of various policies. 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. We also evaluate the current Federal policy of a $7500 subsidy on the purchase of electric car. In our model, this policy yields fairly substantial welfare loss of several billion dollars per year relative to a first-best policy of Pigovian taxes on miles driven.

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 welfare issues.[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 at various spatial scales.[4]

In Section 2 we develop a 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 spatially differentiated policies. 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.

2 Theoretical Model

Consider a discrete choice model in which consumers in the market for a new vehicle choose between two transportation options: a gasoline vehicle and an electric vehicle.[5] Utility

[1]Examples of discrete choice models in include Anderson et al. 1992 and Small and Rosen 1981, and examples of transportation models include De Borger (2001), De Borger and Mayeres (2007), and Parry 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]See Graff Zivin et al (2014).

[3]Previous works in this area 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).

[4]Babaee et al (2014), Graff Zivin et al (2014), Michalek et al (2011), and Tessum et al (2014) analyze the benefits of electric vehicles at the aggregate level. Li et al. (2014) consider spatial damages from electric vehicles but assume uniform damages from gasoline vehicles. Ours study is the first to consider the spatial variation in damages from both gasoline and electric cars at the state and county level.

[5]For examples of general discrete choice models, see Anderson et al. 1992 and Small and Rosen 1981, and for discrete choice transportation models, see de Borger 2001, de Borger and Mayeres 2007. In supplementary

depends on a composite consumption good 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 concave functions. Quasi-linearity implies the marginal utility of income is constant and the purchase of gasoline or electric miles does not depend on income.

We consider several policy variables. 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 (we assume the producer prices are fixed). Per capita tax revenue R is returned in a lump sum manner. We normalize the units so that the price of the composite good is equal to one. Consumers have income I.

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

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

where p_G 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

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

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 assume that the choice of vehicle is influenced by i.i.d. random variables ϵ_g and ϵ_e that follow the extreme value distribution.[6] Accordingly, we define the conditional utility, given that a consumer elects the gasoline vehicle, as

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

Appendix B, we extend the model to include several gasoline vehicles and several electric vehicles.

[6]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.

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

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

A consumer selects the gasoline vehicle if $\mathcal{U}_g > \mathcal{U}_e$. This occurs with probability

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

where μ is proportional to the standard deviation of the extreme value random variables. The expected utility of a new vehicle purchase is given by[7]

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

Consumers create an environmental externality by driving, but ignore this externality when making choices about the type of vehicle and number of miles. The externality causes linear damages.[8] In our empirical analysis, gasoline vehicles cause damages through tailpipe emissions and electric vehicles cause damages though smokestack emissions from the electric power plants that charge them. Because damages from air pollution may have significant spatial effects, we develop a model with multiple regions to analyze regulation issues.

2.1 Uniform vs. differentiated regulation

Consider a simple spatial model in which there there are m regions. Let α_i be the proportion of the total population of new vehicle buyers that resides in region i. The utility functions and (pre-policy) prices are the same across regions. Damages from GHG emissions do not vary across regions, but damages from local air pollution do vary across regions. Moreover, driving in region i leads to damages from local air pollution in that region as well as damages

[7]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.

[8]The linearity assumption is supported by prior research on the damages from local air pollutants that have found strong evidence of constant marginal damages. See Muller and Mendelsohn 2009; Fowlie and Muller, 2013.

from local air pollution in other nearby regions. The sum of these local effects and damages from GHG emissions is called the full damages from region i, and the corresponding marginal full damages (in dollars per mile) are denoted by δ_{gi} for gasoline miles and δ_{ei} for electric miles.

We now determine welfare maximizing policy choices under both uniform and differentiated regulation. Results for a subsidy on the purchase of an electric vehicle are in the main text. Results for taxes on miles are in the Appendix. Because the first-best policy in our model is a Pigovian tax on miles, we refer to the welfare maximizing subsidy as the second-best subsidy.

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 a regional government cares about full damages due to emissions from its region. We will relax this assumption below. Regional government i selects the purchase subsidy s_i to maximize the welfare associated with the purchase of a new vehicle within the region, defined as the difference between expected utility and expected pollution damage:

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

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.

The second-best subsidy on the purchase of an electric vehicle in region i is described in the following Proposition (all proofs are in the Appendix).

Proposition 1. *The second-best subsidy on the purchase of the electric vehicle in region i is given by s_i^* where*

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

The term $\delta_{gi}g - \delta_{ei}e$ 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 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 subsidy is positive. We refer to the difference $\delta_{gi} - \delta_{ei}$ as the environmental benefit of an electric mile. 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 in most of the empirical section below).

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. The government's objective is to maximize the weighted average of welfare across regions (the weights correspond to the α_i's). The next proposition delineates the second-best uniform subsidy. It also describes an approximate formula for the welfare gain in moving from the uniform policy to the differentiated policy.

Proposition 2. *The second-best uniform subsidy on the purchase of an electric vehicle is given by*

$$\tilde{s} = \left((\sum \alpha_i \delta_{gi}) g - (\sum \alpha_i \delta_{ei}) e \right).$$

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

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

where π is evaluated at the 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 the δ_{ei} and δ_{gi}. Using the second-order approximation formula, we see that the welfare gain from using the differentiated subsidies rather than the 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 benefits of abatement). 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 because it depends on the value of μ. Recall that this parameter is proportional to the standard deviation 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.

2.2 Full vs. native damages

So far we have assumed that regional government i is concerned with the full damages caused by the consumption of miles in region i. But this may not always be the case. For example, Pennsylvania regulators may be concerned about environmental damages which occur in Pennsylvania, but may not be as concerned about environmental damages which occur downwind in New York. To account for this possibility, it is useful to break up full damages into *native damages* (i.e. those damages which occur in region i) and *exported damages* (i.e. those which occur in other regions.)

If a regional government only cares about native damages, then its objective is to maximize

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

where β_{gi} and β_{ei} are the proportion of marginal full damages that occur solely in region i. It follows from Proposition 1 that the second-best purchase subsidy based on native damages, denoted by $\hat{s}_i^*$, is given by

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

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 electricity generation. This implies that the subsidy $\hat{s}_i^*$ (which is based on native damages) is likely to be larger than subsidy s_i^* (which was based on full damages). 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.

3 Calculating air pollution damages

The theoretical model illustrates that the environmental benefit of an electric car arises from reduced emissions relative to the gasoline car which it replaces. To calculate this benefit, we need to determine the damages of both gasoline cars and electric cars, and these damages may differ by location and time. We first overview our general procedure and then describe in more detail our two component empirical models: an econometric model that estimates marginal emissions from electric power usage, and the AP2 model (see Muller and Mendelsohn 2009) that determines marginal damages by county for emissions from tailpipes and smokestacks.

Our set of electric vehicles includes each of the eleven pure electric vehicles in the EPA fuel efficiency database for the 2014 model year. Our set of gasoline vehicles is meant to capture the closest substitute in terms of non-price attributes to each electric vehicle. Wherever possible, we use the gasoline-powered version of the identical vehicle, e.g., the gasoline-powered Ford Focus for the electric Ford Focus. In other cases, we identify a make and model which is a close substitute, e.g., the BMW 750i for the Tesla Model S85. For both gasoline and electric vehicles, we consider the damages from air emissions of five pollutants: CO_2, SO_2, NO_X, $PM_{2.5}$, and VOCs.[9] These pollutants account for the majority of GHG and air pollution damages and have been a major focus of public policy.[10]

[9] Graff Zivin et al. (2014) only estimate electric vehicle damages from CO_2.

[10] 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.

To determine the emissions rates in grams per mile for gasoline vehicles, we integrate data from several sources. For CO_2 and SO_2, emissions are directly proportional to gasoline usage so we utilize the conversion factors in GREET scaled by the EPA's MPG for each vehicle.[11] We differentiate urban and non-urban counties by using EPA's city and highway mileage.[12] For NO_X emissions, we use the Tier 2 emission standards for the vehicle "bin". For $PM_{2.5}$ and VOCs, we combine the allowed Tier 2 standards with GREET estimates of $PM_{2.5}$ emissions from tires and brakes and of evaporative emissions of VOCs. The resulting emissions rates for our gasoline vehicles are reported in Appendix Table 1.

For electric vehicles, determining emission rates is more complicated. For each vehicle, we start with the EPA estimate of MPG equivalent (i.e., the estimated kWh per mile) and adjust for the temperature profile of each county.[13] Electric vehicles use more electricity per mile in cold and hot weather due to both the decreased performance of the battery and the increased demand for climate control (Yuksel and Michalek, forthcoming, 2015).[14] Next we use an econometric model (described below) to estimate the marginal emissions factors for each of our pollutants at each of 1486 power plants due to an increase in electricity load by hour of the day and by electricity region. The final steps are to assume a daily charging profile, combine the marginal emissions factors with the temperature adjusted MPG equivalents, and then calculate emissions rates at each power plant per mile driven in each county.[15]

Having calculated marginal emissions rates per mile for gasoline and electric vehicles for each county for each of our five pollutants, we next value the damages.[16] For CO_2, we use

[11]In the 2012 GREET model, developed by Argonne National Laboratory, the SO_2 emissions rate is 0.00616 g/mile at 23.4 mpg. This is slightly higher than the Tier 2 allowed 30 ppm which would be 0.00485 g/mile at 23.4 mpg.

[12]Urban counties are defined as counties which are part of a Metropolitan Statistical Area (MSA). We do not differentiate electric vehicles by urban and rural since regenerative braking leads to smaller differences in city and highway efficiencies.

[13]We model the EV range loss as a Gaussian distribution with no range loss at 68°F but a 33% range loss at 19.4°F. See Supplementary Appendix F.

[14]Gasoline vehicles face similar issues, but the effect of temperature on drivetrain efficiency is much smaller, and the climate control issues at low temperatures are essentially nonexistent, because waste heat from the engine is used to heat the cabin. We do not adjust gasoline MPG for temperature.

[15]We analyze eight charging profiles: our baseline profile using estimates from Electric Power Research Institute (EPRI) (See Appendix Figure 1), a flat profile, and six profiles with non-overlapping four-hour charging blocks.

[16]All damages are in 2014$.

the EPA social cost of carbon of $41 per ton.[17] For local pollutants, we use the AP2 model (described below) which calculates the marginal damages from emissions in each county for each of our four local pollutants. We then add up all the damages from our five pollutants to calculate marginal damages (in $ per mile) from driving in each county for each of our electric or gasoline vehicles.

To analyze any policy which affects multiple counties, we need a sense of the relative importance of driving in the counties. So we weight all summary statistics using Vehicle Miles Travelled (VMT) by county, as estimated by the EPA for their Motor Vehicle Emission Simulator (MOVES).[18]

3.1 Estimation of Marginal Emissions from Electricity Usage

To determine the emissions that result from electricity use to charge an electric vehicle, we must determine which power plants respond (and how they respond) to increases in electricity usage at different locations. The electricity grid in the contiguous U.S. consists of three main "interconnections": Eastern, Western, and Texas. Since there are substantial electricity flows within each interconnection but quite limited flows between interconnections, we model each interconnection separately. Within each interconnection, transmission constraints prevent the free flow of electricity throughout the interconnection. We follow the North American Electric Reliability Corporation (NERC) and divide the three interconnections into nine distinct regions.[19] We use these nine NERC regions to define the spatial scale for measuring electric vehicle emissions. In particular, our estimation strategy assumes that an electric vehicle charged at any place within a given region has the same marginal emissions per kWh as an electric vehicle charged at any other place within the same region.[20]

To estimate the response of each power plant to an increase in electricity usage, we collect

[17] This is the 2015 estimate using a 3% discount rate in 2014$. See http://www.epa.gov/climatechange/EPAactivities/economics/scc.html.

[18] The theoretical model weights by α_i (the number of new vehicle buyers). This is equivalent if vehicles are driven the same number of miles per year in each county, and vehicles last the same number of years in each county.

[19] See http://www.nerc.com 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.

[20] There is some data on electricity load at NERC sub-regions. Due to multi-collinearity, our estimation strategy would likely not work at this level of disaggregation.

data from 2010 to 2012 on hourly emissions of CO_2, SO_2, NO_X, and $PM_{2.5}$ at 1486 power plants.[21] We also collect data on hourly electricity consumption (i.e., electricity load) for each of our nine NERC regions.[22] We estimate the marginal emissions using methods similar to Graff Zivin et al. (2014) and Holland and Mansur (2008) allowing 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 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 the emission factors β_{ijh}, which represents the marginal change in emissions at plant i from an increase in electricity usage in region j in hour h.

For a given pollutant, the marginal damage from increasing electricity usage in region j in hour h is found by summing over all i the product of the β_{ijh} and the marginal damages for a unit of that pollutant emitted at power plant i's location. The marginal damages for local pollutants are determined by the AP2 model, which we now describe in more detail.

[21] CO_2, SO_2, and NO_X data are directly from the EPA CEMS. We construct hourly $PM_{2.5}$ from hourly generation and annual $PM_{2.5}$ emissions rates. Power plant emissions of VOCs are negligible.

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

3.2 Local Air Pollution Damages: The AP2 Model

AP2 begins with an air quality module that maps emissions of NO_X, SO_2, $PM_{2.5}$, and VOCs from each source into ambient concentrations of SO_2, O_3, and $PM_{2.5}$ at all receptor locations, i.e., at all 3,110 counties in the contiguous U.S. The model then links these ambient concentrations to exposures, physical effects and monetary damages. Damages are associated primarily with human health effects but also include crop and timber losses, degradation of buildings and material, and reduced visibility and recreation. For human health effects, ambient concentrations are mapped into increased mortality risk, which is then expressed in terms of monetary damages using a $6 million value of a statistical life (VSL).[23] Finally, AP2 uses an algorithm module to aggregate damages from all receptors to determine the marginal damages associated with emissions of any given source.[24]

In its usual application, the damages calculated in AP2 are the sum of damages at all receptors. However, as discussed above, regulators may be more concerned about native damages than full damages. We use the AP2 model in a novel way to calculate native damages. We disaggregate the plume of damages from a given source and only count those damages which occur at receptors within the a given regulatory jurisdiction.

4 Results

We first determine the environmental benefit of electric vehicles and the corresponding second-best subsidy on the purchase of the electric vehicle. We then analyze the degree to which electric vehicles export pollution from counties and states and the resulting implications for second-best subsidies based on native or full damages. Finally, we turn to the benefits of differentiated policies relative to uniform policies. All results are in 2014$ and all summary statistics are weighted by VMT.

[23]In terms of share of total damage, the most important concentration-response functions are those governing adult mortality. 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. A sensitivity analysis uses more recent concentration response functions from Roman et al 2008.

[24]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.

4.1 Environmental benefit of electric vehicles

The environmental benefit of an electric vehicle depends on the marginal damages for both gasoline and electric vehicles. We present results for these components in turn, beginning with marginal damages of electric vehicles. The right panel of Figure 1 illustrates our baseline estimates of the marginal damages (in cents per mile) for the 2014 electric Ford Focus by county. The variation is largely driven by the NERC regions, although marginal damages vary within a region due to our county-specific temperature correction.

Table 1 shows the variation in marginal damages across the nine NERC regions for an electric Ford Focus by various charging profiles. The damages range from one cent per mile in California and the West (WECC) to over four cents per mile in the Midwest (MRO).[25] These regional differences in emissions reflect both a region's generating capacity and electricity imports from other regions. There is some variation in damages across the charging profiles. For example, damages could be reduced in the Midwest (MRO) by over 1.5 cents per mile by charging between 1pm and 4pm, relative to our baseline EPRI charging profile. However, it is widely assumed, as in the EPRI charging profile, that the vast majority of electric vehicles will be charged at night.

The left-hand-side columns in Table 2 describe the distribution of marginal damages from electric vehicles across counties for all eleven 2014 model year electric vehicles. The mean damage of the electric Ford Focus is about 2.5 cents per mile with the range of damages from under one cent (in the West) to almost 5 cents (in the Midwest) per mile. The damages scale across the electric vehicles because they are only differentiated by their efficiency (in kWh per mile). For example, the mean, minimum, and maximum damages of the dirtiest electric vehicle (the BYD e6) are approximately double those of the cleanest (the Chevy Spark).

Next we present the marginal damages of gasoline vehicles. The left panel of Figure 1 illustrates the marginal damages for the gasoline Ford Focus by county. The counties with large marginal damages correspond to major population centers. Marginal damages from our set of gasoline vehicles are shown in the middle columns of Table 2. For the gasoline Ford Focus, mean damages are two cents per mile (the equivalent of $0.60 per gallon of gasoline)

[25] For a sense of the magnitude of these damages, one cent per mile is approximately $0.30 per gallon at the MPG of the Ford Focus and four cents is $1.20 per gallon.

but range from about a cent per mile to over four cents per mile ($1.20 per gallon).[26]

Taking the difference between the damages from gasoline vehicles and electric vehicles gives us the environmental benefit of electric vehicles, as shown in the right-hand-side columns of Table 2. If damages from gasoline and electric vehicles were highly correlated, then the environmental benefit of electric vehicle would be quite small because there is substantial overlap in the distributions of damages from gasoline and electric vehicles. In fact, the damages are not highly correlated (the correlation is 0.06). As a result, the environmental benefit of an electric vehicle is heterogeneous. For example, gasoline vehicle damages are quite high in Los Angeles (due to the high population and properties of the airshed) but electric vehicle damages are quite small (due to the clean Western power grid). In this situation, the environmental benefit is almost equal to gasoline damages (i.e., three to four cents per mile) and hence electric vehicles have substantial environmental benefits. However, the opposite can also occur, for example in the upper Midwest. Here, the environmental benefit of an electric vehicle is *negative*, and is almost equal to electric vehicle damages. For each of the electric vehicles in Table 2, the average environmental benefit is negative. This is not surprising, given Table 1 shows that only about 30% of the VMT occurs in the three regions with the lowest marginal damages from electricity. The electric Ford Focus is the median electric vehicle in terms of environmental benefit, which is why focus on it throughout the results section.

Using Proposition 2, we can convert the environmental benefit into the second-best subsidy by assuming that both the electric vehicle and the gasoline vehicle are driven 150,000 miles. Figure 2 shows the subsides for each county in the contiguous U.S. Except for a few counties around New York City and Atlanta, the subsidy is negative throughout the eastern part of the country (i.e. consumers should pay a *tax* on the purchase of electric vehicles). It is large and negative in the Upper Midwest. On the other hand, it is positive in most places in the West, and quite large in many counties in California. Overall, the policies range from a subsidy of $5,000 to a purchase tax of $5,000.

In Table 3, we aggregate the environmental benefits to the level of Metropolitan Statistical

[26] The mean damage per gallon of gasoline is $0.62 per gallon for each car since the damages are proportional to gasoline use and our substitute cars are all in the same Tier 2 "bin".

Area (MSA). The highest benefit MSAs are all in California where damages from gasoline vehicles are substantial and damages from electric vehicles are small. In these MSAs, the environmental benefits range from 2 to 3 cents per mile with an second-best subsidy of up to $5000. The lowest benefit MSAs are all in the upper Midwest, where the gasoline vehicle damages are low (due to low population densities) but the electric vehicle damages are high (due to coal-fired generation and the temperature adjustment to electric vehicle range). Here the environmental benefits are negative 3 cents per mile for an second-best tax of about $4000.

Other large MSAs can have either positive or negative environmental benefits. New York and Chicago have some of the highest damages from gasoline cars, but environmental benefits from electric vehicles are small or negative due to the high damages from electric vehicles. Electric vehicles have substantial environmental benefits in the major Texas MSAs, due to relatively low electric vehicle damages in Texas. However, for non-urban regions as well as for MSAs in the Southeast, Northeast, and Midwest, the benefits from electric vehicles are negative.

Table 4 presents the environmental benefit of an electric vehicle across states. Compared to MSAs, the environmental benefits of electric vehicles are smaller at the state level because of negative benefits in non-urban areas. The highest environmental benefits are in California (a second-best subsidy of $3,000) and the West. The lowest benefits are in the Upper Midwest (a second-best tax of almost $5,000 in North Dakota.) There are only 12 states in which the environmental benefit is positive, and Texas is the only high VMT state outside the West in which the environmental benefit is positive. In the average state, a 2014 electric Ford Focus causes $724 more environmental damages over its lifetime than the equivalent gasoline Ford Focus.

Despite these modest (or negative) environmental benefits of electric vehicles, the current Federal subsidy for electric vehicles is $7500. Many states have additional policies designed to encourage the adoption of electric vehicles. Clearly these modest environmental benefits cannot explain the enthusiasm for these subsidies.

4.2 Exporting pollution: Full and native damages

As discussed in Section 2, using a vehicle in a given region may lead to damages in that region as well as in surrounding regions. In this section we break up full damages (the sum of all the damages across all receptors) into native damages (damages within the given region) and exported damages (damages in other regions).

Although both gasoline and electric vehicles export pollution, electric vehicles export to a remarkable degree. Panel A in Figure 4 illustrates the change in $PM_{2.5}$ associated with driving a gasoline-powered Ford Focus for 150 million miles in Fulton County, Georgia.[27] Most of the increase in $PM_{2.5}$ is centered within a few nearby counties. Panel B in Figure 4 shows the change in $PM_{2.5}$ associated with the same number of miles driven by an electric powered Ford Focus that is charged in Fulton County, thereby increasing the generation of electricity in the Southeast (SERC). Clearly the spatial footprint of $PM_{2.5}$ is much greater for the electric vehicles than for the gasoline vehicle.

Table 5 shows native damages at both the state and county levels for both electric and gasoline vehicles. For electric vehicles, full damages from local pollutants are 1.6 cents per mile on average. Native state damages are only 0.15 cents per mile, and native county damages are only 0.02 cents per mile. Thus on average 91% of electric vehicle damages are exported from the state and 99% (!) of damages are exported from the county. Gasoline vehicle damages are also exported but to a much smaller extent. On average only 18% of gasoline damages are exported from a state and only 57% of damages are exported from a county.

Replacing full damages with native damages changes the environmental benefit calculation quite dramatically, especially at the lower tail of the distribution. This lower tail corresponds to low gasoline damages and high electric vehicle damages. Because most electric vehicle damages are exported, the native damages for both gasoline and electric vehicles are small, and there is not a large negative environmental benefit, i.e., the environmental benefit increases from -3.5 cents per mile to approximately zero. On the upper tail of the distribution, electric vehicle damages were already low, so exporting electric vehicles damages has little impact on the environmental benefit. By increasing the lower tail of the distribu-

[27] Or equivalently, a fleet of 10,000 vehicles driven 15,000 miles each.

tion, the average environmental benefit based on (county or state) native damages becomes positive. As illustrated in the right panel of Figure 3, the state environmental benefit for an electric vehicle, using native damages, is positive in 34 out of 49 states.

This analysis of full and native damages suggests interesting implications for local electric vehicle policy. Accounting for full damages, the second-best subsidy for an electric car is negative in the vast majority of states. But accounting for native damages, the second-best subsidy for an electric car is positive in the vast majority of states. This naturally leads to the question as to whether state policymakers will place greater emphasis on full or native damages when considering electric vehicle subsidies.

We conduct a preliminary analysis of this issue in supplementary Appendix G. Eight states have implemented subsidies for the adoption of electric vehicles, above and beyond the federal subsidy: California ($2500), Colorado ($6000), Georgia ($5000), Illinois ($4000), Maryland ($3000), Massachusetts ($2500), Texas ($2500) and Utah ($1500). Because one might be concerned this number of states is too small for a meaningful analysis, we also consider a broader policy category consisting of all electric vehicle incentive programs. States offer a variety of these incentives, including carpool lane access, electricity discounts, and parking benefits.[28] Although it may be possible to place an explicit monetary value on these other incentives, we are content here to simply enumerate them. As shown in supplementary Appendix G, regardless of whether we consider subsidies or the number of other incentives, the state data is more highly correlated with the native damage subsidy than it is with the full damage subsidy. This preliminary evidence suggests that native damages may help explain policymakers' support for electric vehicle subsidies.

4.3 Benefits of differentiated policies

Our analysis shows that the environmental benefits of electric cars are quite heterogeneous: ranging from substantial benefits in some locations to large costs in others. This raises the question of whether differentiated policies, which reflect this spatial heterogeneity, can lead to large enough welfare gains to offset any additional implementation costs of differentiated policies. To calculate the benefits from differentiated policies, we develop a more complete

[28]A small number of states impose a special registration fee for electric vehicles.

calibration of the discrete choice model developed in Section 2.[29] We then calculate the efficiency gains from two sets of differentiated policies: fuel-specific taxes on miles driven (i.e. VMT taxes) and electric vehicle purchase subsidies.

Table 6 shows the results for the Ford Focus, expressed as a welfare loss from the first-best policy. The three different parameterizations of the model correspond to BAU electric vehicle market shares of 1%, 5%, and 10%. To see the benefits of policy differentiation we compare the entries across rows. The right-hand columns of Table 6 show fuel-specific VMT taxes. The first three rows show policies based on full damages. The first-best outcome occurs with county-level taxes on electric miles and gasoline miles set at the Pigovian level $t_{ei} = \delta_{ei}$ and $t_{gi} = \delta_{gi}$. Moving from uniform Federal federal taxes to state level taxes yields a welfare gain of \$5 to \$20 per vehicle sold. Moving from state-level taxes to county-level taxes yields an additional \$6 to \$8 per vehicle sold. The last two rows of Table 6 show policies based on native damages. The gains from differentiation are slightly lower than those found for full damages (a gain about \$5 per vehicle for moving from state native to county native). But in comparison with the full damages taxes, the policies based on native damages lead to large welfare losses of approximately \$75-120 per vehicle. To provide some context, annual vehicle sales in the United States are approximately 15 million.

Next we turn to the gains from differentiating electric vehicle purchase subsidies, shown in the first three columns of Table 6. Spatially differentiated subsidies lead to smaller welfare gains than differentiated taxes, on the order of \$1-\$16 for Federal vs state policy. Compared directly with VMT taxes, subsidies perform much worse, leading to welfare losses of approximately \$130-\$180 per vehicle. Another interesting comparison is between state policy with native damages and uniform federal policy base on full damages. For subsidies, these two regulatory structures lead to roughly the same welfare. In contrast, under taxes on miles, state policy performs significantly worse than the uniform federal taxes.

We can also evaluate the current Federal policy of a uniform \$7500 subsidy for the purchase of an electric car. The bottom row of Table 6 shows that relative to first-best, this uniform policy leads to a welfare loss of approximately \$180-\$700 per car. Given 15 million car sales per year, this corresponds to 2.7- 10 Billion dollars per year. Actual welfare losses

[29] See Supplementary Appendix D for more detail.

are likely on the lower end of this range because current electric car adoption rates are less than one percent, even with the subsidy.

4.4 Sensitivity Analysis

Our analysis requires us to make assumptions about a variety parameters, many of which may be subject to considerable debate. Table 7 shows the sensitivity of our baseline calculation of environmental benefit to some of our key parameter assumptions. In each case, changing the parameters changes the electric vehicle damages, gasoline damages, and environmental benefit in the expected direction. In all cases, the distributions of electric and gasoline damages are uncorrelated and have wide ranges, leading to substantial heterogeneity in the environmental benefit of electric vehicles.

5 Effects CAFE standards and other regulations

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.

One 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.[30] 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.[31] 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, the CAFE induced environmental cost under current CAFE standards turns out to be $1439. The magnitude of this is significant in comparison with even the largest optimal subsidy for an electric vehicle found in our study ($3025, in California).

As another 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.

[30] 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.

[31] With respect to the 2017 CAFE standards, double counting the electric vehicle more than doubles its CAFE induced environmental cost.

6 Conclusion

On average, electric vehicles generate greater end-of-pipe environmental damage than directly comparable gasoline vehicles in the U.S. This difference amounts to about \$0.005 per mile, and \$0.015 for vehicles driven outside metropolitan areas. We find considerable variation around this central result; electric vehicles used in Los Angeles, California produce benefits of \$0.03 per mile while those used in Grand Forks, North Dakota, produce costs of -\$0.03 per mile. The spatial resolution employed in the empirical modelling 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 reduce air pollution in their state. However, 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. One implication of this finding is the dependence of policy orientation (whether a policy should encourage or discourage electric vehicle adoption) on the policymaker's jursidiction. Given our results, we would not be surprised to see a proliferation of state-specific subsidies for electric vehicles.

Of course, given the spatial heterogeneity in the magnitude and the sign of benefits of an electric vehicles, spatially-differentiated policy is 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 years 2010-2012. 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: Marginal Damages for Gas and Electric Cars by County

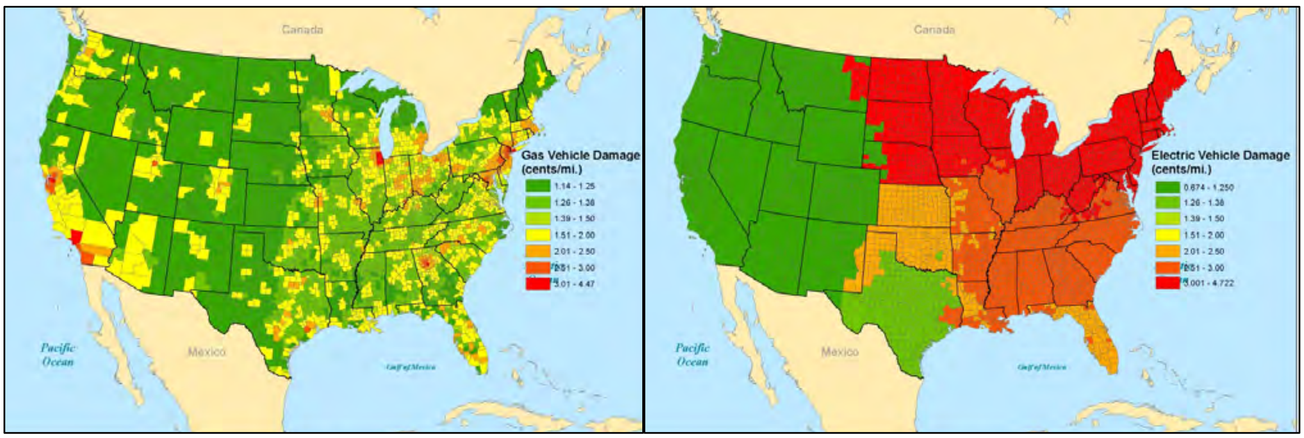

Figure 2: Optimal Electric Vehicle Subsidy by County

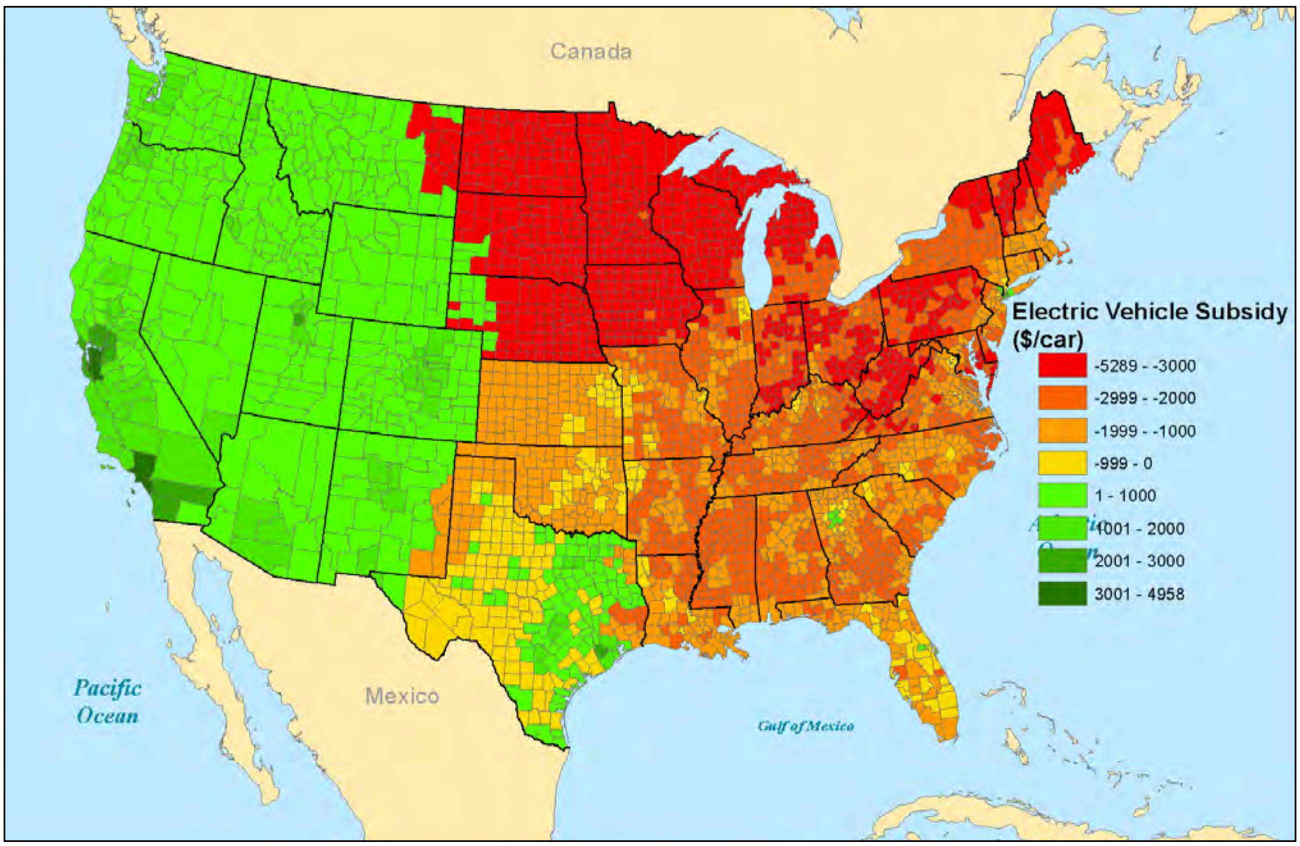

Figure 3: Optimal Electric Vehicle Subsidy by State (Full and Native Damages)

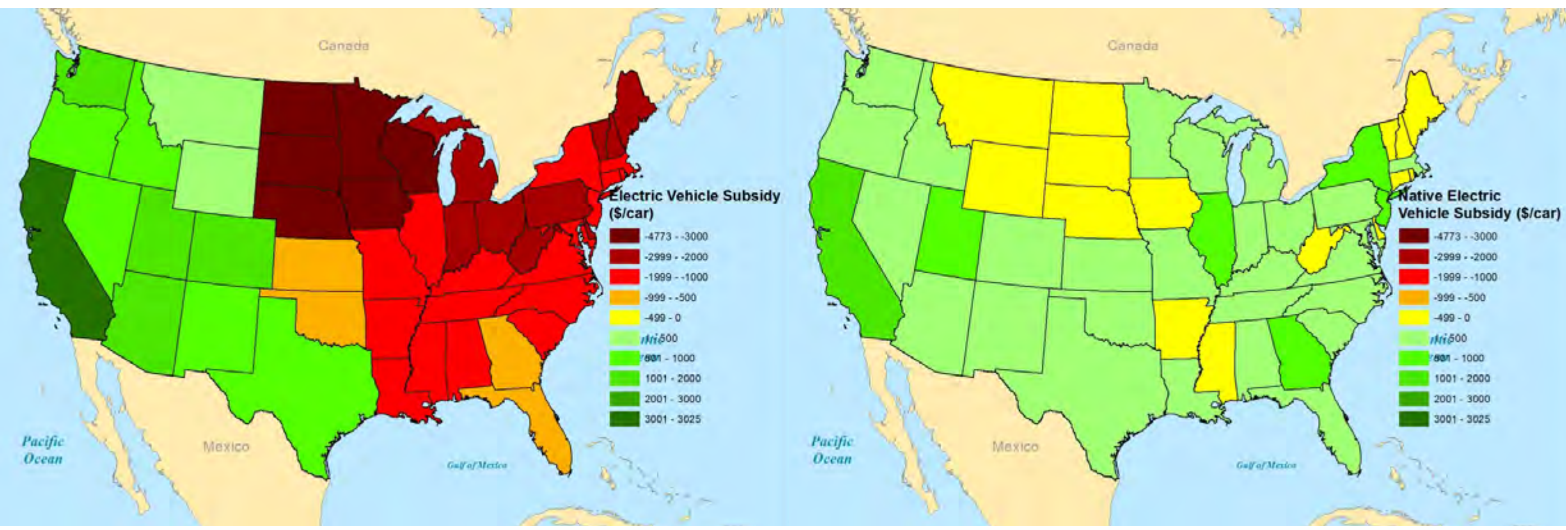

Figure 4 Panel A: Change in $PM_{2.5}$ Preliminary Fulton County: 1000 ICE Focus

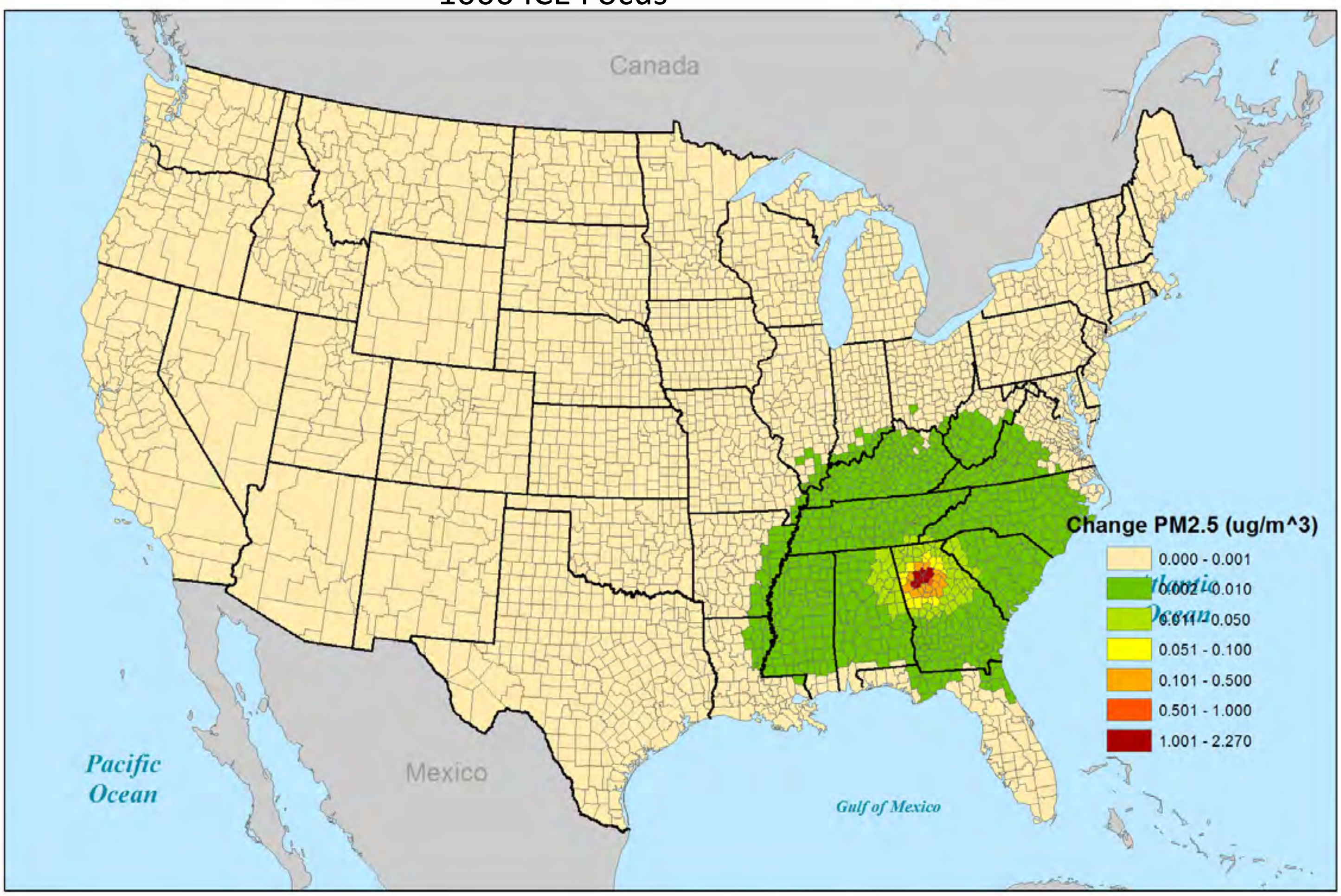

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Figure 4 Panel B: Change in $PM_{2.5}$: 1000 EV Focus in SERC Region

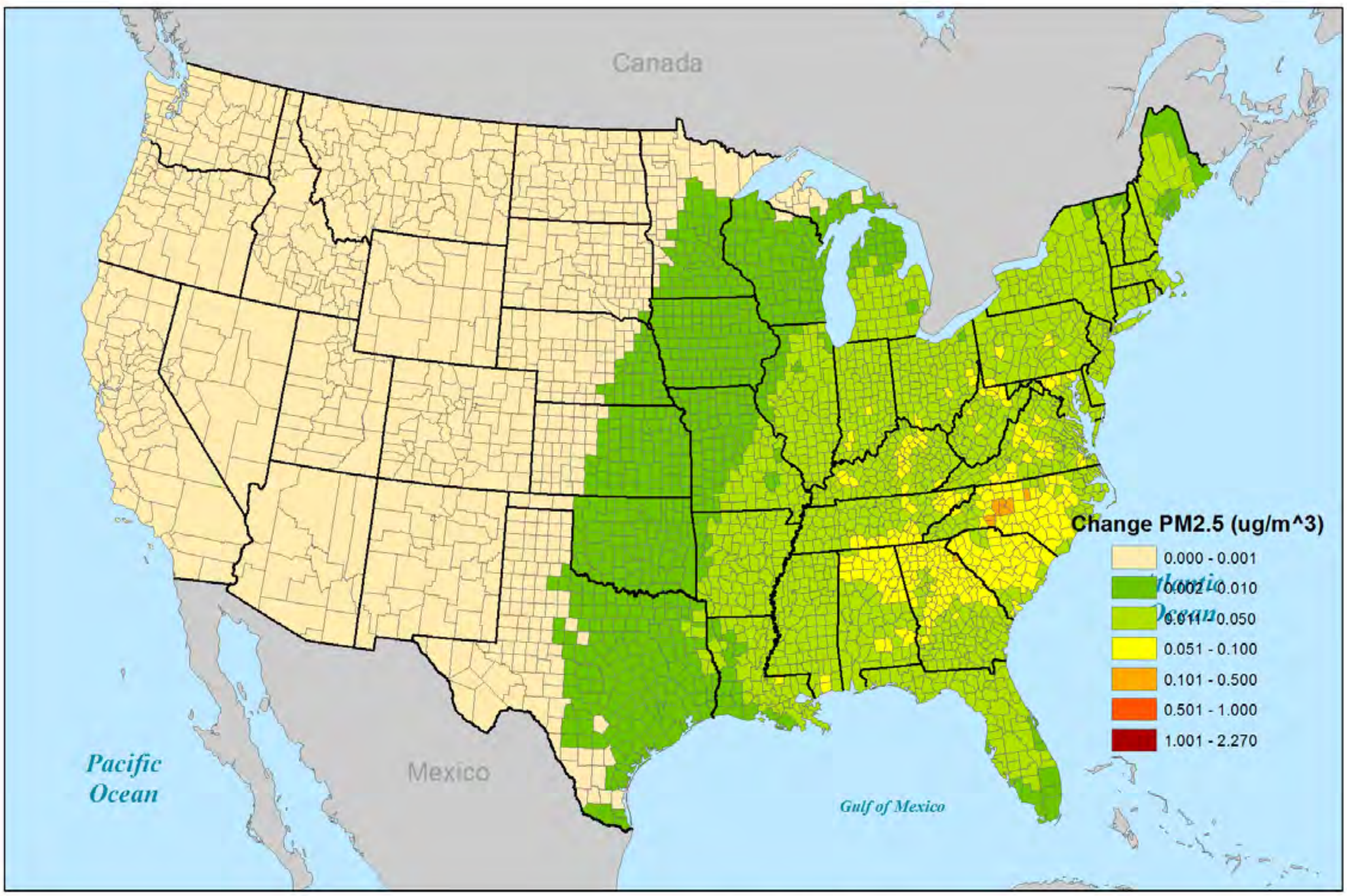


Table 1: Mean damages in cents per mile by NERC electricity region for a 2014 Ford Focus EV for different charging profiles.

	Damages in cents per mile								
Region	EPRI	Flat	Hr 1-4	Hr 5-8	Hr 9-12	Hr 13-16	Hr 17-20	Hr 21-24	VMT (pct)
California	0.69	0.75	0.65	0.78	0.78	0.84	0.82	0.64	12%
WECC w/o CA	1.03	0.92	1.18	0.98	0.84	0.76	0.73	0.99	10%
ERCOT	1.28	1.21	1.50	1.41	1.10	1.07	1.05	1.16	8%
FRCC	2.48	2.14	3.21	2.36	2.25	1.39	1.53	2.11	7%
SERC	2.75	2.68	2.76	2.26	2.73	2.97	2.64	2.72	24%
SPP	2.24	2.74	2.07	4.91	2.30	2.89	2.39	1.89	4%
NPCC	3.11	2.75	4.19	3.75	1.61	2.12	2.49	2.35	9%
RFC	3.65	3.56	3.44	3.39	3.85	3.07	3.44	4.17	22%
MRO	4.39	3.61	5.77	4.01	3.11	2.63	2.37	3.78	5%
Total	2.50	2.38	2.69	2.49	2.30	2.18	2.18	2.44	100%

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 (in cents per mile) are weighted across counties by car VMT.

Table 2: Summary statistics of damages and environmental benefit in cents per mile for 2014 electric vehicles and equivalent 2014 gasoline vehicles across counties

	Electric Vehicle			Gas Vehicle			Enviro. Benefit		
Vehicle	mean	min	max	mean	min	max	mean	min	max
Chevy Spark	2.20	0.59	4.17	1.81	1.05	4.42	-0.39	-3.05	3.20
Honda Fit	2.22	0.60	4.20	2.07	1.24	4.96	-0.15	-2.88	3.73
Fiat 500e	2.26	0.61	4.27	1.87	1.03	4.75	-0.39	-3.17	3.45
Nissan Leaf	2.30	0.62	4.35	1.31	0.81	3.60	-1.00	-3.44	2.29
Mitsubishi i-Miev	2.34	0.63	4.41	1.81	1.05	4.42	-0.53	-3.30	3.17
Smart fortwo	2.45	0.66	4.63	1.78	1.08	4.61	-0.67	-3.48	3.24
Ford Focus	2.50	0.67	4.72	2.00	1.13	4.47	-0.49	-3.53	3.31
Tesla S (60 kWh)	2.72	0.73	5.15	2.64	1.41	5.68	-0.09	-3.65	4.48
Tesla S (85 kWh)	2.96	0.80	5.59	2.89	1.63	5.96	-0.07	-3.87	4.77
Toyota Rav4	3.45	0.93	6.52	2.25	1.32	5.18	-1.21	-5.11	3.66
BYD e6	4.20	1.13	7.94	2.25	1.32	5.18	-1.96	-6.52	3.45

Notes: Damages are from power plant emissions or tailpipe emissions of NOx, VOCs, PM2.5, SO2, and CO2e. Electric cars assume the EPRI charging profile. 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. Damages are in cents per mile and are weighted across counties by car VMT.

Table 3: Environmental benefit in cents per mile by Metropolitan Statistical Areas for a 2014 Ford Focus (electric v. gasoline)

Metropolitan Statistical Area	Environmental benefit per mile	VMT (pct)	Damage per mile (gasoline)	Damage per mile (electric)	Purchase Subsidy
Highest Benefit MSAs					
Los Angeles, CA	3.31	2.88%	3.99	0.69	$4,958
Oakland, CA	2.35	0.80%	3.04	0.68	$3,531
San Jose, CA	2.26	0.57%	2.94	0.69	$3,388
San Francisco,CA	2.06	0.47%	2.74	0.68	$3,086
Santa Ana, CA	2.01	0.99%	2.68	0.67	$3,016
Other High VMT MSAs					
San Diego, CA	1.99	1.03%	2.67	0.68	$2,986
Riverside, CA	1.31	1.41%	2.02	0.71	$1,972
Phoenix, AZ	0.89	1.11%	1.92	1.03	$1,328
Dallas, TX	0.76	1.91%	2.05	1.29	$1,144
Houston, TX	0.76	1.83%	2.16	1.40	$1,140
New York, NY	0.12	2.08%	3.30	3.17	$184
Tampa, FL	-0.20	0.96%	2.27	2.47	-$305
Atlanta, GA	-0.21	1.95%	2.52	2.73	-$314
Chicago, IL	-0.60	1.20%	3.12	3.72	-$900
Washington DC-VA	-0.72	1.81%	2.31	3.03	-$1,077
U.S. and Non-Urban					
U.S. Average	-0.49	100%	2.00	2.50	-$742
Non-urban	-1.46	19%	1.30	2.77	-$2,193
Lowest Benefit MSAs					
St. Cloud, MN	-2.73	0.07%	1.76	4.49	-$4,094
Bismarck, ND	-2.83	0.04%	1.67	4.49	-$4,240
Fargo, ND-MN	-2.93	0.07%	1.69	4.61	-$4,388
Duluth, MN-WI	-2.95	0.09%	1.62	4.56	-$4,418
Grand Forks, ND-MN	-3.00	0.03%	1.66	4.66	-$4,495

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. Non-urban includes all counties that are not part of an MSA. The vehicle subsidy assumes car is driven 150,000 miles.

Table 4: Environmental benefit in cents per mile by state for a 2014 Ford Focus (electric v. gasoline)

State	Environmental benefit per mile	VMT (pct)	Damage per mile (gasoline)	Damage per mile (electric)	Purchase Subsidy
Highest Benefit States					
California	2.02	12%	2.71	0.69	$3,025
Utah	0.88	1%	1.92	1.04	$1,320
Colorado	0.75	2%	1.78	1.03	$1,123
Washington	0.74	1%	1.76	1.02	$1,108
Arizona	0.73	2%	1.75	1.02	$1,093
Other High VMT States					
Texas	0.52	9%	1.90	1.38	$784
Florida	-0.55	7%	1.94	2.49	-$829
Georgia	-0.64	4%	2.10	2.74	-$955
New York	-0.75	5%	2.35	3.10	-$1,122
New Jersey	-0.91	3%	2.70	3.61	-$1,367
Virginia	-1.02	4%	1.87	2.89	-$1,532
Ohio	-1.62	5%	2.02	3.65	-$2,437
Pennsylvania	-1.65	3%	2.00	3.64	-$2,472
Indiana	-1.70	3%	1.96	3.65	-$2,543
Michigan	-1.81	3%	1.93	3.75	-$2,720
Lowest Benefit States					
South Dakota	-2.52	0%	1.40	3.92	-$3,787
Minnesota	-2.57	1%	1.57	4.14	-$3,856
Nebraska	-2.63	2%	1.85	4.48	-$3,951
Iowa	-2.75	1%	1.49	4.24	-$4,118
North Dakota	-3.18	0%	1.39	4.58	-$4,773
U.S. Average	-0.49	100%	2.00	2.50	-$742

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. The vehicle subsidy assumes car is driven 150,000 miles.

Table 5: Native damages in cents per mile by state and county and export percentages

Vehicle	Damages	mean	med	std. dev.	min	max
Electric	All	2.50	2.74	1.11	0.67	4.72
	Non-GHG	1.62	1.86	0.95	0.16	3.50
	State	0.15	0.16	0.07	0.04	0.33
	Export %	91%	91%			91%
	County	0.02	0.02	0.01	0.00	0.06
	Export %	99%	99%			98%
Gasoline	All	2.00	1.91	0.60	1.13	4.47
	Non-GHG	0.54	0.37	0.53	0.01	2.92
	State	0.44	0.27	0.51	0.00	2.76
	Export %	18%	27%			5%
	County	0.23	0.11	0.38	0.00	2.03
	Export %	57%	71%			30%
Environmental	All	-0.49	-0.81	1.34	-3.53	3.31
Benefit	Non-GHG	-1.08	-1.44	1.14	-3.43	2.28
	State	0.29	0.12	0.51	-0.32	2.46
	County	0.21	0.09	0.37	-0.06	2.00

Note: Damages in cents per mile. "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 6: Welfare Losses from Uniform Policies: Vehicles Subsidies and Fuel-Specific VMT Taxes

	Vehicle Subsidy			VMT taxes		
BAU EV Share	1%	5%	10%	1%	5%	10%
County policies	133	146	161	0	0	0
State policies	134	147	164	6	7	8
Federal policy	135	155	180	11	19	28
County policies (native damages)	135	155	179	78	97	121
State policies (native damages)	135	156	182	83	102	127
Current Federal Policy ($7500 Subsidy)	184	401	668			

Note: Deadweight loss is measured in dollars per car. The BAU EV Share is the proportion of electric vehicles if there were no regulation. This share is determined by the assumed value for μ (10735.3, 16753.7, 22451.1) which is proportional to the standard deviation of the unobserved relative preference shock. The uniform federal vehicle subsidy is -$742 per car. The uniform federal tax is 2.5 cents per mile for electric cars and 2.0 cents per mile for gasoline cars.

Table 7: Sensitivity analysis of damages and environmental benefit in cents per mile for 2014 electric and gasoline Ford Focus

	Electric Vehicle			Gas Vehicle			Enviro. Benefit		
Vehicle	mean	min	max	mean	min	max	mean	min	max
Baseline	2.50	0.67	4.72	2.00	1.13	4.47	-0.49	-3.53	3.31
Carbon cost									
SCC=$51	2.71	0.80	5.02	2.36	1.41	4.84	-0.35	-3.55	3.56
SCC=$31	2.28	0.55	4.42	1.65	0.86	4.09	-0.64	-3.50	3.06
No temperature adjustment	2.35	0.67	3.90	2.00	1.13	4.47	-0.35	-2.74	3.32
Average MPG	2.50	0.67	4.72	1.87	1.36	4.23	-0.63	-3.30	3.02
Charging profile									
Flat	2.38	0.74	3.88	2.00	1.13	4.47	-0.38	-2.69	3.24
Double gasoline emissions rates	2.50	0.67	4.72	2.54	1.15	7.38	0.04	-3.48	5.75
$2 Million VSL	1.57	0.71	2.64	1.68	1.13	2.69	0.12	-1.49	1.78
PM dose response	3.59	1.25	6.89	2.31	1.14	6.10	-1.28	-5.65	4.05

Notes: Damages are from power plant emissions or tailpipe emissions of NOx, VOCs, PM2.5, SO2, and CO2e. Electric cars assume the EPRI charging profile. Damages are in cents per mile and are weighted across counties by car VMT.

Notes: "Carbon cost" uses a social cost of carbon of $51 or $31. "No temperature adjustment" assumes EVs have no range degradation at low temperatures. "Average MPG" uses the average MPG for gasoline cars instead of using the city MPG in urban counties and the highway MPG in non-urban counties. "Flat" charging profile assumes EV charging occurs equally in all hours instead of following the estimated EPRI charging profile. "$2 Million VSL" assumes the VSL is $2 million instead of the baseline $6 million. "PM dose response" assumes the higher PM2.5 adult-mortality dose-response from Roman etal 2008 instead of the baseline dose response.

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*

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

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

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

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

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

Using this result we can derive the following

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

and

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

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

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

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

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

■

Proof of Proposition 1. Throughout the proof we can drop the subscript i. 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

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

So the optimal s is given by

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

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 $\tilde{s}$

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

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

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

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

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

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

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

and

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

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. ■

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.[32] 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.

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

[32] 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).

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

The inputs to the air quality module are the emissions of ammonia (NH_3), fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), nitrogen oxides (NO_X), and volatile organic compounds (VOC)—from all of the sources in the contiguous U.S. that report emissions to the USEPA.[33] 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

[33]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.

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.[34] 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.[35] This value of an incremental change in mortality risk yields a VSL of $\$6 \text{ x } 10^6 = \$600/0.0001$.

AP2 is used to compute marginal (\$/ton) damages over a large number of individual sources (power plants in the present analysis) and source regions (counties within which vehicles are driven). First, baseline emissions data that specifies reported values for all emissions at all sources is used to compute baseline damages. (For this paper, we use emissions data from USEPA (2014) that contains year 2011 emissions.) Next, one ton of one pollutant, NO_X perhaps, is added to baseline emissions at a particular source, perhaps a power plant in Western Pennsylvania. Then AP2 is re-run to estimate concentrations, exposures, physical effects, and monetary damage at each receptor conditional on the added

[34]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.

[35]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.

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

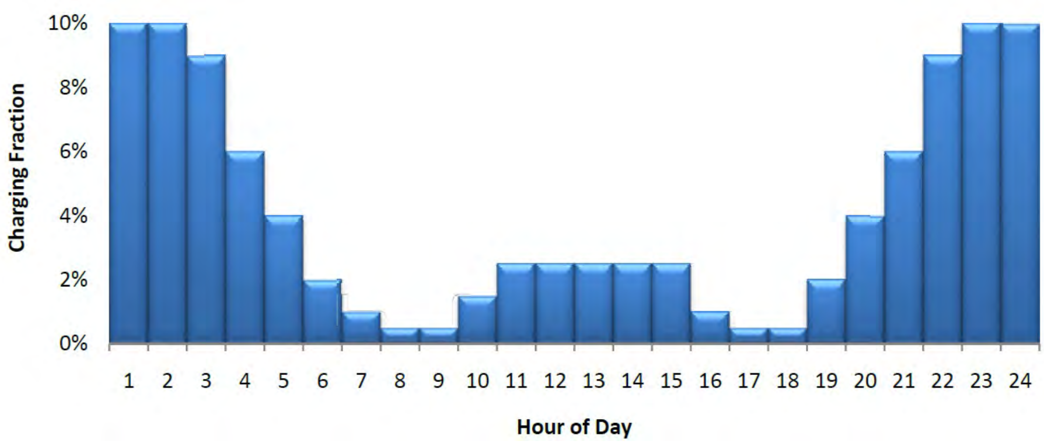
[36] We can also analyze the marginal damages at each receptor.

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

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

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

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

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

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

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

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

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

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

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

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

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

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 constant elasticity functional form for the utility of consuming electric miles and gasoline miles. For gasoline miles we have

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

and for electric miles we have

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

We determined the values for k_g and k_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 and H are shown in Table A. The elasticity of demand for gasoline miles ($-1/\gamma_g$) comes from Espey (1998). The elasticity of demand for electric miles ($-1/\gamma_e$) is assumed to be equal to the elasticity of demand for gasoline miles.

The values for μ and H were determined such that two conditions held. First, in the absence of any policy intervention, the consumer would select the gasoline car with some given probability. Second, consistent with Li et al (2015)'s observation, at the current Federal subsidy of $7500, half of electric cars sales would be due to the subsidy.

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

Parameter	Value	Economic Interpretation	Source/Notes
I	438641	Income	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/
p_g	0.1126	Price of gasoline miles ($ per mile)	CNN : 3.49 $ per gallon / 31 miles/gal
p_Ω	35170	Price of electric car ($)	Ford Motors
p_G	16810	Price of gasoline car ($)	Ford Motors
kg	$2.58x10^9$	Gas miles preference parameter	Calculated so that $g = 150,000$.
ke	$8.93x10^8$	Electric miles preference parameter	Calculated so that $e = 150,000$.
γ_g	2	Gives elasticity for gas miles of -0.5	Espey 1998
γ_e	2	Gives elasticity for electric miles of -0.5	Assumption

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

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

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

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:

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

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

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

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.[37] 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.

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

The basic welfare equation becomes

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

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

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

We see that the optimal subsidy is decreased by the amount equal to the CAFE induced environmental cost $(\delta_a - \delta_b)g$. Using our Ford Focus baseline numbers, the CAFE induced environmental cost turns out to be \$1439.[38]

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

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

[38] The right-hand-side of (13) is given by $1/30 - 1/105 = 0.0238$. Assuming this equation holds with equality, we have $(\delta_a - \delta_b) = 0.403 * 0.0238$. Multiplying by a lifetime of 150,000 miles gives \$1439. We should also note that the EPA posted MPG number for a given 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.

Which simples to

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

Comparing (13) with (14), we see that the effect of double counting the electric car is to 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 $1/k$.

Supplementary Appendix F: The effect of temperature on electric vehicle energy use

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

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

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

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

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

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

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

There is clear evidence in these studies that significant range loss in electric vehicles occurs both at low and high temperatures.[39] We use a Gaussian function to describe this range loss

$$R(T) = R_{68} e^{-\frac{(T-68)^2}{y}}, \tag{15}$$

where R_{68} is the range at the baseline temperature of 68°F and y is a parameter to be fitted from the range loss data. The transport Canada study indicates a 20 percent range loss at 19.4°F with the heat off and a 45 percent range loss at 19.4°F with the heat on. We took the average of these figures and assumed a 33 percent range loss. This gives[40]

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

Temperature data was obtained from the CDC website.[41] This gave us the average monthly temperature in each county for the years 1979-2011. In a given month j with temperature T_j, the energy usage per mile in that month is given by

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

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

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

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

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

[40] The assumed range loss is $(R(19.4)-R_{68})/R_{68} = -0.33$ which implies $R(19.4)/R_{68} = 0.67$. Using this in (15), we have $0.67 = e^{-\frac{(19.4-68)^2}{y}}$, which we can then solve for y.

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

months.

Supplementary Appendix G: State electric vehicle incentives

The Department of Energy maintains a database of alternative fuels policies by state.[42] Using this information, we determined four measures of state electric vehicle policy. The first measure is the actual subsidies for the purchase of an electric vehicle. The second measure is equal to the total number electric car of policies- including both incentives and regulations. The third measure is equal to the number of policies that were classified as by the Department of Energy as incentives. The fourth measure is equal to the number of incentives that were deemed by us to be significant (thus excluding, for example, an incentive that would only apply to the first 100 consumers to install electric vehicle charging equipment).

The four measures are shown in Table C for each state along with the optimal subsidy (based on full damages) and the political economy subsidy (based on native damages). Each of the four measures is more highly correlated with the political economy subsidy than with the optimal subsidy.

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

Table C: State electric vehicle policies

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