Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors*

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Abstract

We combine a theoretical discrete-choice model of vehicle purchases, an econometric analysis of electricity emissions, and the AP2 air pollution model to estimate the geographic variation in the environmental benefits from driving electric vehicles. The second-best electric vehicle purchase subsidy ranges from $2785 in California to -$4964 in North Dakota, with a mean of -$1095. Ninety percent of local environmental externalities from driving electric vehicles in one state are exported to others, implying they may be subsidized locally, even when the environmental benefits are negative overall. Geographically differentiated subsidies can reduce deadweight loss, but only modestly.

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1 Introduction

For a variety of reasons, including technological advances, environmental concerns, and entrepreneurial audacity, the market for pure electric vehicles, which was moribund for more than a century, is poised for a dramatic revival.[1] Several models are already selling in considerable volumes, the portfolio of electric vehicles is beginning to span the vehicle choice set, and almost all major manufacturers are bringing new models to the market. The Federal Government is encouraging these developments by providing a significant subsidy for the purchase of an electric vehicle, and some states augment the federal policy with their own additional subsidy.[2]

Proponents of these subsidies argue electric vehicles generate a range of short-term and long-term benefits such as reduced environmental impacts, innovation spillovers, and reduced reliance on imported oil.[3] In this paper we analyze whether electric vehicles do indeed generate short-term environmental benefits by examining air pollution damages from driving gasoline vehicles and charging electric vehicles. In particular, we focus on the importance of local factors by including global and local pollution, spatial heterogeneity of damages, pollution export across political jurisdictions, and policy that may vary by location.

Three main considerations motivate our analysis. First, prior studies of electric vehicles have focused on calculating the emissions of electric vehicles but have not had a conceptual framework for analyzing electric vehicle subsidies.[4] We analyze a model of vehicle choice, which gives us the theoretically sound and intuitive result that the subsidy should be equal to the difference in lifetime damages between an electric vehicle and a gasoline vehicle. Our theoretical framework also allows us to address additional policy questions regarding the best policies for different jurisdictional levels and the welfare gains from policy differentiation.[5]

Second, despite being treated by regulators as "zero emission vehicles", electric vehicles are not necessarily emissions free (National Academy of Sciences 2010). In 2014, the U.S.

[1] http://energy.gov/articles/history-electric-car.

[2] Internal Revenue Code Section 30D (Notice 2009-89) provides a tax credit of up to $7500.

[3] energy.gov/eere/vehicles/ev-everywhere-grand-challenge-does-10-year-vision-plug-electric-vehicles.

[4] See for example, Graff Zivin et al (2014) and Michalek et al (2011).

[5] Examples of theoretical discrete choice transportation models include De Borger (2001), De Borger and Mayeres (2007), and Parry and Small (2005). Differentiated policy is analyzed by Weitzman (1974), Mendelsohn (1986), Banzhaf and Chupp (2012), and Fowlie and Muller (2013).

Department of Energy reported that nearly 70 percent of electricity generated in the U.S. is produced by burning coal and natural gas. In many locations, the comparison between a gasoline vehicle and an electric one is really a comparison between burning gasoline or a mix of coal and natural gas to move the vehicle. However, average emissions of regional power plants can be a misleading indicator of the environmental impact of electric cars because all power plants do not respond proportionally to an increase in electricity usage and because electricity flows do not respect regional (e.g., state) boundaries.[6] To assess the emissions from charging an electric vehicle, we use an econometric model to estimate the effect of charging an electric vehicle on the marginal emissions of multiple pollutants at each power plant.[7]

Third, there are significant physical differences between emissions from gasoline and electric vehicles. This is due to the distributed nature of the electricity grid, the height at which emissions occur, and the chemistry of fuel combustion. As a result, pollutants and emissions rates may be spatially distinct even if gasoline and electric vehicles are driven in the same place. For local pollutants, an additional problem is that the same vehicle driven in different places leads to different damages. For this reason, many prior studies consider only carbon dioxide.[8] We use an integrated assessment model to value damages across local and global pollutants for both electric and gasoline vehicles.[9]

Addressing these three considerations yields a powerful modeling framework for analyzing electric vehicle policy. In particular, our study is the first to consider the geographic variation in damages from both local and global pollutants emitted by both gasoline and electric vehicles and to tie this variation to a choice model.[10] This framework enables us not only to

[6] EPA's calculated CO_2 emissions rates for electric vehicles (www.fueleconomy.gov) are regional averages.

[7] This builds on Graff Zivin et al (2014) and Holland and Mansur (2008).

[8] See for example, Graff Zivin et al (2014) and Archsmith et al (2015).

[9] Previous air pollution integrated assessment research 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), and Henry et al (2011). We model both ground-level emissions and power plant emissions throughout the contiguous U.S. In contrast to prior work, we report damages within the county of emission, within the state of emission, and in total (across all receptors).

[10] 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 (2015) consider variation in damages from electric vehicles but assume uniform damages from gasoline vehicles. Grissom (2013) considers variation in damages from gasoline vehicles but does not account for local pollution from electric vehicle charging. Archsmith et al (2015) assess the life cycle GHG benefits from electric vehicles.

evaluate the environmental benefit of electric cars, but also to address questions of political economy and fiscal federalism.

Our first set of results documents the considerable heterogeneity in the environmental benefits of an electric vehicle relative to a gasoline vehicle. These benefits can be large and positive, large and negative, or negligible, depending on the location. For example, California has relatively large damages from gasoline vehicles and a relatively clean electric grid, which implies large positive environmental benefits of an electric vehicle. These conditions are reversed in North Dakota. The variation in the sign of the environmental benefits stems almost entirely from local air pollution. If we account only for greenhouse gases, then electric vehicles are superior to gasoline vehicles almost everywhere. Using our model, we determine the welfare maximizing subsidies on electric vehicle purchases. We refer to these subsidies as second-best, but we stress that they only account for the relative differences in environmental impacts from driving electric and gasoline vehicles in the short run. Even in locations like California, subsidy values are significantly less than the current federal subsidy. The national average subsidy for the purchase of an electric vehicle is estimated to be -\$1095. Thus, on average in the U.S., the second-best purchase policy is a tax, not a subsidy.

Our second set of results shows the remarkable degree to which electric vehicles driven in one location lead to environmental externalities in other locations. At the state level, 91% of local pollution damages from driving an electric vehicle are exported to states other than the state in which the vehicle is driven. In contrast, only 19% of local pollution damages from driving a gasoline vehicle are exported to other states. This discrepancy casts doubt on the efficacy of policy selected by local regulators. It is not obvious whether a given state will consider full damages (damages across all states), or only native damages (those damages which actually occur in the given state) when setting policy. Moreover, state regulators face incentives in current air pollution policy that emphasize within-state consequences of emissions. The National Ambient Air Quality Standards (NAAQS) emphasize compliance with ambient pollution limits within states. Although there are constraints on the extent of exported pollution, especially from power plants, the NAAQS clearly encourage local compliance. This leads state regulators to focus on in-state damage and hence prefer a technology that exports pollution to other regions. The difference between using full and native damages in determining the second-best subsidy may be considerable. Accounting for full damages the second-best subsidy is positive in 11 states. Accounting for only native damages, the second-best subsidy is positive in 32 states.

The final set of results assesses the deadweight loss of various policies as well as the welfare gains from differentiated policy. Our theoretical analysis reveals that the welfare gains from differentiated subsidies depend on the higher order moments of the distribution of environmental benefits. Calibrating this model gives us an estimate of the magnitude of these gains. For electric vehicle subsidies, we find large deadweight loss and small welfare gains from differentiation. For taxes on miles, we find small (or zero) deadweight loss and larger welfare gains from differentiation.

There are several important caveats to our calculation of the environmental benefits of electric vehicles. First, it only captures air pollution emissions associated with driving or charging the vehicles. It does not account for "upstream" environmental externalities associated with producing either fuels or vehicles. Second, it is based on the electricity grid in the years 2010-2012 and current gasoline vehicle technology.[11] Over time, both the grid and gasoline vehicles may become cleaner. Third, it depends on marginal emissions from an increase in the demand for electric power to charge electric vehicles. This may not be appropriate when electric vehicles comprise a substantial fraction of the vehicle fleet. Fourth, it ignores pre-existing environmental polices such as the Corporate Average Fuel Economy (CAFE) standards and cap and trade markets for various local pollutants. For each of these caveats, we consider the degree to which they affect our calculated environmental benefits.

With these caveats in mind, our main results show that the subsidy for electric vehicles is not justified by environmental benefits. But, as noted above, there are other arguments in favor of electric vehicle subsidies. Perhaps most important is the possibility of the long-term benefits due to a combination of innovation spillovers, learning by doing, and dynamic changes to the electricity grid. Any such long-term benefits may be at least partially offset by the short-term costs associated with current electric vehicle use. Our analysis provides an estimate of these short-term costs. Moreover, by shedding light on issues related to

[11]The emissions inventory used by our integrated assessment model (AP2) is from 2011. These are the latest years for which all data are available.

differentiated regulation and pollution export, we provide a policy framework for subsequent analysis of long-term issues.

In Section 2 we develop a simple general equilibrium model that includes discrete choice over vehicle type as well as environmental externalities from driving. 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 discuss the caveats to our analysis. Section 6 concludes.

2 Theoretical model

Consider a theoretical discrete choice transportation model in which consumers in the market for a new vehicle choose between a gasoline vehicle and an electric vehicle.[12] Consumers obtain utility from a composite consumption good x (with price normalized to one) and from miles driven over the life of the selected vehicle, either gasoline miles g or electric miles e. We allow for several policy variables. The government may provide a subsidy s for the purchase of an electric vehicle, place a tax t_g on gasoline miles, a tax t_e on electric miles, or some combination of these policies.[13] We hold fuel and vehicle prices fixed.[14]

The indirect utility of purchasing a gasoline vehicle is

$$V_g = \max_{x,g}\ x + f(g) \text{ such that } x + (p_g + t_g)g = I - p_\Psi,$$

where p_Ψ is the price of the gasoline vehicle, p_g is the price of a gasoline mile, I is income, and f is a concave function. Likewise, the indirect utility of purchasing an electric vehicle is

$$V_e = \max_{x,e}\ x + h(e) \text{ such that } x + (p_e + t_e)e = I - (p_\Omega - s),$$

[12]Examples of general discrete choice models are Anderson et al (1992) and Small and Rosen (1981). Applications to transportation models are de Borger (2001) and de Borger and Mayeres (2007). In Supplementary Appendix A, we extend the model to include several vehicles of each type.

[13] Alternatively, we might consider a tax on fuel consumption. These taxes are equivalent in our model, but may not be equivalent in a model with multiple vehicles of each type. See Fullerton and West (2002).

[14]This is consistent with a model in which vehicles and miles are produced by price-taking firms using constant returns to scale technology.

where p_Ω is the price of the electric vehicle, p_e is the price of an electric mile, and h is a concave function. Any difference in attributes between the gasoline and electric vehicle are captured by differences in the functions f and g. Because the objective function in these optimization problems is quasi-linear, there are no income effects.[15]

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 drawn from a common extreme value distribution with zero expected value and standard deviation that is proportional to a parameter μ.[16] Accordingly, we define

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

and

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

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

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

The expected utility of a new vehicle purchase is given by

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

Consumers create negative environmental externalities by driving, but ignore the damages from these externalities when making choices about the type of vehicle and number of miles. In our empirical analysis, gasoline vehicles emit several pollutants from their tailpipes and electric vehicles cause emissions of several pollutants from the smokestacks of electric power plants that charge them. Because the damages from these pollutants may be global or local, we introduce multiple locations into the model.

[15]The marginal utility of income is equal to one, the number of miles driven does not depend on income, and the choice of vehicle does not depend on income.

[16]The variance is $\mu^2(3.14159)^2/6$.

2.1 Uniform vs. differentiated regulation

Let m denote the number of locations and let α_i denote the proportion of the total population of new vehicle buyers that resides in location i. An important feature of our model is that driving in one location may lead to local damages in that location, as well as local damages in other locations. Accordingly, we define *full damages* due to driving in location i as the sum across all locations of local damages plus the global damages. Assuming that both global and local damage functions are linear allows us to characterize full damages with a single variable for each type of vehicle.[17] Let δ_{gi} denote the marginal full damages (in dollars per mile) from driving a gasoline vehicle in location i, and δ_{ei} denote the marginal full damages (in dollars per mile) from driving an electric vehicle in location i.

We determine welfare maximizing purchase subsidies under both *uniform regulation* (the same policy applies to all locations) and *differentiated regulation* (policy may vary from location to location). Because the first-best policy in our model is differentiated Pigovian taxes on both types of miles, we refer to the welfare maximizing subsidies as second-best.[18]

First we study differentiated regulation. Here there are m local governments that select location-specific purchase subsidies. Let R_i denote the expected government revenue generated by the purchase of a new vehicle in location i.[19] For the moment, we assume local government i cares about full damages due to driving in location i. It selects the purchase subsidy s_i to maximize the welfare $\mathcal{W}_i$ associated with the purchase of a new vehicle within location i, defined as the sum of expected utility and expected revenue less expected pollution damage:[20]

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

Optimizing the welfare function gives the the following Proposition (all proofs are in

[17] Constant marginal damages is consistent with the EPA's social cost of carbon calculations as well as prior research on local air pollution (Muller and Mendelsohn 2009; Fowlie and Muller 2013).

[18] Results for uniform taxes on miles are in Supplementary Appendix B.

[19] Alternatively we could have a single revenue equation and assume that a central government makes the location-specific policy choices. But, given our subsequent distinction between full and native damages, it is natural to consider distinct local governments.

[20] Because there are no income effects, the consumer component of welfare is equivalent to the standard notion of compensating variation (Small and Rosen 1981).

Supplementary Appendix A).

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

$$s_i^* = (\delta_{gi} g_i - \delta_{ei} e_i) .$$

The term $\delta_{gi} g_i - \delta_{ei} e_i$ is simply the difference between the full damages over the driving lifetime of a gasoline vehicle and the full damages over the driving lifetime of an electric vehicle.[21] 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 benefits* of an electric vehicle. This concept assumes that the number of miles driven by the two types of vehicles is the same (an assumption we will maintain in most of the empirical section below).

Next we study uniform regulation. Here a central government selects a uniform subsidy that applies to all m locations. The government's objective is to maximize $\sum \alpha_i W_i$, which is the weighted average of welfare across locations. The next proposition delineates the second-best uniform subsidy. It also describes an approximation formula for the welfare gain in moving from uniform regulation to differentiated regulation.

Proposition 2. *Assume that prices, income, and the functions h and g are the same across locations. The second-best uniform subsidy on the purchase of an electric vehicle is given by $\tilde{s}$, where*

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

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

[21] The formula for s_i^* has a simple structure because there are two vehicles in the choice set. If the choice set is larger, then s_i^* will depend on the various cross-price elasticities (see Supplementary Appendix A).

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.

These results are most easily interpreted in the special case in which the population of new vehicle buyers is the same in each location ($\alpha_i = \frac{1}{n}$) and the electric vehicle and gasoline vehicle are driven the same number of miles ($g = e$).[22] Here the second-best uniform subsidy $\tilde{s}$ is equal to the average environmental benefits multiplied by the number of miles driven. And the approximate welfare gain from differentiation is a function of the second and third moments of the distribution of the environmental benefits. To understand these results, consider marginal welfare in region i:

$$\frac{\partial \mathcal{W}_i}{\partial s_i} = \frac{\pi(1-\pi)}{\mu}(-s_i + g(\delta_{gi} - \delta_{ei})).$$

When set equal to zero in a first-order condition, the policy variable s_i can be solved for as a linear function of the environmental benefits. But the marginal welfare function itself is a non-linear function of s_i (through the variable π). If it had been linear in s_i, then the approximate welfare gain from differentiation would not have been a function of the third moment.[23]

Proposition 2 provides a point of comparison to previous work on differentiated regulation. But the practical application of the approximation 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.

[22]To test the robustness of the results in Propositions 1 and 2, we also analyze a model in which consumers make a continuous choice between gasoline and electric miles. See Supplementary Appendix C.

[23]For more details and a comparison with Mendelsohn (1986), see Supplementary Appendix D. See also Jacobsen et al (2015).

2.2 Full vs. native damages

So far we have assumed that local government i is concerned with the full damages caused by driving in location i. But this may not necessarily hold. For example, when an electric vehicle in driven in Pennsylvania, regulators in Pennsylvania may be more concerned about environmental damages which occur in Pennsylvania than they are about downwind damages that occur 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 location i) and *exported damages* (i.e. those which occur in other locations.)

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

$$\hat{\mathcal{W}}_i = \mu \left(\ln(\exp(V_{ei}/\mu) + \exp(V_{gi}/\mu))\right) + R_i - (\hat{\delta}_{gi}\pi_i g_i + \hat{\delta}_{ei}(1-\pi_i)e_i),$$

where $\hat{\delta}_{gi}$ and $\hat{\delta}_{ei}$ are the marginal native damages in location i due to driving a vehicle in location i. It follows from Proposition 1 that the second-best purchase subsidy based on native damages, denoted by $\hat{s}_i^*$, is given by

$$\hat{s}_i^* = \left(\hat{\delta}_{gi} g_i - \hat{\delta}_{ei} e_i\right).$$

We would expect considerable heterogeneity across locations in the relationship between native and full damages due to the various chemical and physical processes that govern the flow of local pollution. In general, however, we would expect electric vehicles to export more pollution than gasoline vehicles, due to the distributed nature of electricity generation as well as the fact that smokestacks release emissions much higher in the atmosphere than tailpipes. The greater the extent to which the electric emissions are exported to other locations, the greater the extent to which a given location may want to subsidize the purchase of an electric vehicle.

3 Calculating air pollution damages

The theoretical model illustrates that the environmental benefits of an electric vehicle arises from reduced damages relative to the gasoline vehicle it replaces. We calculate this benefit by determining emissions per mile for electric and gasoline vehicles, and then mapping emissions into damages, accounting for the fact that both emissions and damages may differ by location. In these calculations, we use the county as the basic unit of location. We first give an overview of our general procedure, and then describe the details of our two component empirical models.

We consider damages from five pollutants: CO_2, SO_2, NO_X, $PM_{2.5}$, and VOCs. These pollutants account for the majority of global and local air pollution damages and have been a major focus of public policy.[24] Our set of electric vehicles includes each of the eleven pure electric vehicles in the EPA fuel efficiency database for the 2014 model year.[25] 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.[26]

To determine the emissions per mile for each gasoline vehicle, we integrate data from several sources.[27] For CO_2 and SO_2, emissions are directly proportional to gasoline usage, so we use conversion factors in GREET scaled by the EPA's MPG.[28] We differentiate urban and non-urban counties by using EPA's city and highway mileage.[29] For NO_X emissions, we use the Tier 2 emission standards for the vehicle "bin". For $PM_{2.5}$ and VOCs, we combine the Tier 2 standards with GREET estimates of $PM_{2.5}$ emissions from tires and brakes and VOC emissions from evaporation. The implication of this procedure is that emissions per

[24] We do not analyze emissions of CO and toxics like mercury. Most CO emissions are from vehicles, and most toxics are from power plants, so the direction of bias from these omissions is unclear.

[25] The federal purchase subsidy depends on the size of the battery. All eleven pure electric vehicles are eligible for the maximum subsidy of $7500.

[26] Survey data on new vehicle purchases provided by MaritzCX was used to verify that these choices were reasonable. See Supplementary Appendix E for details.

[27] We do not make state-level adjustments to car emissions, although fuel blend regulations in California have been shown to improve air quality (Auffhammer and Kellogg 2011).

[28] 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.

[29] Urban counties are defined as counties which are part of a Metropolitan Statistical Area (MSA).

mile for each gasoline vehicle only differ across urban and non-urban counties.[30]

For electric vehicles, determining emissions per mile is more complicated. We begin with the EPA estimate of MPG equivalent (i.e., the estimated kWh per mile).[31] We adjust this figure to account for the temperature profile of each county, because electric vehicles use more electricity per mile in cold and hot weather.[32] Next we use an econometric model (described below) to estimate the marginal emissions factors (e.g., tons per kWh) for each of our pollutants at each of 1486 power plants due to an increase in regional electricity load. We combine these estimates with an assumed daily charging profile to determine the emissions per mile at each power plant due to the charging of an electric vehicle in a given county.[33] The implication of this procedure is that emissions per mile for each electric vehicle may differ across any two counties.

Next we map emissions into damages. For CO_2, we use the EPA social cost of carbon of \$41 per ton.[34] For local pollutants, we use the AP2 model. This model calculates damages per unit of a given local pollutant in each county (as described below). By multiplying emissions per mile and damages per unit emitted, and then aggregating across pollutants (and, for electric vehicles, across power plants) we obtain the full damages per mile for each gasoline vehicle and each electric vehicle in each county. As in the theoretical section, these full damages account for global effects, local effects in the given county, and local effects in other counties.

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

[30]The emissions per mile for our gasoline vehicles are reported in Table A in Supplementary Appendix E.

[31]We use the combined city/highway EPA figure and do not differentiate electric vehicles by urban and rural since regenerative braking leads to smaller differences in city and highway efficiencies.

[32]This is due to both the decreased performance of the battery and the increased demand for climate control (Yuksel and Michalek 2015). Temperature has a smaller effect on the performance of gasoline vehicles, so we do not adjust gasoline MPG for temperature. We model the electric vehicle 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 G. We explore how sensitive our findings are to this assumption, as well as others, in Section 4.4.

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

[34]See http://www.epa.gov/climatechange/EPAactivities/economics/scc.html. We use the year 2015, 3% discount rate estimate and convert it to 2014 dollars. Moreover, all monetary values in all model components are also converted to 2014 dollars.

Simulator (MOVES).[35]

3.1 Econometric model: estimation of marginal emission factors from electricity use

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. Accordingly, we follow the North American Electric Reliability Corporation (NERC) and divide the three interconnections into nine distinct regions.[36] We use these nine NERC regions to define the spatial scale for measuring emissions per kWh. In particular, our estimation strategy assumes that an electric vehicle charged at any county within a given NERC region has the same marginal emission factors as an electric vehicle charged at any other county within the same region.[37]

Our data consists of hourly emissions of CO_2, SO_2, NO_X, and $PM_{2.5}$ at 1486 power plants as well as hourly electricity consumption (i.e., electricity load) for each of our nine NERC regions, for the years 2010-2012.[38] We use these data to estimate the effect of electricity load on emissions, employing methods similar to Graff Zivin et al (2014) and Holland and Mansur (2008). Like them, we allow for an integrated market where electricity consumed within an interconnection may be provided by any power plant within that interconnection. In contrast, however, we estimate the effect of changes in electricity load *separately* for each power plant in the interconnection.

[35] If vehicle life and miles driven per year per vehicle are the same across counties, then these weights are equivalent to the weights α_i (the number of new vehicle buyers) used in the theoretical model.

[36] See Supplementary Appendix H for our procedure for assigning counties to NERC regions.

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

[38] 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. More details about this data are in Supplementary Appendix I.

The dependent variable in our analysis, 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. To account for different charging profiles, 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. We regress:

$$y_{it} = \sum_{h=1}^{24} \sum_{j=1}^{J(i)} \beta_{ijh} HOUR_h LOAD_{jt} + \sum_{h=1}^{24} \sum_{m=1}^{36} \alpha_{ihm} HOUR_h MONTH_m + \varepsilon_{it}, \tag{1}$$

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, $MONTH_m$ indicates month of the sample m, and $LOAD_{jt}$ is the electricity consumed in region j at time t. The coefficients of interest are the marginal emission factors β_{ijh}, which represent the change in emissions at plant i from an increase in electricity usage in region j in hour of the day h.

3.2 The AP2 model: determining damages from local air pollution

The AP2 model is an integrated assessment air pollution model.[39] AP2 connects reported emissions (USEPA, 2014) to estimates of ambient concentrations using an air quality model. In particular, the air quality model maps emissions of ammonia, NO_X, SO_2, $PM_{2.5}$, and VOCs from each reported source of air pollution in the contiguous U.S. into ambient concentrations of SO_2, O_3, and $PM_{2.5}$ at all receptor locations (i.e., the 3,110 counties in the contiguous U.S.). The remaining components of AP2 then link these ambient concentrations to exposures, physical effects, and monetary damages. Welfare endpoints covered by the model include: human health, crop and timber yields, degradation of buildings and material, and reduced visibility and recreation (Muller and Mendlsohn, 2007). Human exposures are calculated using county-level population data for 2011 which are reported by the U.S. Census. Crop and timber yields are reported by the U.S. Department of Agriculture. Damages associated with built structures, visibility, and recreation contribute a very small share of total damage (Muller et al 2011).

[39]See Muller (2011). More details of our implementation of AP2 are given in Supplementary Appendix I.

Exposures are translated into physical effects (e.g., premature deaths, cases of illness, lost crop yields) using concentration-response functions reported in the related literature. In terms of the share of total damages, 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 all-age mortality rates.[40] Mortality risks, which comprise the vast majority of damage from local air pollution, are then expressed in terms of monetary terms using a $6 million value of a statistical life (VSL). Crop and timber yield effects from pollution exposure are valued using 2011 market prices.

Because of the focus of this paper on small changes to the vehicle fleet, calculation of incremental damages per-unit mass emitted is necessary. The algorithm used to compute damages per ton herein has been used in prior research (Muller and Mendelsohn, 2009; Muller et al 2011). Briefly, this entails the following steps. With all sources in the U.S. emitting at their reported level in 2011, exposures, physical effects, and monetary damages are computed. Then, for an emission from a particular power plant, AP2 adds one ton of SO_2, for example, to reported emissions for 2011. Exposures, physical effects, and monetary damage are re-computed. The incremental damages per-unit mass is tabulated as the difference in monetary damage between the baseline case and the add-one-ton case.

Importantly, in computing per-unit emitted damages, AP2 aggregates the difference in damages across all county receptors affected by the additional ton. As discussed above, local governments may be more concerned about native damages rather than full damages. We use the AP2 model in a novel way to determine both types of damages. To determine full damages, we follow the usual procedure and aggregate damages at *all* receptors. To determine native damages, we disaggregate the plume of damages resulting from emissions at a given source in two ways. For in-state effects, native damages are limited to the change in damages that occur within the state of emission. For in-county effects, native damages encompass damages which occur within the county of emission.

[40]In our sensitivity analysis, we study a more recent concentration response function (Roman et al. 2008).

4 Results

4.1 Environmental benefits of electric vehicles

The environmental benefits of electric vehicles depends on the difference between damages from gasoline and electric vehicles. We begin with damages from electric vehicles. The right panel of Figure 1 illustrates our baseline estimates of the damages (in cents per mile) for the 2014 electric Ford Focus by county.[41] The variation is largely driven by the NERC regions, although damages do vary within a region due to our county-specific temperature correction.

Table 1 summarizes the data in Figure 1 and shows sensitivity with respect to charging profiles.[42] In the baseline EPRI profile, mean damages are 2.6 cents per mile (the equivalent of 8.1 cents per kWh) but range from one cent or less per mile in California and the West (WECC) to over four cents per mile in the Midwest (MISO). These regional differences in emissions reflect the pollution intensity of the fuels used in each region's generating capacity as well as its electricity imports from other regions. There is some variation in damages across the charging profiles. Our baseline results are based on the EPRI charging profile, in which most electric vehicle charging occurs at night. However, damages could be reduced in the Midwest (MISO) by over 1.5 cents per mile by charging between 1pm and 4pm, for example. But generally, variation across charging profiles is much smaller than the variation across NERC regions.

The left columns in Table 2a summarize the distribution of damages across counties for the electric Ford Focus as well as all other 2014 model year electric vehicles. For the electric Ford Focus, the mean is 2.59 cents per mile with a range from under one cent (in the West) to almost 5 cents (in the Midwest). The difference across vehicles is due solely to differences in their efficiency (in kWh per mile). For example, the BYD e6 (the dirtiest electric vehicle) uses approximately twice as many kWh per mile as the Chevy Spark (the cleanest electric vehicle). Correspondingly, the mean, minimum, and maximum damages of the BYD e6 are approximately double those of the Chevy Spark.

We now turn to the damages from gasoline vehicles. The left panel of Figure 1 illustrates

[41] See Supplementary Appendix Q for full page color versions of all figures.

[42] All results are in 2014$ and all summary statistics are weighted by VMT.

the damages (in cents per mile) for the gasoline Ford Focus by county. The counties with large damages correspond to major population centers because air pollution damages are mostly comprised of premature mortality risks. These damages are summarized in the middle columns of Table 2a. For the gasoline Ford Focus, mean damages are 1.86 cents per mile (the equivalent of $0.51 per gallon) but range from about a cent per mile to over four cents per mile.[43]

Notice that there is substantial overlap in the distributions of damages from gasoline and electric vehicles. If these damages were highly correlated, then the environmental benefits of an electric vehicle would be small in most counties. In fact, the damages are not highly correlated (the correlation is 0.07). As a result, the environmental benefits vary substantially, as shown in the right columns of Table 2a. For example, gasoline vehicle damages are large in Los Angeles (due to the large population and properties of the airshed) but electric vehicle damages are small (due to the clean Western power grid). In this situation, the environmental benefits are almost equal to gasoline damages (i.e., three to four cents per mile) and hence electric vehicles have substantial environmental benefits. The opposite occurs in the upper Midwest where gasoline vehicle damages are small (due to low population densities) but electric vehicle damages are large (due to the prevalence of coal-fired generation in the region and the temperature adjustment to electric vehicle range). Here the environmental benefits of an electric vehicle are *negative*, and is almost equal to the electric vehicle damages. Overall, the environmental benefits are negative on average for each of the electric vehicles in Table 2a.[44] The electric Ford Focus is the median electric vehicle in terms of environmental benefits, and we focus on it throughout the results section.

Table 2b decomposes the environmental benefits into global benefits and local benefits. Just about every electric vehicle, in just about every place, creates global environmental benefits relative to gasoline vehicles. In contrast, the local environmental benefits from electric vehicles can be positive or negative depending on the place. But on average, for all electric vehicles, the negative local environmental benefits outweighs the positive global en-

[43]Mean damages per gallon of gasoline range from $0.48 to $0.62 across the vehicles. For the Ford Focus, damages across counties range from $0.37 to $1.12 per gallon.

[44]This is due in large part to the fact that only 30% of the VMT occurs in the three regions with the lowest marginal damages from electricity (see the last column of Table 1).

vironmental benefits. Focusing solely on global environmental benefits provides a misleading impression of the environmental consequences of electric vehicles.[45]

Using Proposition 2, we can convert the environmental benefits into the second-best purchase subsidy by assuming that both the electric vehicle and the gasoline vehicle are driven 150,000 miles.[46] Figure 2 shows the second-best subsidies by county. Except for a few counties around New York City and Atlanta, the subsidy is negative throughout the eastern part of the country (i.e., it is a *tax* on the purchase of electric vehicles). The subsidy 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 second-best subsidy ranges from about positive $5,000 to negative $5,000.

In Table 3, we aggregate to the level of Metropolitan Statistical Area (MSA). The MSAs with the highest environmental benefits are all in California because electricity generation in the West does not produce much air pollution. In these MSAs, the environmental benefits are about two to three cents per mile (a second-best subsidy of up to $5000). The MSAs with the lowest environmental benefits are all in the upper Midwest, again because of the prevalence of coal-fired power stations. Here the environmental benefits are negative three cents per mile (a second-best purchase tax of about $4000). Other large MSAs can have either positive or negative environmental benefits. New York and Chicago have some of the largest damages from gasoline vehicles, but environmental benefits from electric vehicles are small or negative due to the large 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 contains a similar analysis at the state level. Compared to MSAs, the environmental benefits of electric vehicles are smaller at the state level because of negative benefits in non-urban areas. The largest environmental benefits are in California (a second-best sub-

[45]Several prominent online sites that compare gasoline and electric vehicles (EPA, Union of Concerned Scientists) only consider global environmental benefits.

[46]We assume both vehicles have 10 year lifetimes, regardless of the number of miles driven, and that both are driven 15,000 miles a year in the absence of any taxes on miles. In practice, vehicle life depends on both years and miles driven. Moreover, it is not clear whether electric vehicles will be driven more (due to lower costs per mile) or less (due to the inconvenience of charging) than gasoline vehicles.

sidy of $3,000) and other Western states. The lowest benefits are in the Upper Midwest (a second-best tax of almost $5,000 in North Dakota.) There are only 11 states in which the environmental benefits are positive, and Texas is the only high VMT state outside the Western interconnection in which the environmental benefits are positive. The left panel of Figure 3 shows the second-best purchase subsidy by state. When driven in the average state, a 2014 electric Ford Focus causes $1095 more environmental damages over its driving lifetime than the equivalent gasoline Ford Focus.[47]

4.2 Exporting pollution: full and native damages

Although both gasoline and electric vehicles export pollution, electric vehicles export pollution to a remarkable degree (the grid itself is distributed and emissions from power plants are released from tall smokestacks intended to disperse pollutants over a wide area).[48] To illustrate this discrepancy, we first analyze transport of a specific pollutant from a specific county. The left panel in Figure 4 illustrates the change in $PM_{2.5}$ associated with driving gasoline-powered Ford Focus vehicles in Fulton County Georgia. Most of the increase in $PM_{2.5}$ is centered within a few nearby counties. The right panel in Figure 4 shows the change in $PM_{2.5}$ associated with equivalent driving by electric powered Ford Focus charged in the same county. The spatial footprint of $PM_{2.5}$ in this case encompasses the entire eastern U.S.

Our definition of native damages allows a more comprehensive analysis of pollution export. 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 1.7 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 from local pollutants are exported from the state and 99% of are exported from the county. Local damages from gasoline vehicles are exported to a much smaller extent. On average only 19% of these damages are exported from a state and only 57% are exported from a county.

[47]Although our main focus is on variation from this average, and the main focus in Michalek et al (2011) is on life-cycle costs, we can compare our results to theirs. They find, on average, a battery electric vehicle causes $181 more environmental damages over its driving lifetime than a gasoline vehicle. See Supplementary Appendix O for details.

[48] Similarly, any electricity consuming good will export pollution.

Using native damages rather than full damages changes the environmental benefits calculation quite dramatically, especially at the lower tail of the distribution. In this lower tail, gasoline full damages are small and electric full damages are large. Because most electric vehicle damages are exported, both native gasoline damages and native electric damages are small. This implies that the lower tail of environmental benefits moves from approximately -3.6 cents per mile to approximately -0.06 cents per mile for county-level native damages. In contrast, at the the upper tail of the distribution, electric vehicle damages were already low, so accounting for native damages has a smaller impact on the environmental benefits. On average, the environmental benefits calculated using native damages is positive at both the state and county level. Correspondingly, as illustrated in the right panel of Figure 3, the state level second-best purchase subsidy, using native damages, is positive in 32 out of 48 states.

Do state policymakers place greater emphasis on full or native damages when considering electric vehicle subsidies? A number of states have implemented subsidies for the adoption of electric vehicles, above and beyond the federal subsidy, such as California ($2500), Colorado ($6000), Georgia ($5000), Illinois ($4000), and Maryland ($3000). In addition, some states offer a variety of other incentives, including carpool lane access, electricity discounts, and parking benefits.[49] As shown in supplementary Appendix J, both actual subsidies and the number of other incentives are more highly correlated with our calculated native damage subsidy than with our calculated full damage subsidy. This evidence suggests that native damages may help explain state policymakers' support for electric vehicle subsidies.

4.3 State and county differentiated policies

Our analysis shows that the environmental benefits of electric vehicles vary substantially across locations. This raises the question of whether differentiated policies can lead to large enough welfare gains to offset any additional implementation costs. To calculate these welfare gains, we calibrate the discrete choice model developed in Section 2.[50] In addition to electric

[49]The Department of Energy maintains a database of alternative fuels policies by state: http://www.afdc.energy.gov/laws/matrix?sort_by=tech. A few states impose a special registration fee for electric vehicles. Our data accounts for policies in place on July 28, 2014.

[50] See Supplementary Appendix K for more details.

vehicle purchase subsidies, we also consider fuel-specific taxes on miles driven (i.e. VMT taxes), because such taxes at the county level correspond to first-best policy in our model.

Table 6a shows the deadweight losses for differentiated VMT tax policies. County-specific taxes on electric miles and gasoline miles set at the Pigovian levels $t_{ei} = \delta_{ei}$ and $t_{gi} = \delta_{gi}$ have zero deadweight loss. To calculate deadweight losses of other policies, we need to specify the share of new vehicle purchases that would be electric under a default policy in which there is no subsidy at all (or business as usual.) If the share would be 2%, we refer to this as the 2% BAU EV share case. Given a 2% BAU EV share, state-specific taxes have a deadweight loss of $92 million per year, and uniform federal taxes has a deadweight loss of $191 million per year.[51] This implies a gain from differentiation of $100 million (moving from federal to state) and of $191 million (moving from federal to county). The middle and right columns of Table 6a show differentiated policies in which there is only a single tax on one of the fuels. The second-best single tax is smaller than the Pigovian tax, because consumers can avoid taxation by substituting into the untaxed vehicle (see Supplementary Appendix L). For single tax policies, the gains from differentiation are on the order of $25-$200 million. However, the deadweight losses are large particularly for taxes on electric miles only ($1.7 billion). The last three rows of Table 6a show differentiated taxes based on native damages. The gains from differentiation are small or even negative. These policies lead to large deadweight losses ($0.7-$1.5 billion), because taxes based on native damages are much too low.

Table 6b shows the deadweight losses for differentiated electric vehicle purchase subsidies. Gains from differentiation are relatively small: on the order of $10-$60 million at 2% BAU EV share. These gains are much smaller than the gains from differentiation of VMT taxes. The distribution of environmental benefits is right skewed. Because the probability of adopting the gas vehicle is close to one, it follows from Proposition 2 that this skewness leads to an increase in the gains from differentiation. Deadweight losses from electric vehicle subsidies are large: around $1.8 billion per year. Electric vehicle subsidies based on native damages have similarly large deadweight losses and small gains from differentiation.

Finally, Table 6b shows the deadweight loss from the current federal policy of a $7500 subsidy on the purchase on an electric vehicle and the deadweight loss from the default no-

[51] For context, annual vehicle sales are approximately 15 million in the United States.

subsidy policy. The deadweight loss from the current federal subsidy is \$3.4 billion per year at 2% BAU EV share. This exceeds the deadweight loss from the no-subsidy policy by \$1.6 billion per year. The BAU EV shares shown in the table represent plausible shares in the near future and are appropriate for evaluating policy looking forward. To evaluate the recent past, we calculate deadweight losses of the two policies for a BAU EV share of 0.375% which is consistent with the actual 2014 electric vehicle market share of approximately 0.75%.[52] The deadweight loss from the current federal subsidy is \$2.0 billion and the deadweight loss from the no-subsidy policy is \$1.7 billion. Regardless of BAU EV share, the current federal subsidy has larger deadweight loss than the no subsidy policy. And the welfare difference between the two polices increases substantially as the BAU EV share increases.

4.4 Sensitivity analysis

Our analysis takes data from a number of different sources, uses estimated coefficients from regressions in the electricity model and the AP2 model, and makes assumptions about variables such as charging behavior and the effects of temperature on electric vehicle range. Although there is uncertainty associated with each of these factors, we do not attempt to assign standard errors to our results. Instead we perform a sensitivity analysis to see the effects of various deviations from our baseline model.[53]

The first parameter that we explore in Table 7 is the social cost of carbon (SCC). Our baseline value is \$41. A higher value for the SCC leads to higher damage estimates for both electric and gasoline vehicles, but the environmental benefits are not highly sensitive to the assumed SCC.

Several of our assumptions affect only one type of vehicle. On the electric side, our baseline calculation makes a temperature adjustment to account for the reduced performance of electric vehicles in weather extremes and uses the EPRI charging profile. Table 7 shows that our results are not sensitive to these choices. On the gasoline side, our baseline calculation differentiates the MPG of gasoline vehicles by city and highway driving and assumes emissions throughout the lifetime of the vehicle are the same as when new. Using an average

[52] Li et al (2015) estimate that 50% of electric vehicle sales are due to the subsidy.

[53] Additional sensitivity for the welfare analysis is in Supplementary Appendix K.

MPG instead leads to slightly lower gasoline vehicle damages. Doubling emissions rates for local pollutants primarily affects the upper tail of the gasoline vehicle damages and hence the upper tail of the environmental benefits.

Another set of assumptions relate to parameters in the AP2 model. In particular, in the baseline case, AP2 uses a VSL of approximately \$6 million. A lower VSL of about \$2 million leads to lower damages for both electric and gasoline vehicles and hence a narrower distribution for the environmental benefits. Another important parameter in AP2 is the dose-response function that links $PM_{2.5}$ exposure to adult mortality. We find that a higher dose response parameter leads to higher damages for both vehicles which widens the distribution of environmental benefits.

The next calculation examines changes to the electricity grid and the gasoline vehicle fleet. Our baseline uses observed power plant emissions in 2010-2012 to estimate the damages from electric vehicles. New air pollution and climate regulations on power plants will likely lead to lower emissions in the future. In addition, there is an ongoing transition from coal plants to gas plants. For a rough estimate of these effects, we model a power grid in which all of the coal-fired power plants are replaced with new gas-fired power plants. This procedure implies that the replacement plants would be in the same location and would be dispatched identically to the old coal-fired plants.[54] Turning to the gasoline vehicle fleet, our baseline uses the gasoline Ford Focus as the comparison vehicle to the electric Ford Focus. New regulations on gasoline vehicles will likely lead to lower emissions in the future. For a rough estimate of these effects, we use the Toyota Prius as a proxy for the vehicle of the future. The effect of these changes on the environmental benefits of electric vehicles is given by the "Future grid & vehicle" row in Table 7. Damages from both vehicles are lower, and damages from electric vehicles are much lower. However the mean environmental benefits of 0.56 cents per mile implies an electric vehicle subsidy of \$840, which is still substantially less than current subsidies.

Finally, we consider statistical uncertainty associated with the marginal damages pro-

[54]Modeling different plant locations and a new load curve is beyond the scope of the present analysis. Here we scale the plant-specific coefficients for coal plants by a ratio. The numerator is the average emissions rate for combined cycle gas turbine plants that started operating after 2007, namely their total emissions in 2010 over their total net generation that year. The denominator is a similar emissions rate for each coal plant in our sample that is not a co-generation plant.

duced by AP2 for both gas and electric vehicles. The procedure is described in Supplementary Appendix I. The results using the 5th and 95th percentiles for the damages are reported in Table 7.

5 Caveats and other considerations

There are several important caveats to our calculation of the environmental benefits of an electric vehicle due to decreased air pollution emissions. First, we have only considered air pollution emissions associated with driving the vehicles. There are other "upstream" environmental externalities associated with electric and gasoline vehicles.[55] It is unlikely, however, that these upstream externalities have the same degree of heterogeneity found in the air pollution emissions from driving. So the effect of including them would likely be a shift in the distribution of second-best subsidies but not a significant change in the variance of this distribution. Previous research has shown that electric vehicles have approximately $1500 greater upstream externalities than gasoline vehicles (Michalek et al 2011).[56]

Second, our analysis is 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 benefits of electric vehicles will depend on the relative rates of changes of these two factors. Table 7 has an analysis of a future grid, but it is important to stress that our estimates are based on the dispatch and emissions of the electricity grid in 2010-2012.

Third, we focus 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. In Supplementary Appendix M, we discuss large scale adoption of electric vehicles.

Fourth, we analyze the environmental benefits of electric vehicles in isolation from other environmental regulations. In practice, these regulations may impact the market for vehicles

[55] These include emissions from making vehicles and batteries, extracting oil, refining gasoline, transporting gasoline to retail stations, mining coal and natural gas, and transporting these resources to electric plants.

[56] See Supplementary Appendix O. See also Tamayao et al (2015) and the references therein.

and/or the electricity market, and hence have an effect on the environmental benefits of electric vehicles.[57]

Some regulations will have a negative effect on the environmental benefits of electric vehicles. Consider the Corporate Average Fuel Economy (CAFE) standards. CAFE stipulates that 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 value for this calculation. These values are much larger than any existing gasoline vehicle. Assuming that the CAFE requirement is initially binding, selling an electric vehicle enables manufacturers to meet a lower standard for the rest of their fleet. 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 N, we determine the CAFE-induced environmental cost and show that the second-best 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 is $1555 per vehicle.[58] This value is significant in comparison with even the largest second-best subsidy for an electric vehicle found in our study ($2785, in California).

Other regulations, such as cap and trade programs and Renewable Portfolio Standards (RPS), will have a positive effect on the environmental benefits. EPA programs cap emissions of NO_X and SO_2 and the Regional Greenhouse Gas Initiative caps emissions of CO_2 in the Northeast. In our model of the electricity market, we determine the marginal increase in emissions due to an increase in electricity consumption. We do not model the constraint that power plant emissions are capped. During the period of our analysis, permit prices were exceedingly low in many markets, especially those for SO_2. In all permit markets, the stock of banked allowances was increasing significantly despite low prices. This suggests that the cap may not have been binding in these markets.[59] Nevertheless, in Supplementary Appendix P, we perform calculations to approximate the effect of binding caps. Under the assumption that caps on NO_X, SO_2, and CO_2 are all binding, damages from an electric

[57]In addition, there may be pre-existing distortions in both the electricity market (e.g., regulatory pricing policy) and the gasoline market (e.g., OPEC.)

[58] A more thorough analysis would use a complete model of both supply and demand for the entire new vehicle market and relax our assumption of constant prices. See also Jenn et al (2016).

[59] A non-binding cap may still yield positive permit prices due to transactions costs.

vehicle decrease from 2.59 cents per mile to 0.94 cents per mile (with ninety-two percent of this decrease due to the cap on SO_2). Equivalently, the second-best subsidy increases from -$1095 to $1380. Turning to RPS, these programs require a fixed percentage of electricity be produced by low emission technologies such as solar and wind. In a region with a RPS, an increase in the electricity load will result in a increase in low emission generation. Therefore, electric vehicle damages can be scaled by $1 - R$, where R is the RPS share, if the renewables operate at the same time and location as EV charging.

In addition to the environmental benefits studied in our paper, there are a variety of other considerations that are put forth in favor of electric vehicle subsidies. First, reducing the consumption of oil may generate geo-political benefits, reduced military expenditures, and economic benefits from insulation to oil price shocks. Michalek et al (2011) determined these benefits to be approximately $1400. Notice that this number has about the same magnitude, but the opposite sign, as the difference in upstream externalities between electric and gasoline vehicles.

Second, electric vehicle subsidies may be justified due to innovation spillovers. If innovation is a public good, then markets may provide too little innovation. Similarly, the inability of firms to appropriate the full gains from innovation (e.g., consumers may also benefit) may reduce innovation incentives. Our analysis cannot speak to the appropriateness of these justifications for electric vehicle subsidies. However, it is worth noting that electric vehicle subsidies are a “demand pull” innovation policy and hence are subject to all the limitations of demand pull policies (Jaffe et al 2005).

Third, subsidizing electric vehicles today helps boost demand, which in turn increases incentives to provide electric vehicle charging infrastructure.[60] The increase in demand may also lead to lower production costs in the future due to learning by doing. Both of these effects increase adoption in the future, which will presumably be desirable due to a cleaner electric grid. This argument may indeed have merit, but any such long-term benefits may be at least partially offset by the short-term costs associated with current electric vehicle use. Our analysis provides an estimate of these costs.

[60] Li et al (2015) examine the relative effectiveness of the current policy with alternative policies aimed at building out the charging network.

6 Conclusion

The comparison of environmental externalities from driving gasoline and electric vehicles depends critically on damages from local pollution. Ignoring local pollution leads to an overestimate of the benefits of electric vehicles and an underestimate of the geographic heterogeneity. Accounting for both global and local pollution, we find electric vehicles generate a negative environmental benefits of 0.73 cents per mile on average relative to comparable gasoline vehicles. There is considerable variation around this average: electric vehicles used in Los Angeles, California produce benefits of 3.2 cents per mile while those used in Grand Forks, North Dakota, produce negative benefits of -3.1 cents per mile. On average, electric vehicles driven in metropolitan areas generate benefits of about one cent per mile while those driven outside metropolitan areas generate negative benefits of -1.7 cents per mile.

These findings raise questions regarding the sign, the magnitude, and the one-size-fits-all nature of the uniform federal subsidy of $7,500 for purchasing a pure electric vehicle. Our results imply subsidies of -$1095 on average with a range from $2785 in California to -$4964 in North Dakota. Thus environmental benefits from driving cannot, alone, justify the federal subsidy. As discussed above, other studies have estimated upstream environmental benefits of electric vehicles of about -$1500 and have estimated benefits of $1400 due to reduced oil consumption. Combining these three factors cannot justify the federal subsidy. It remains an open question as to whether or not additional considerations (such as innovation spillovers, network effects, or learning by doing) generate enough benefits to justify the federal subsidy.

At first blush, our finding of significant geographic heterogeneity in benefits suggests a need for local discretion. However, the pollution export phenomena we identify calls into question whether or not local regulation would be effective. In most 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 eleven 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. Given this, states may implement subsidies even though a tax might be more appropriate. Hence there may be a need for federal policy to account for exported damages.

This suggests the appropriate policy for electric vehicles should be at the federal level, but differentiated by location. We find that differentiated taxes on miles driven lead to greater welfare gains 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 analysis suggests that the interaction of these policies may have significant consequences.

Public policy evaluation is especially difficult and important in contexts characterized by: (i) strong prior beliefs as to the merits of the policy and/or its targeted outcome, (ii) complex interactions among economic and physical systems, and (iii) economically significant outcomes. The federal policy which encourages the purchase of electric vehicles exhibits each of these traits. Although we have focused on 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.

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Figures

Figure 1: Marginal Damages for Gas and Electric Vehicles by County

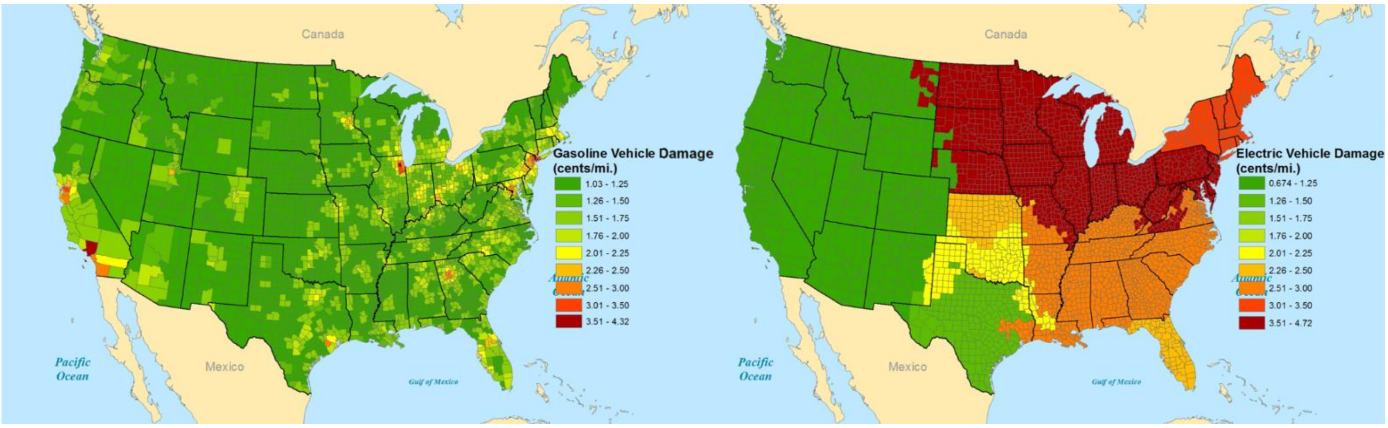


Figure 2: Second-Best Electric Vehicle Subsidy by County

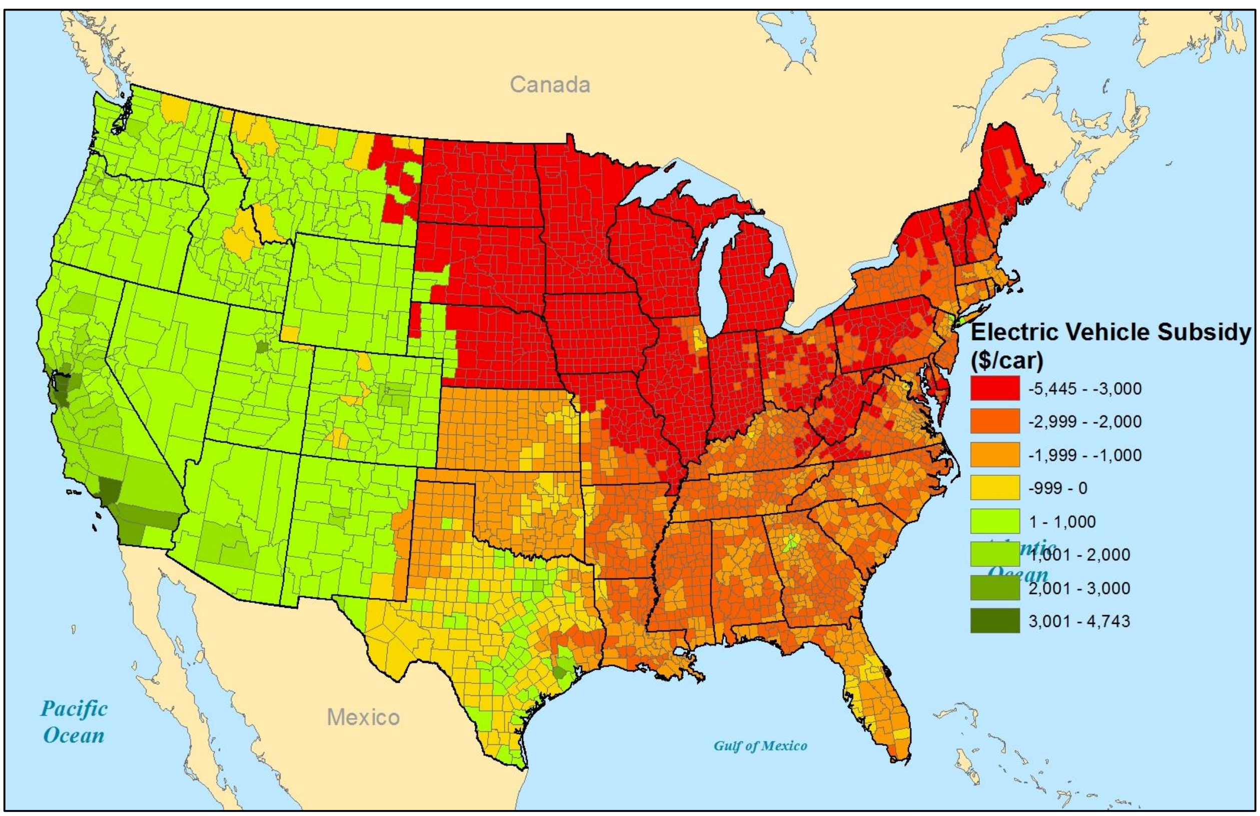


Figure 3: Second-Best Electric Vehicle Subsidy by State (Full and Native Damages)

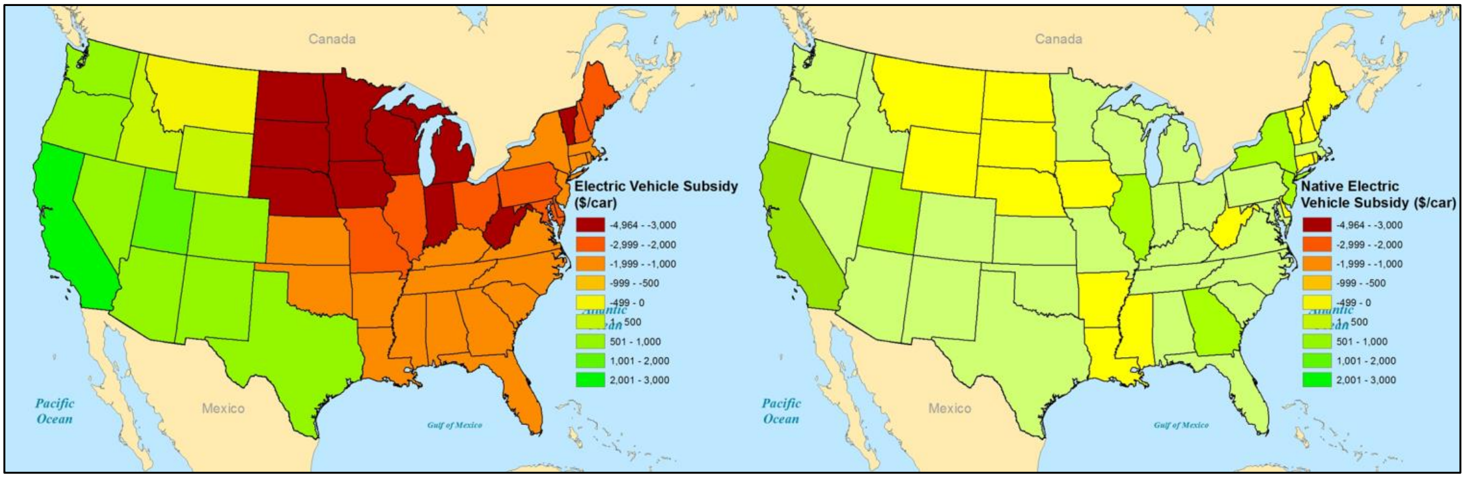
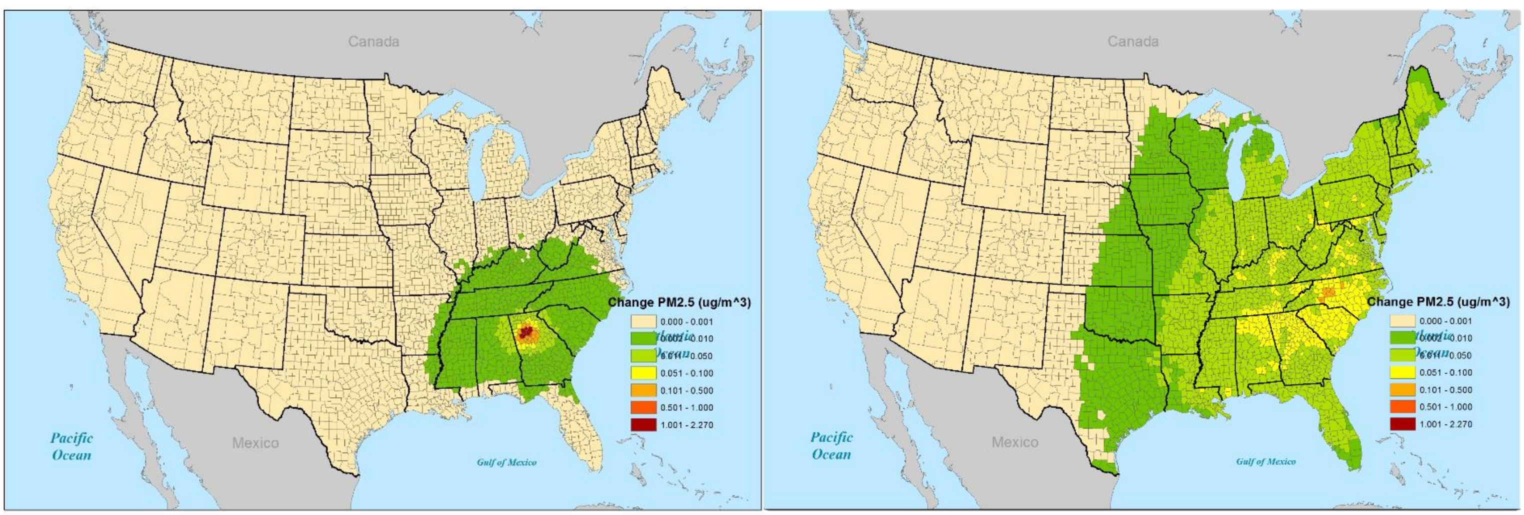


Figure 4: Change in $PM_{2.5}$ from Gasoline v. Electric Vehicle in Fulton County, Georgia



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Notes: The left panel illustrates the change in $PM_{2.5}$ associated with a fleet of 10,000 gasoline-powered Ford Focus vehicles, each driven 15,000 miles in a year in Fulton County. The right panel illustrates the change in $PM_{2.5}$ associated with the same number of miles driven by electric powered Ford Focus vehicles charged in Fulton County, thereby increasing the consumption of electricity in the Southeast (SERC).

Tables

Table 1: Mean damages in cents per mile by electricity demand region for a 2014 Ford Focus electric vehicle 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	11%
WECC w/o CA	1.03	0.92	1.18	0.98	0.84	0.76	0.73	0.99	11%
ERCOT	1.28	1.21	1.50	1.41	1.10	1.07	1.05	1.16	7%
SPP	2.24	2.74	2.07	4.91	2.30	2.89	2.39	1.89	4%
FRCC	2.48	2.14	3.21	2.36	2.25	1.39	1.53	2.11	6%
SERC	2.75	2.67	2.75	2.26	2.72	2.96	2.63	2.71	22%
NPCC	3.11	2.75	4.19	3.75	1.61	2.12	2.49	2.35	9%
RFC	3.64	3.55	3.42	3.38	3.83	3.06	3.43	4.15	17%
MISO & MRO	4.29	3.52	5.63	3.91	3.03	2.57	2.32	3.69	14%
Total	2.59	2.41	2.90	2.56	2.28	2.15	2.12	2.46	100%

Notes: The regions are ordered by the damage per mile under the EPRI charging profile. The EPRI charging profile is illustrated in Figure B in Supplementary Appendix F; the Flat charging profile assumes charging is equally likely across hours; and other profiles assume charging occurs only in the indicated hours. Damages (in cents per mile) are weighted across counties by passenger vehicle VMT. "California" is the California ISO; "WECC w/o CA" is the Western US excluding California; "ERCOT" is Texas; "SPP" is Kansas and Oklahoma; "FRCC" is Florida; "SERC" is the Southeast; "NPCC" is the Northeast; "RFC" is the Mid-Atlantic and Midwest; and "MISO" is the upper Midwest. See Figure C in Supplementary Appendix H for a map of the regions.

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

	Electric Vehicle			Gasoline Vehicle			Environmental Benefits		
Vehicle	mean	min	max	mean	min	max	mean	min	max
Chevy Spark	2.28	0.59	4.17	1.69	0.95	4.30	-0.60	-3.15	3.08
Honda Fit	2.30	0.60	4.20	1.93	1.13	4.83	-0.37	-3.00	3.60
Fiat 500e	2.34	0.61	4.27	1.74	0.93	4.62	-0.60	-3.26	3.33
Nissan Leaf	2.38	0.62	4.35	1.23	0.74	3.53	-1.16	-3.52	2.22
Mitsubishi i-Miev	2.42	0.63	4.41	1.69	0.95	4.30	-0.73	-3.40	3.05
Smart fortwo	2.54	0.66	4.63	1.67	0.98	4.50	-0.87	-3.57	3.13
Ford Focus	2.59	0.67	4.72	1.86	1.03	4.32	-0.73	-3.63	3.16
Tesla S (60 kWh)	2.82	0.73	5.15	2.44	1.28	5.48	-0.38	-3.78	4.28
Tesla S (85 kWh)	3.06	0.80	5.59	2.67	1.48	5.74	-0.39	-4.02	4.55
Toyota Rav4	3.58	0.93	6.52	2.09	1.20	5.02	-1.49	-5.23	3.50
BYD e6	4.35	1.13	7.94	2.09	1.20	5.02	-2.27	-6.64	3.30

Table 2b: Decomposition of environmental benefits into global and local environmental benefits.

	Environmental Benefit			Global Env. Benefits			Local Env. Benefits		
Vehicle	mean	min	max	mean	min	max	mean	min	max
Chevy Spark	-0.60	-3.15	3.08	0.35	-0.14	0.72	-0.95	-3.01	2.37
Honda Fit	-0.37	-3.00	3.60	0.52	0.02	0.89	-0.89	-3.02	2.71
Fiat 500e	-0.60	-3.26	3.33	0.32	-0.19	0.71	-0.92	-3.08	2.63
Nissan Leaf	-1.16	-3.52	2.22	-0.09	-0.40	0.28	-1.07	-3.16	1.99
Mitsubishi i-Miev	-0.73	-3.40	3.05	0.30	-0.21	0.69	-1.04	-3.20	2.36
Smart fortwo	-0.87	-3.57	3.13	0.18	-0.24	0.57	-1.06	-3.34	2.57
Ford Focus	-0.73	-3.63	3.16	0.44	-0.21	0.89	-1.17	-3.43	2.28
Tesla S (60 kWh)	-0.38	-3.78	4.28	0.83	-0.07	1.36	-1.21	-3.72	2.93
Tesla S (85 kWh)	-0.39	-4.02	4.55	0.96	0.01	1.54	-1.36	-4.04	3.02
Toyota Rav4	-1.49	-5.23	3.50	0.23	-0.51	0.81	-1.72	-4.73	2.71
BYD e6	-2.27	-6.64	3.30	-0.04	-0.88	0.65	-2.23	-5.78	2.66

Notes: Damages are from power plant emissions or tailpipe emissions of NOx, VOCs, PM2.5, SO2, and CO2e. Electric vehicles assume the EPRI charging profile. Substitute vehicles are defined as the identical make where possible. The substitute vehicle 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 VMT.

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

Metropolitan Statistical Area	Environmental benefits per mile	VMT (pct)	Damage per mile (gasoline)	Damage per mile (electric)	Purchase Subsidy
Highest Benefit MSAs					
Los Angeles, CA	3.16	2.69%	3.85	0.69	$4,743
Oakland, CA	2.21	0.75%	2.89	0.68	$3,315
San Jose, CA	2.11	0.54%	2.80	0.69	$3,166
San Francisco,CA	1.91	0.45%	2.59	0.68	$2,867
Santa Ana, CA	1.87	0.93%	2.54	0.67	$2,800
Other High VMT MSAs					
San Diego, CA	1.85	0.97%	2.53	0.68	$2,770
Riverside, CA	1.17	1.35%	1.88	0.71	$1,756
Phoenix, AZ	0.74	1.16%	1.77	1.03	$1,112
Houston, TX	0.67	1.74%	2.01	1.35	$1,003
Dallas, TX	0.62	1.52%	1.91	1.29	$926
New York, NY	-0.02	1.97%	3.16	3.18	-$32
Atlanta, GA	-0.36	1.92%	2.38	2.73	-$535
Chicago, IL	-0.74	1.75%	2.98	3.72	-$1,116
Washington DC-VA	-0.89	1.40%	2.19	3.08	-$1,335
Minneapolis, MN	-2.39	1.06%	2.08	4.46	-$3,578
U.S. and Non-Urban					
U.S. Average	-0.73	100%	1.86	2.59	-$1,095
Non-urban	-1.67	20%	1.20	2.87	-$2,500
Lowest Benefit MSAs					
St. Cloud, MN	-2.87	0.08%	1.62	4.49	-$4,310
Bismarck, ND	-2.97	0.04%	1.52	4.49	-$4,456
Fargo, ND-MN	-3.07	0.07%	1.54	4.61	-$4,605
Duluth, MN-WI	-3.09	0.10%	1.47	4.56	-$4,635
Grand Forks, ND-MN	-3.14	0.03%	1.52	4.66	-$4,711

Notes: The environmental benefits are the difference in damages between the gasoline-powered Ford Focus and the electric Ford Focus. Environmental benefits are weighted by VMT by county within each MSA. Non-urban includes all counties that are not part of an MSA. The vehicle subsidy assumes vehicle is driven 150,000 miles.

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

State	Environmental benefits per mile	VMT (pct)	Damage per mile (gasoline)	Damage per mile (electric)	Purchase Subsidy
Highest Benefit States					
California	1.86	11%	2.55	0.69	$2,785
Utah	0.73	1%	1.77	1.04	$1,089
Colorado	0.60	2%	1.63	1.03	$902
Arizona	0.59	2%	1.62	1.02	$889
Washington	0.58	2%	1.59	1.02	$865
Other High VMT States					
Texas	0.34	8%	1.75	1.41	$505
Florida	-0.70	7%	1.80	2.49	-$1,049
Georgia	-0.78	4%	1.96	2.74	-$1,166
New York	-0.91	5%	2.19	3.10	-$1,371
North Carolina	-1.07	4%	1.67	2.74	-$1,611
Virginia	-1.20	3%	1.72	2.93	-$1,807
Illinois	-1.56	3%	2.31	3.87	-$2,345
Ohio	-1.76	4%	1.89	3.65	-$2,640
Pennsylvania	-1.78	3%	1.86	3.64	-$2,675
Michigan	-2.48	3%	1.76	4.24	-$3,720
Lowest Benefit States					
South Dakota	-2.66	0%	1.27	3.93	-$3,992
Minnesota	-2.76	2%	1.72	4.48	-$4,145
Wisconsin	-2.79	2%	1.59	4.37	-$4,180
Iowa	-2.93	1%	1.37	4.30	-$4,394
North Dakota	-3.31	0%	1.27	4.58	-$4,964
U.S. Average	-0.73	100%	1.86	2.59	-$1,095

Notes: The environmental benefits are the difference in damages between the gasoline-powered Ford Focus and the electric Ford Focus. Environmental benefits are weighted by gasoline-vehicle VMT within each state. The vehicle subsidy assumes the vehicle 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	2.59	2.74	1.18	0.67	4.72
	Non-GHG	1.70	1.86	1.02	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	1.86	1.76	0.59	1.03	4.32
	Non-GHG	0.53	0.36	0.52	0.01	2.92
	State	0.43	0.26	0.51	0.00	2.76
	Export %	19%	28%			5%
	County	0.23	0.10	0.37	0.00	2.03
	Export %	57%	72%			30%
Environmental Benefits	All	-0.73	-1.01	1.39	-3.63	3.16
	Non-GHG	-1.17	-1.48	1.19	-3.43	2.28
	State	0.28	0.12	0.51	-0.32	2.46
	County	0.21	0.08	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 VMT.

Table 6a: Deadweight losses of differentiated VMT taxes

	Gas and Electric Tax			Gas Tax Only			Electric Tax Only		
	BAU EV Share			BAU EV Share			BAU EV Share		
	1%	2%	5%	1%	2%	5%	1%	2%	5%
County policies	0	0	0	201	391	905	1709	1717	1740
State policies	89	92	102	289	482	1005	1712	1721	1752
Federal policy	162	191	277	343	542	1095	1736	1770	1874
County (Native)	989	1073	1325						
State (Native)	1067	1153	1412						
Federal (Native)	778	809	903						

Table 6b: Deadweight losses of differentiated electric vehicle purchase subsidies

	BAU EV Share		
	1%	2%	5%
County policies	1754	1806	1960
State policies	1758	1815	1983
Federal policy (-$742 subsidy)	1783	1864	2107
County policies (native damages)	1788	1874	2134
State policies (native damages)	1792	1881	2152
Federal policy (native damages, -$1692 subsidy)	1785	1868	2188
Current Federal Policy ($7500 subsidy)	2581	3459	6079
BAU Federal Policy (Zero subsidy)	1791	1880	2148

Notes: Deadweight loss in millions of dollars per year is based on 15 million annual vehicle sales normalized to the emissions profile of the Ford Focus. The BAU EV Share is the proportion of electric vehicles sold if there were no subsidy. This share is determined by the assumed value for μ (10664, 10508,10037) which is proportional to the standard deviation of the unobserved relative preference shock. In Table 6a, federal taxes in the joint tax case are 1.9 cents per mile on gasoline miles and 2.6 cents per mile on electric miles.

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

	Electric Vehicle			Gasoline Vehicle			Environmental Benefits		
	mean	min	max	mean	min	max	mean	min	max
Baseline	2.59	0.67	4.72	1.86	1.03	4.32	-0.73	-3.63	3.16
Carbon cost									
SCC=$51	2.80	0.80	5.02	2.18	1.28	4.67	-0.62	-3.68	3.38
SCC=$31	2.37	0.55	4.42	1.53	0.78	3.98	-0.84	-3.58	2.95
No temperature adjustment	2.43	0.67	3.90	1.86	1.03	4.32	-0.57	-2.84	3.18
Flat charging profile	2.41	0.74	3.88	1.86	1.03	4.32	-0.55	-2.79	3.10
Average MPG	2.59	0.67	4.72	1.74	1.23	4.11	-0.85	-3.42	2.89
Double gasoline emissions rates	2.59	0.67	4.72	2.39	1.05	7.24	-0.20	-3.58	5.60
$2 Million VSL	1.61	0.71	2.64	1.54	1.02	2.55	-0.06	-1.59	1.63
PM dose response	3.74	1.25	6.89	2.16	1.04	5.96	-1.58	-5.76	3.91
Future grid & vehicle	0.67	0.37	1.39	1.23	0.74	3.53	0.56	-0.57	2.73
High estimates*	2.65	0.69	4.46	2.13	1.15	3.90	-0.52	-2.86	2.36
Low estimates*	2.53	0.68	4.15	1.59	0.78	2.90	-0.94	-3.12	1.87

Notes: Baseline corresponds to Ford Focus row from Table 2a. "Carbon cost" uses a social cost of carbon of $51 or $31. "No temperature adjustment" assumes electric vehicle range is independent of temperature. "Flat charging profile" assumes electric vehicle charging occurs equally in all hours. "Average MPG" uses the average MPG for the gasoline vehicle regardless of where it is driven. "Double gasoline emissions rates" doubles the gasoline vehicle emissions rates for local pollutants."$2 Million VSL" assumes the VSL is $2 million instead of the baseline $6 million. "PM dose response" assumes a higher PM2.5 adult-mortality dose-response from Roman etal 2008. "Future grid & vehicle" assumes all coal-fired power plants replaced by identically dispatched natural gas plants and a Toyota Prius gasoline vehicle. "High estimates" assumes 95th percentile damages for all local pollutants for all counties. "Low estimates" assumes 5th percentile damages for all local pollutants for all counties. "*" indicates the "min" and "max" counties are replaced by the 5th and 95th percentile counties.

For Online Publication: Supplementary Appendices

A Choice over several gasoline and electric vehicles and proofs of propositions

Proof of propositions

Preliminary calculations. For the moment we drop the i subscript. Let $G = \pi g$ and $E = (1-\pi)e$. For a generic policy variable ρ we have

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

which simplifies to

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

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

$$\frac{\partial \pi}{\partial \rho} = \frac{\pi(1-\pi)}{\mu}(\frac{\partial V_g}{\partial \rho}-\frac{\partial V_e}{\partial \rho}). \tag{A-2}$$

Using this result we can derive the following

$$\frac{\partial G}{\partial \rho} = g\frac{\partial \pi}{\partial \rho}+\pi\frac{\partial g}{\partial \rho} = g\frac{\pi(1-\pi)}{\mu}(\frac{\partial V_g}{\partial \rho}-\frac{\partial V_e}{\partial \rho})+\pi\frac{\partial g}{\partial \rho} \tag{A-3}$$

and

$$\frac{\partial E}{\partial \rho} = -e\frac{\partial \pi}{\partial \rho}+(1-\pi)\frac{\partial e}{\partial \rho} = -e\frac{\pi(1-\pi)}{\mu}(\frac{\partial V_g}{\partial \rho}-\frac{\partial V_e}{\partial \rho})+(1-\pi)\frac{\partial e}{\partial \rho}. \tag{A-4}$$

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

Proof of Proposition 1. Throughout the proof we can drop the subscript i. From the Envelope Theorem, we have $\frac{\partial V_g}{\partial s} = 0$ and $\frac{\partial V_e}{\partial s} = 1$. The first-order condition for s comes from substituting these expressions into (A-1) with $\rho = s$, setting the resulting expression equal to zero, and simplifying. This gives

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

Expected 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

$$\left(s\frac{\partial \pi}{\partial s}\right) - \left(\delta_g \frac{\partial G}{\partial s} + \delta_e \frac{\partial E}{\partial s}\right) = 0. \tag{A-5}$$

So the optimal s is given by

$$s = \frac{\delta_g \frac{\partial G}{\partial s} + \delta_e \frac{\partial E}{\partial s}}{\frac{\partial \pi}{\partial s}} \tag{A-6}$$

From (A-3) and (A-4), 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.

Let $\mathcal{W}(S)$ denote the sum of welfare across regions as a function of an arbitrary vector of subsidies $S = (s_1, s_2, \ldots, s_n)$. We have

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

First consider the derivation of the second-best uniform subsidy. Here the central government selects the same subsidy s for each location. Except for δ_{gi}, δ_{ei}, and α_i, the locations are identical, and the government is selecting the same subsidy for each location. Therefore, the values for e_i, g_i, R_i and π_i will be same across locations. Under these conditions, the derivative of $\mathcal{W}(S)$ with respect to s can be written as

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

It follows that

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

Solving for s gives the second-best uniform subsidy $\tilde{s}$

$$\tilde{s} = \frac{1}{\frac{\partial \pi}{\partial s}} \left(\sum \alpha_i \delta_{gi} \frac{\partial G}{\partial s} + \sum \alpha_i \delta_{ei} \frac{\partial E}{\partial s} \right). \tag{A-7}$$

The equation in the Proposition for $\tilde{s}$ now follows from the same manipulations used in the proof of Proposition 1.

Next we want to determine a second-order Taylor series approximation to $\mathcal{W}(S)$ at the point $\tilde{S} = (\tilde{s}, \tilde{s}, \dots, \tilde{s})$. First we take the derivatives at an arbitrary point. 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 (A-2), (A-3), and (A-4) we have: $\frac{\partial \pi_i}{\partial s_i} = -\frac{\pi_i(1-\pi_i)}{\mu}$, $\frac{\partial G_i}{\partial s_i} = -\frac{\pi_i(1-\pi_i)}{\mu} g_i$ and $\frac{\partial E_i}{\partial s_i} = \frac{\pi_i(1-\pi_i)}{\mu} e_i$. Using these we can write the derivative as

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

Now take the second derivative. We have

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

Evaluating the first and second derivatives at $\tilde{S}$ gives

$$\left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{\tilde{S}} = \frac{\alpha_i}{\mu}\pi(1-\pi)(\delta_{gi}g - \delta_{e_i}e - \tilde{s}), \tag{A-8}$$

and

$$\left.\frac{\partial^2 \mathcal{W}}{\partial s_i^2}\right|_{\tilde{S}} = -\frac{1}{\mu}(1-2\pi)\left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{\tilde{S}} - \frac{\alpha_i}{\mu}\pi(1-\pi). \tag{A-9}$$

We have dropped the subscripts from g, e, and π because prices, income, and the functions f and h are the same across locations, and, at the point $\tilde{S}$, the subsidy is the same across locations. In addition, because the subsidy does not effect the number of miles driven, it follows from Proposition 1, that $s_i^* = (\delta_{gi}g - \delta_{ei}e)$. Thus

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

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 (A-9) and (A-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. ■

Choice over several gasoline and electric vehicles

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

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

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

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

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

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

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

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

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

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

The probability of selecting the electric vehicle j is

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

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

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

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

Differentiated subsidies on purchase of electric vehicle

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

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

From the Envelope Theorem, we have

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

and, for $j \neq k$,

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

For $j = k$ we have

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

Substituting these expressions into the first-order condition gives

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

Now

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

Substituting this into the first-order condition gives

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

Because there are no income effects,

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

and

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

Substituting these derivatives into the first-order condition gives

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

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 vehicle

Now suppose that the government places a uniform subsidy s on the purchase of any electric vehicle. Expected government revenue is given by $R = -\sum_j \tilde{\pi}_j s$. The optimal s can be found as a special case of (A-11). Let $s_k = s$ for every k. Then (A-11) becomes

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

Solving for s gives

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

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

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

Using this gives

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

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

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

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

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

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

From the definition of π_i it follows that

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

Substituting into the expression for s gives

$$s = g \left(\frac{\delta_{g1} \pi_1 + \delta_{g2} \pi_2}{\pi_1 + \pi_2} \right) - e\delta_e. \tag{A-12}$$

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

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

It follows that

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

We can use (A-12) to describe the likely effect of including an additional gasoline vehicle in the consumers choice set on the welfare gains from differentiated regulation. Consider a baseline two-vehicle case in which the electric vehicle pollutes more than gasoline cars, so that the optimal uniform policy is a tax on electric vehicle purchase. Starting at this baseline, we consider an expanded choice set with an additional gasoline vehicle. Suppose initially that the original gasoline vehicle and the additional gasoline vehicle are exactly the same (they have the same purchase price, price for miles, and external costs). Then, of course, adding the additional gasoline vehicle to the choice set will not have any welfare consequences. Now suppose that in each region, the external costs from the additional gasoline vehicle are D units less than the external costs from the original gasoline vehicle. Thus the additional vehicle lowers the mean of the distribution of environmental benefits, but does not change the variance or skewness. We now make two observations. First, because the purchase price and price for miles are still the same we have $\pi_1 = \pi_2$. Second, the additional vehicle leads to lower average environmental damages from gasoline vehicles in each region. Combining these two observations with (A-12) implies that the tax on electric vehicle purchases increases in each region. Because the gasoline vehicles are the same from the point of view of the consumer, Proposition 2 still applies. Thus the additional gasoline vehicle lowers the welfare gain from differentiation.[61] This result is reversed if the additional vehicle raises the mean of the distribution of environmental benefits.

[61] Including the additional vehicle increases the taxes on electric vehicle purchases, which increases π, which in turn decreases both $\pi(1-\pi)$ and $\pi(1-\pi)(2\pi-1)$. Because the variance and skewness have not changed, the second order approximation to the welfare gain from differentiation decreases.

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

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

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

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

and

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

The first-order condition for t_g comes from substituting these expressions into (A-1) with $\rho = t_g$, setting the resulting expression equal to zero, and simplifying. This gives

$$\left(\frac{\partial R}{\partial t_g} - \pi g\right) - \left(\delta_g \frac{\partial G}{\partial t_g} + \delta_e \frac{\partial E}{\partial t_g}\right) = 0. \tag{A-13}$$

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

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

Using this in the first-order condition gives

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

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

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

Similar calculations with respect to t_e gives

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

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

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

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

We have

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

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

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

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

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

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

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

and

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

At $\tilde{T}$, taxes equal in each location, so the gasoline miles and electric miles will be the same each each location. Thus we can drop the subscripts from g, e, G, E and π. From (A-3) 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 location is the same and $e = g$, first term in the formula for $\mathcal{W}(T^*) - \mathcal{W}(\tilde{T})$ is proportional to the variance of the difference between the list of numbers δ_{gi} and δ_{ei}, the second term is proportional to the variance the list of numbers δ_{gi}, and the third term is proportional to the variance of the list of numbers δ_{ei}.

C Continuous Choice Model

Consider an alternative model of vehicle choice and consumption of miles. Here consumers rent vehicles on a per mile basis from a competitive leasing market. We use the same notation for variables that also appear in the main text, and introduce new variables as needed.

Consumers obtain utility from a composite consumption good x (with price normalized to one) and from miles driven over the course of a year, either gasoline miles g or electric miles e. The rental price of gasoline miles is r_g and the rental price of electric miles is r_e. A consumer's indirect utility function is given by

$$V = \max_{x,g,e} u(g,e) + x \text{ such that } x + r_e e + r_g g = I,$$

where I is income and $u(g,e)$ is a function that delineates the utility of consuming gas and electric miles.

Firms in the leasing market buy vehicles from producers and rent them to consumers. Let p_ψ be the price of a gasoline vehicle, and let p_g be the price of a gasoline mile. To break even, the leasing firm must charge rental price

$$r_g = \frac{p_\psi}{\ell} + p_g,$$

where ℓ is the number of miles in the lifetime of the vehicle. Likewise, for electric cars

$$r_e = \frac{p_\Omega - s}{\ell} + p_e,$$

where p_Ω is the price of a electric vehicle, p_e is the price of an electric mile, and s is the electric vehicle purchase subsidy. In equilibrium, leasing firms buy enough vehicles of each type in a given year to satisfy the total demand for miles from consumers. This implies the number of electric car purchases and gasoline car purchases (normalized per consumer) are given by

$$\frac{e}{\ell} \text{ and } \frac{g}{\ell}.$$

Consumers create negative environmental externalities by driving, but ignore the damages from these externalities when making choices about the number of miles. Because the damages from these pollutants may be global or local, we introduce multiple locations into the model.

Uniform vs. differentiated regulation

Let m denote the number of locations and let α_i denote the proportion of the total population of consumers that reside in location i. Let δ_{gi} denote the marginal full damages (in dollars per mile) from driving a gasoline vehicle in location i, and δ_{ei} denote the marginal full damages (in dollars per mile) from driving an electric vehicle in location i.

First we study differentiated regulation. Here there are m local governments that select location-specific purchase subsidies. Let R_i denote the per capita government revenue generated by the purchase of vehicles by the leasing firms in location i. Local government i selects the purchase subsidy s_i to maximize the welfare $\mathcal{W}_i$ associated with driving vehicles within the location, defined as the sum of utility and revenue less pollution damage:

$$\mathcal{W}_i = V + R_i - (\delta_{gi} g_i + \delta_{ei} e_i).$$

Optimizing the welfare function gives the the following Proposition.

Proposition 3. *The second-best differentiated subsidy on the purchase of the electric vehicle in location i is given by s_i^* where*

$$s_i^* = \ell \left(-\delta_{gi} \frac{\frac{\partial g_i}{\partial s_i}}{\frac{\partial e_i}{\partial s_i}} - \delta_{ei} \right). \tag{A-14}$$

If we assume that the subsidy does not effect the total number of miles driven, it follows that

$$s_i^* = \ell \left(\delta_{gi} - \delta_{ei} \right).$$

Proof. Revenue is equal to the subsidy multiplied by the number of electric car sales.

$$R_i = -s_i \frac{e_i}{\ell}.$$

So welfare is

$$\mathcal{W}_i = (V_i - s_i \frac{e_i}{\ell} - \delta_{gi} g_i - \delta_{ei} e_i.)$$

The first-order condition is

$$\frac{\partial V_i}{\partial s_i} - \frac{e_i}{\ell} - \frac{s_i}{\ell} \frac{\partial e_i}{\partial s_i} - \delta_{gi} \frac{\partial g_i}{\partial s_i} - \delta_{ei} \frac{\partial e_i}{\partial s_i} = 0.$$

We have

$$\frac{\partial V_i}{\partial s_i} = \frac{\partial V_i}{\partial r_e} \frac{\partial r_e}{\partial s_i} = (-e_i)(-\frac{1}{\ell}),$$

where the second equality comes from Roy's identity (and the fact that the marginal utility of income is equal to one). Substituting into the first-order condition gives

$$-\frac{s_i}{\ell} \frac{\partial e_i}{\partial s_i} - \delta_{gi} \frac{\partial g_i}{\partial s_i} - \delta_{ei} \frac{\partial e_i}{\partial s_i} = 0.$$

Solving for s_i gives (A-14).

If the subsidy does not effect the total number of miles driven, then $e_i + g_i$ is constant with respect to s. It follows that

$$\frac{\partial e_i}{\partial s} + \frac{\partial g_i}{\partial s} = 0. \tag{A-15}$$

Using this in (A-14) completes the proof. □

The second result in Proposition 3 is the same as the result in Proposition 1, provided that the vehicle lifetime miles are the same. In the discrete choice model, the subsidy does not effect either the number of electric miles driven or the number of gasoline miles driven. In the continuous choice model, we can make the weaker assumption that the subsidy does not effect the total number of miles driven and still obtain the same result for the second-best subsidy.

Next we study uniform regulation. Here a central government selects a uniform subsidy that applies to all m locations. The government's objective is to maximize $\sum \alpha_i W_i$, which is the weighted sum of welfare across locations. The next proposition delineates the second-best uniform subsidy. It also describes an approximation formula for the welfare gain in moving from uniform regulation to differentiated regulation.

Proposition 4. *Assume that the subsidy does not effect the total number of miles driven. Also assume that prices, income, and the function u are the same across locations. The second-best uniform subsidy on the purchase of an electric vehicle is given by $\tilde{s}$, where*

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

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

$$\mathcal{W}(S^*) - \mathcal{W}(\tilde{S}) \approx \frac{1}{2}\left.\frac{\partial e}{\partial s}\right|_{\tilde{s}} \frac{1}{\ell}\sum \alpha_i (s_i^* - \tilde{s})^2 + \frac{1}{2}\left.\frac{\partial^2 e}{\partial s^2}\right|_{\tilde{s}} \frac{1}{\ell}\sum \alpha_i (s_i^* - \tilde{s})^3.$$

Proof. Let $\mathcal{W}(S)$ denote the sum of welfare across regions as a function of an arbitrary vector of subsidies $S = (s_1, s_2, \ldots, s_n)$. We have

$$\mathcal{W}(S) = \sum \alpha_i (V_i - s_i \frac{e_i}{\ell} - \delta_{gi} g_i - \delta_{ei} e_i.)$$

First consider the derivation of the second-best uniform subsidy. Here the central government selects the same subsidy s for each location. Except for δ_{gi}, δ_{ei}, and n_i, the locations are identical, and the government is selecting the same subsidy for each location. Therefore, the values for e_i, g_i, and R_i will be same across locations. Under these conditions, the derivative of $\mathcal{W}(S)$ with respect to s can be written as

$$\sum \alpha_i \left(-\frac{s}{\ell}\frac{\partial e}{\partial s} - \delta_{gi}\frac{\partial g}{\partial s} - \delta_{ei}\frac{\partial e}{\partial s}\right) = 0.$$

Solving for s gives

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

Applying (A-15) gives the equation in the proposition.

Next we want to determine a second-order Taylor series approximation to $\mathcal{W}(S)$ at the point $\tilde{S} = (\tilde{s}, \tilde{s}, \ldots, \tilde{s})$. First we take the derivatives at an arbitrary point. 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

$$\frac{\partial \mathcal{W}}{\partial s_i} = \alpha_i\left(-\frac{s_i}{\ell}\frac{\partial e_i}{\partial s_i} - \delta_{gi}\frac{\partial g_i}{\partial s_i} - \delta_{ei}\frac{\partial e_i}{\partial s_i}\right) = \alpha_i \frac{\partial e_i}{\partial s_i}\left(-\frac{s_i}{\ell} - \delta_{gi}\frac{\frac{\partial g_i}{\partial s_i}}{\frac{\partial e_i}{\partial s_i}} - \delta_{ei}\right)$$

$$= \alpha_i \frac{\partial e_i}{\partial s_i}\left(-\frac{s_i}{\ell} + \delta_{gi} - \delta_{ei}\right),$$

where the third equality follows from (A-15).

Now take the second derivative. We have

$$\frac{\partial^2 \mathcal{W}}{\partial s_i^2} = \alpha_i\left(-\frac{s_i}{\ell}\frac{\partial^2 e_i}{\partial s_i^2} - \frac{1}{\ell}\frac{\partial e_i}{\partial s_i} + \delta_{gi}\frac{\partial^2 e_i}{\partial s_i^2} - \delta_{ei}\frac{\partial^2 e_i}{\partial s_i^2}\right) = -\frac{\alpha_i}{\ell}\frac{\partial e_i}{\partial s_i} + \alpha_i \frac{\partial^2 e_i}{\partial s_i^2}\left(-\frac{s_i}{\ell} + \delta_{gi} - \delta_{ei}\right),$$

where we have used the derivative of (A-15) with respect to s in simplifying.

Evaluating the first and second derivatives at $\tilde{S}$ gives

$$\left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{\tilde{S}} = \alpha_i \left.\frac{\partial e}{\partial s}\right|_{\tilde{s}}\left(-\frac{\tilde{s}}{\ell} + \delta_{gi} - \delta_{ei}\right) = \frac{\alpha_i}{\ell}\left.\frac{\partial e}{\partial s}\right|_{\tilde{s}}\left(-\tilde{s} + s_i^*\right), \tag{A-16}$$

and

$$\left.\frac{\partial^2 \mathcal{W}}{\partial s_i^2}\right|_{\tilde{S}} = -\frac{\alpha_i}{\ell}\left.\frac{\partial e}{\partial s}\right|_{\tilde{s}} + \alpha_i \left.\frac{\partial^2 e}{\partial s^2}\right|_{\tilde{s}}\left(-\frac{\tilde{s}}{\ell} + \delta_{gi} - \delta_{ei}\right) = -\frac{\alpha_i}{\ell}\left.\frac{\partial e}{\partial s}\right|_{\tilde{s}} + \frac{\alpha_i}{\ell}\left.\frac{\partial^2 e}{\partial s^2}\right|_{\tilde{s}}\left(-\tilde{s} + s_i^*\right), \tag{A-17}$$

where the second equality in both cases follows from Proposition 3. We have dropped the subscripts from g and e because prices, income, and the function u are the same across locations, and, at the point $\tilde{S}$, the subsidy is the same across locations.

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

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

We use this expansion to evaluate $\mathcal{W}(S^*) - \mathcal{W}(\tilde{S})$. From (A-16) and (A-17) we have

$$\mathcal{W}(S^*) - \mathcal{W}(\tilde{S}) \approx \frac{\partial e}{\partial s}\bigg|_{\tilde{s}} \frac{1}{\ell} \sum \alpha_i (s_i^* - \tilde{s})^2 - \frac{1}{2} \frac{\partial e}{\partial s}\bigg|_{\tilde{s}} \frac{1}{\ell} \sum \alpha_i (s_i^* - \tilde{s})^2 + \frac{1}{2} \frac{\partial^2 e}{\partial s^2}\bigg|_{\tilde{s}} \frac{1}{\ell} \sum \alpha_i (s_i^* - \tilde{s})^3.$$

It follows that

$$\mathcal{W}(S^*) - \mathcal{W}(\tilde{S}) \approx \frac{1}{2} \frac{\partial e}{\partial s}\bigg|_{\tilde{s}} \frac{1}{\ell} \sum \alpha_i (s_i^* - \tilde{s})^2 + \frac{1}{2} \frac{\partial^2 e}{\partial s^2}\bigg|_{\tilde{s}} \frac{1}{\ell} \sum \alpha_i (s_i^* - \tilde{s})^3.$$

□

Proposition 4 is most easily interpreted in the special case in which the population is the same in each location ($\alpha_i = \frac{1}{n}$). Here the second-best uniform subsidy $\tilde{s}$ is equal to average environmental benefits multiplied by the number of miles driven in a vehicle's life. And the approximate welfare gain from differentiation is a function of the second and third moments of the distribution of the environmental benefits. Once again we see that under the weaker assumption that the subsidy does not effect the total miles driven, we get similar results to the discrete choice model in the main text.

D Welfare Gains from Differentiation: Additional Details and Comparison with Mendelsohn (1986)

First consider the discrete choice model in the main text, under the assumptions of Proposition 2. Marginal welfare in region i is given by

$$\frac{\partial \mathcal{W}_i}{\partial s_i} = \frac{\pi(1-\pi)}{\mu}(-s_i + g(\delta_{gi} - \delta_{ei})). \tag{A-18}$$

Next considere the continuous choice model in Supplementary Appendix C, under the assumptions of Proposition 4. Marginal welfare in region i is given by

$$\frac{\partial \mathcal{W}_i}{\partial s_i} = \frac{\partial e}{\partial s}\left(-\frac{s_i}{\ell} + \delta_{gi} - \delta_{ei}\right). \tag{A-19}$$

Finally, consider the model in Mendelsohn (1986). Here the regulator selects an emission standard q_i and the environmental variable is denoted by x_i. Marginal welfare in region i is given by

$$\frac{\partial \mathcal{W}_i}{\partial q_i} = a + x_i - bq_i. \tag{A-20}$$

These equations all have a similar feature. When set equal to zero in a first-order condition, one can solve for the policy variable as a linear function of the environmental variable. This ensures that the welfare benefits of differentiation can be written as a function of the moments of the distribution of the environmental variable. But these equations differ with respect to whether the overall equation is linear in the policy variable, and this difference determines the whether or not the second moment is sufficient to describe the benefits of differentiation.

In Mendelsohn's model (A-20), marginal welfare is linear in x_i. And the welfare gain from differentiation is a function of only the second moment of the distribution of the environmental variable. In contrast, in the discrete choice version of our model (A-18), marginal welfare is non-linear, because $\pi(1-\pi)$ is a non-linear function s_i. And, as described by Proposition 2, the welfare gain from differentiation is a function of both the second and third moments of the distribution of the environmental variable. In the continuous version of our model (A-19), marginal welfare may be linear or non-linear, depending on the properties of the demand function e. If the demand function is linear, then $\frac{\partial e}{\partial s_i}$ is a constant, and hence marginal welfare is linear in s_i. In this case, we get the same result as with Mendelsohn: the welfare gain from differentiation is a function of only the second moment. (This follows from Proposition 4, because $\frac{\partial^2 e}{\partial s^2}$ will be equal to zero.) If the demand function is non-linear, then $\frac{\partial e}{\partial s_i}$ is not constant, and hence marginal welfare in nonlinear in s_i. In this case, we get the same result as with our discrete choice version: the welfare gain from differentiation is a function of both the second and third moment.

A graphical illustration of these ideas for a three region example is given in Figure A. Here we use Mendelsohn's notation with units normalized such that the optimal differentiated policy variable is equal to the environmental variable (thus, for example, in (A-20), $a = b = 1$). Assume for the moment that marginal welfare is a linear function of the policy variable q_i. We have superimposed all the marginal welfare functions for all three regions on the same coordinate axis. In the first case, shown on the left-hand-side, the environmental variable x takes on the values (1,4,4) in the three regions. Notice that regions two and three have the same marginal welfare. Under differentiated regulation, the optimal values are $(q_1^*, q_2^*, q_3^*) = (1, 4, 4)$. Under uniform regulation, the optimal value for $\tilde{q}$ is three, which is simply the average of the x_i's. The welfare loss from uniform regulation is equal to the area A plus two times the area B. In the second case, shown on the right-hand-side, the environmental variable takes on the values (2,2,5) and region one and two now have the same marginal welfare. Notice that the two cases have the same mean and variance for the distribution of x, but the third moment is different. The welfare loss from uniform regulation in the second case is equal to the area A plus two times the area B. Because these triangles have the same area in both cases, the welfare loss from uniform regulation is the same in both cases. Thus the third moment does not effect the welfare loss, provided that marginal welfare is linear in the policy variable. If we relax this assumption, however, then the welfare loss will no longer be the same across the two cases, and hence will depend on the third moment.

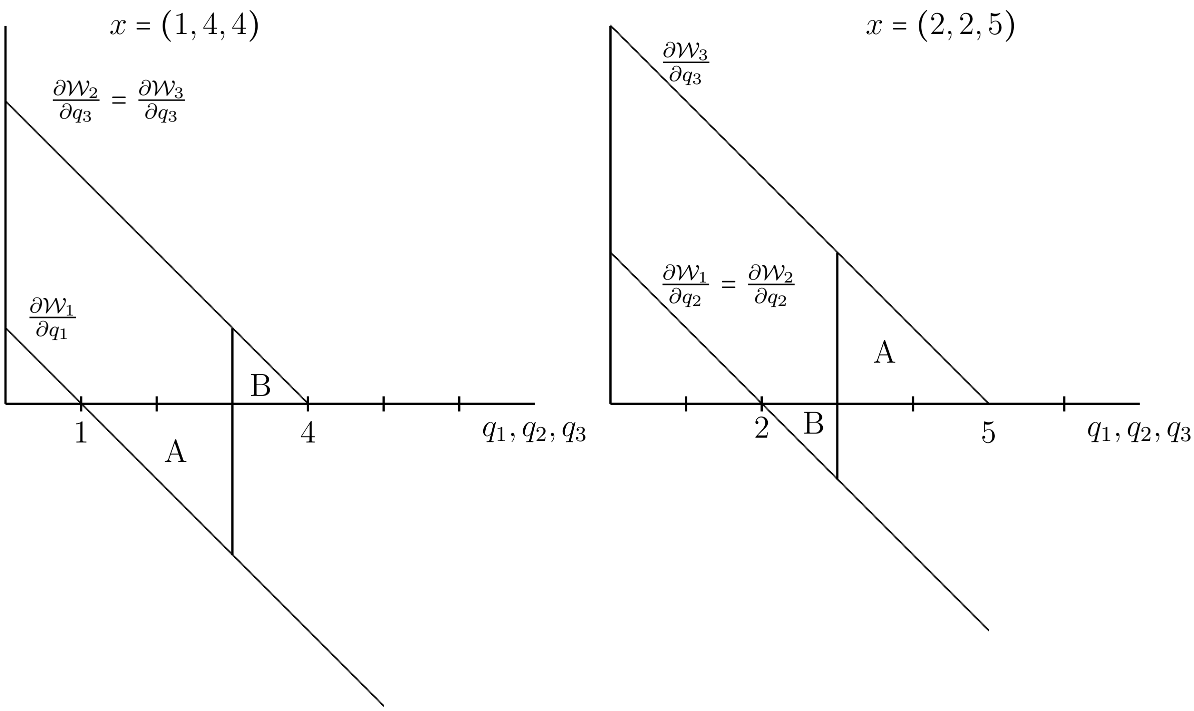
As a final point, our welfare approximation was defined relative to the reference point of uniform regulation. Suppose instead we define the reference point to be the second-best differentiated regulation. In this case we are measuring the welfare loss of using uniform regulation rather than differentiated regulation.[62] Modifying (A-8) to evaluate the derivative at S^* rather than $\tilde{S}$ gives

$$\left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{S^*} = \frac{\alpha_i}{\mu}\pi_i(1-\pi_i)(-s_i^* + \delta_{gi}g - \delta_{ei}e) = \frac{\alpha_i}{\mu}\pi_i(1-\pi_i)(-s_i^* + s_i^*) = 0. \tag{A-21}$$

As we would expect, the first derivative of the welfare function is equal to zero at the second-

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

Figure A: Effect of Third Moment on Welfare Gain From Differentiation: Linear Case



best differentiated regulation. Similar modifications of (A-9) gives

$$\left.\frac{\partial^2 \mathcal{W}}{\partial s_i^2}\right|_{S^*} = -\frac{1}{\mu}(1-2\pi_i)\left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{s_i^*} - \frac{\alpha_i}{\mu}\pi_i(1-\pi_i) = -\frac{\alpha_i}{\mu}\pi_i(1-\pi_i), \tag{A-22}$$

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

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

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

E Substitute gasoline vehicles and their emissions

In the main text, we assigned an substitute gasoline vehicle to each electric vehicle. These substitute gasoline vehicles represent the forgone vehicle when a consumer purchases an electric vehicle. Emissions data for the substitute gasoline vehicles are given in Table A.

To test to see if our choices were reasonable, we obtained data from the market research company MaritzCX. They conduct a new vehicle customer survey in which participants are asked: "When shopping for your new vehicle, did you consider any OTHER cars or trucks?" (emphasis in original). If the participants responded yes, then they were asked to state the "model most seriously considered". We obtained data on responses from participants who purchased one of the electric vehicles listed in Table 2 during the years 2013-2015.

The responses are summarized in Tables B to Tables D for the Ford Focus, Nissan Leaf and Tesla S. The most notable thing about the responses is that the vast majority of respondents either report most seriously considering another EV or not seriously considering another vehicle. Thus the survey provides information on the substitute *gasoline vehicle* for only a small share of respondents.

Table A: Emissions data for 2014 electric vehicles and substitute gasoline vehicles

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

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

For this small share of respondents, the substitute gasoline vehicle is largely consistent with our choices. For the Ford Focus EV, the most common substitute gasoline vehicle are the Toyota Prius with 55 respondents; the Audi A3 and Chevrolet Spark with 21 respondents each; and the Ford Focus (our choice), the Ford Fusion Hybrid, the Volkswagen Golf, and an unspecified Nissan car with 20 respondents each. For the Nissan Leaf, the Toyota Prius (our choice) was by far the most common substitute gasoline vehicle with 2166 respondents. For the Tesla S, the Audi A-Series were the most common substitute gasoline vehicle. But the Audi A7 and A8 have very similar emission profiles to our choices (the BMW 750 and BMW 740). The results for the other electric vehicles follow a similar pattern. For the Spark EV and Smart fortwo EV, our choice was one of the most popular substitute gasoline vehicles. For the Mitsubishi i-MEV and Toyota Rav4 EV, our choice was not one of the most popular substitute gasoline vehicles, but our choice has a similar emission profile as these vehicles. Finally, for the Honda Fit EV, Fiat 500 EV, and BYD e6, there were no responses in the data.

Most of the results in the main paper are based on the comparison of the Ford Focus EV with the gasoline Ford Focus. Changing the substitute gasoline vehicle to one of the other gasoline vehicles identified in Table B would affect these results. For example, the Toyota

Prius is substantially cleaner than the gasoline Ford Focus. Using the Toyota Prius as the substitute gasoline vehicle would shift the distribution of environmental benefits of the Ford Focus EV downward. Using the numbers in Table 2a, mean environmental benefits would decrease from -0.73 to -1.36 cents per mile. Conversely, using the Audi A3 or Volkswagen Golf (dirtier cars than the gasoline Ford Focus) would shift the distribution of environmental benefits of the Ford Focus EV upward. Thus our choice of the gasoline Ford Focus as the substitute vehicle can be viewed as a moderate one given the alternatives.

Table B: Ford Focus EV: Model most seriously considered

Response	Frequency	Share
Nissan Leaf *	1128	30%
No Other Considered	1108	30%
Chevrolet Volt *	327	9%
Tesla Model S *	116	3%
Fiat 500 Electric *	105	3%
Ford Fusion Plug In Hybrid *	76	2%
Honda Fit EV *	67	2%
Toyota RAV4 EV *	61	2%
Ford C-Max Energi *	57	2%
Toyota Prius	55	1%
Toyota Prius Plug-in *	52	1%
Chevrolet Spark Electric *	47	1%
BMW i3 *	33	1%
Volkswagen e-Golf *	32	1%
Mitsubishi i-MiEV *	25	1%
Audi A3	21	1%
Chevrolet Spark	21	1%
Ford Focus	20	1%
Ford Fusion Hybrid	20	1%
Volkswagen Golf	20	1%
Nissan Car Unspecified	20	1%
Ford Fusion	18	0%
Honda Accord	17	0%
Nissan Unspecified	17	0%
Fiat 500	15	0%
Lincoln MKZ Hybrid	13	0%

Notes: The survey has 3754 responses from Ford Focus EV purchasers. * indicates plug-in vehicles.

As an additional robustness check, we created "composite" substitute gasoline vehicles by taking the weighted average of emissions of the top 10 gasoline substitute vehicles for

Table C: Nissan Leaf EV: Model most seriously considered

Response	Frequency	Share
No Other Considered	31,081	61%
Chevrolet Volt *	3372	7%
Toyota Prius	2166	4%
Ford Focus Electric *	1889	4%
Toyota Prius Plug-in *	1073	2%
Tesla Model S *	903	2%
Honda Fit EV *	590	1%
BMW i3 *	502	1%
Ford C-Max Energi *	459	1%
Fiat 500 Electric *	448	1%
Kia Soul	344	1%
Mitsubishi i-MiEV *	332	1%
Ford Fusion	301	1%
Honda Accord	263	1%
Nissan Juke	249	0%
Ford Fusion Plug In Hybrid *	241	0%
Lexus CT200h	231	0%
Toyota Prius v	227	0%
Kia Soul EV *	217	0%
Audi A5	201	0%
Chevrolet Spark Electric *	200	0%
Nissan Altima	189	0%
Honda CR-V	182	0%
Toyota RAV4 EV *	181	0%
Honda Accord Hybrid	172	0%
Honda Civic	157	0%
Nissan Rogue	146	0%
Toyota Corolla	136	0%
smart fortwo electric *	136	0%
MINI Cooper Countryman	135	0%

Notes: The survey has 51,002 responses from Nissan Leaf EV purchasers. * indicates plug-in vehicles.

Table D: Tesla S EV: Model most seriously considered

Response	Frequency	Share
No Other Considered	24,109	26%
Audi A7	648	1%
Chevrolet Volt *	592	1%
Nissan Leaf *	480	1%
Audi A8	337	0%
Porsche Panamera	280	0%
Audi S7	262	0%
Mercedes-Benz S550	260	0%
Audi A6	247	0%
Lexus Car Unspecified	235	0%
Misc. Division Car Unspecified	219	0%
Mercedes-Benz Car Unspecified	219	0%
BMW 650	205	0%
Land Rover Range Rover	199	0%
Fisker Karma *	169	0%
Chevrolet Corvette Stingray	163	0%
Porsche Panamera S Hybrid *	163	0%
Porsche 911	138	0%
BMW Car Unspecified	136	0%
BMW 5-Series Unspecified	132	0%
Audi Car Unspecified	125	0%
Lexus LS460	121	0%
Audi RS 7	116	0%
Tesla Car Unspecified *	113	0%
Jaguar F-Type	111	0%
BMW ActiveHybrid 3	102	0%
Infiniti Q50 Hybrid	97	0%
BMW 750	96	0%
Cadillac Car Unspecified	94	0%
Jeep Grand Cherokee	94	0%
Lexus ES300h	91	0%
Land Rover Evoque	90	0%
Cadillac CTS	90	0%
Lincoln Car Unspecified	90	0%
Porsche Car Unspecified	87	0%
Lincoln MKZ Hybrid	86	0%
Toyota Prius	85	0%
BMW Unspecified	78	0%
BMW 6-Series Unspecified	78	0%
Audi S5	78	0%
BMW M5	76	0%
Mercedes-Benz E550	74	0%

Notes: The survey has 92,437 responses from Tesla S EV purchasers. * indicates plug-in vehicles.

each electric vehicle, where the weights correspond to the response frequencies. Table E compares the environmental benefits with respect to our original substitute vehicle and the environmental benefits with respect to the composite substitute vehicle.[63] In about half of the cases the composite substitute vehicle is cleaner than the original substitute vehicle and in about half the cases it is dirtier.

Table E: Environmental benefits (cents/mile) relative to two substitute gasoline vehicles

Electric Vehicle	Environmental Benefits Original Substitute	Environmental Benefits Composite Substitute
Chevy Spark EV	-.60	-0.45
Nissan Leaf	-1.16	-.92
Mitsubishi i-Miev	-0.73	-0.70
Smart fortwo electric	-0.87	-0.73
Ford Focus electric	-0.73	-1.02
Tesla Model S (85 kWhr)	-0.39	-0.54
Toyota Rav4 EV	-1.49	-1.93

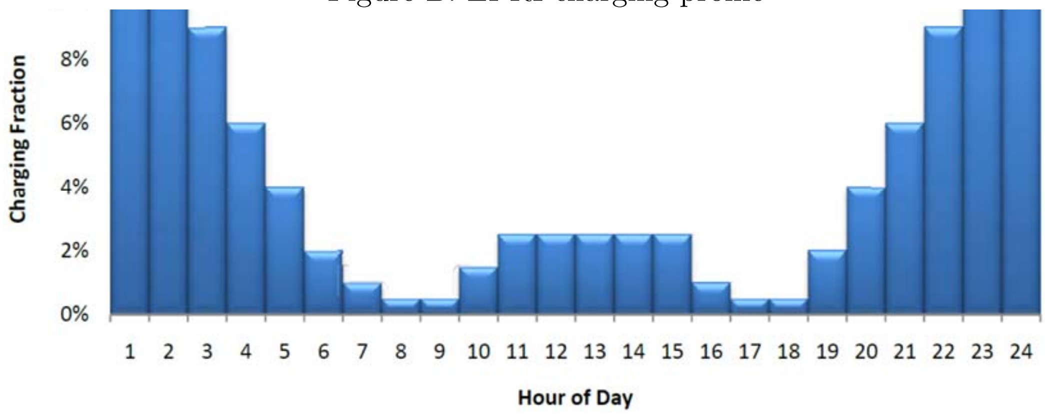
Notes: Data for original substitute column is from Table 2. Composite substitute is formed by taking the weighted average of the top 10 substitutes for the relevant electric vehicle.

F EPRI charging profile

The EPRI charging profile is given in Figure B.

[63]We did not have any data for the Honda Fit EV, Fiat 500 EV, and BYD e6. The data for Tesla was not broken out between the 60 and 85 kWhr models, so we did the calculation for the 85 kWhr model.

Figure B: EPRI charging profile



Source: Electric Power Research Institute (2007).

G 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 at 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 tem-

peratures (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.[64] We use a Gaussian function to describe this range loss

$$R(T) = R_{68} e^{-\frac{(T-68)^2}{y}}, \tag{A-23}$$

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[65]

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

Temperature data was obtained from the CDC website.[66] 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

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

[65] The assumed range loss is $(R(19.4) - R_{68})/R_{68} = -0.33$ which implies $R(19.4)/R_{68} = 0.67$. Using this in (A-23), we have $0.67 = e^{-\frac{(19.4-68)^2}{y}}$, which we can then solve for y.

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

usage is given by the formula

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

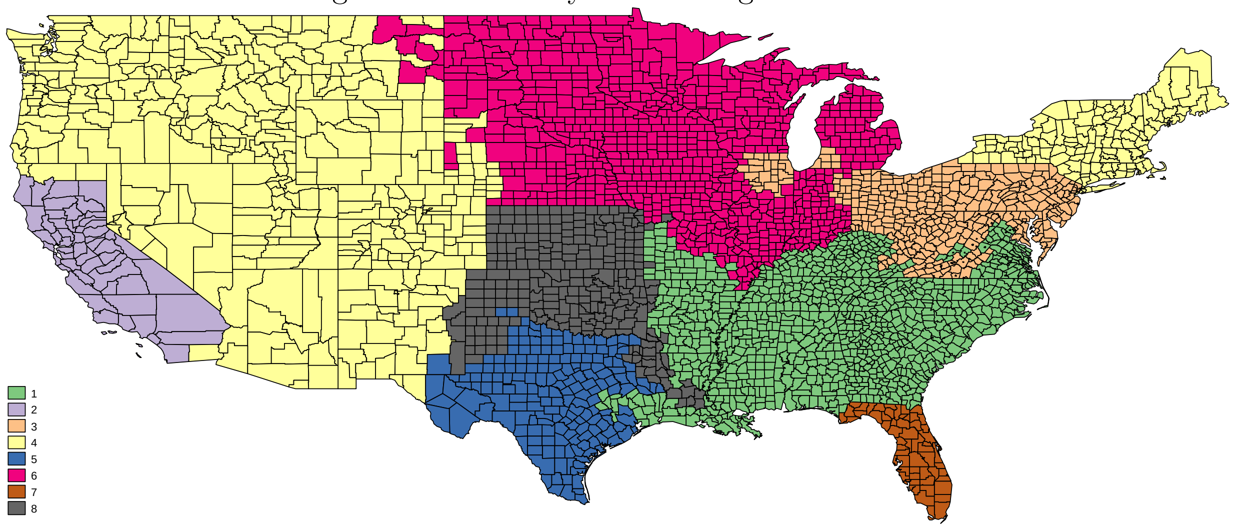
We evaluate this formula assuming the number of miles driven per day is constant over all months.

H Procedure for assigning counties to electricity regions

We model nine electricity demand regions for the contiguous US. Most are based on NERC regions (see http://www.nerc.com for a general description). The Eastern interconnection has six NERC regions: FRCC, MRO, NPCC, RFC, SERC, and SPP. We modify these regions by removing those counties that are served by the Midwest Independent Transmission System (MISO) circa 2012 from the overlapping NERC regions: MRO, RFC, SERC, and SPP. This new region is then merged with the remaining MRO area. Thus, only the FRCC and NPCC regions are exact NERC regions. We split the Western interconnection between California (specifically, the CA-MX NERC subregion) and the rest of the WECC. The Texas interconnection is simply the coterminous ERCOT.

Given this set of NERC regions, we assign each county to specific region using the following procedure. The EPA power profiler (http://www.epa.gov/energy/power-profiler, year 2010 data) provides a mapping from zip code to eGrid subregion. More specifically, it identifies the primary, secondary, and tertiary eGrid subregion. We only use the primary subregion, and map this into the appropriate NERC region. From the U.S. Department of Housing and Urban Development, we obtained a county to zip code crosswalk (http://www.huduser.gov/portal/datasets/usps_crosswalk.html, first quarter 2010). This provided all the zip codes in a given county as well as the number of addresses for each zip code. Combining the EPA power profiler data with the county to zip crosswalk enabled us to assign a NERC region to each county. In the cases in which this procedure assigned more than one NERC region to a given county, we selected the NERC region which

Figure C: Electricity demand regions



Notes: Codes are 1-SERC; 2-California; 3-RFC; 4-WECC w/o CA or NPCC; 5-ERCOT; 6-MISO & MRO; 7-FRCC; and 8-SPP.

corresponded to the largest number of addresses in the county.

Finally, we recode counties as part of MISO as follows. First, we use EIA 860 data on power plants to determine which utilities serve the ISO. Then the utility IDs are merged with EIA 861 files that list the counties that each utility serves. If a utility in a given county serves MISO, that county was included. Next, we included all other counties in the Eastern Interconnection that are in Iowa, Illinois, Indiana, Michigan, North Dakota, or Wisconsin. Finally we excluded all utilities in Ohio as well as the Commonwealth Edison Co. and Indiana Michigan Power Co. territories.

The overall result is shown in Figure C

I Methods details

Data sources for emissions of gasoline vehicles

The emissions of SO_2 and CO_2 follow directly from the sulfur or carbon content of the fuels. Since emissions per gallon of gasoline does not vary across vehicles, emissions per mile can be simply calculated by the efficiency of the vehicle.[67] For emissions of NO_X, VOCs and $PM_{2.5}$, we use the Tier 2 standards for NO_X, VOCs (NMOG) and PM. We augment the VOC emissions standard with GREET's estimate of evaporative emissions of VOCs and augment the PM emissions standard with GREET's estimate of $PM_{2.5}$ emissions from tires and brake wear. Electric vehicles are likely to emit far less $PM_{2.5}$ from brake wear because they employ regenerative braking. We had no way of separating emissions into tires and brake wear separately, so we elected to ignore both of these emissions from electric vehicles. This gives a small downward bias to emissions of electric vehicles.

Data sources for the electricity demand regressions

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

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

[67] 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).

Details of the AP2 model

AP2 is a standard integrated assessment model in that it links emissions to damages.[68]

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

The inputs to the economic valuation module are the ambient concentrations of SO_2, O_3, and $PM_{2.5}$ and the outputs are the monetary damages associated with the physical effects of exposure to these concentrations. The majority of the damages are associated with human

[68]See Muller, 2011; 2012; 2014. The AP2 model is an updated version of the APEEP model (Muller and Mendelsohn 2007; 2009; 2012; National Academy of Sciences 2010; Muller et al 2011; Henry et al 2011).

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

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.[70] 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.[71] 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 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.[72] This routine is repeated for all pollutants and all sources in the model, first for full damages, and then second for native damages (which only looks at receptors in the state or county of interest).

To assess the statistical uncertainty associated with the marginal damages produced by AP2 for both gas and electric vehicles, we use results from Muller (2011) that executes

[70] 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.

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

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

a Monte Carlo simulation for each marginal damage for the data year 2005 (by source and pollutant). We use these simulation results in the following way. First, we compute the coefficient of variation for each pollutant-source marginal damage (standard deviation/arithmetic mean). We then multiply these coefficients times the matching 2011 marginal damages. This yields an estimate of the standard deviation for each source-pollutant marginal damage. We then estimate confidence intervals in order to estimate the 5th and 95th percentiles for the damages from gas and electric vehicles. These are used to calculate the environmental benefits reported in Table 7.

Finally, we provide three pieces of evidence that AP2 gives similar marginal damage estimates as other air pollution models. First, Weis et al (2015) test AP2 results (for 2005) against the EASIUR model and find some variation in damages from electric vehicles. But overall, they find that using different integrated assessment models does not fundamentally overturn their results. Second, Barnett et al (2015) and Holland et al (2016) both analyzed the damages and expected deaths from excess emissions from VW diesel engines. Holland et al use AP2, Barnett et al use a different air pollution model. Nevertheless, the results are essentially the same in the two papers. The third and final piece of evidence comes from comparing the performance of AP2 relative to EPA emissions monitoring data. Jaramillo and Muller (2016) perform a battery of tests and document that AP2 performs quite well using standard performance metrics.

J State electric vehicle incentives

The Department of Energy maintains a database of alternative fuels policies by state.[73] Using this information, we determined four measures of state electric vehicle policy. (These data reflect policies in place on July 28, 2014.) The first measure is the actual subsidies for the purchase of an electric vehicle. The second measure is equal to the total number of electric vehicle policies (including both incentives and regulations). The third measure is equal to the number of policies that were classified 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

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

(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 F for each state along with the full damage subsidy and the native damage subsidy. Each of the four measures is more highly correlated with the native damage subsidy than with the full damage subsidy.

K Calibration and welfare sensitivity

To analyze welfare issues, we must calibrate a numerical version of the model. This requires specifying functional forms for the utility of miles $f(g)$ and $h(e)$, determining "exogenous" parameters that correspond directly to observed economic data, and determining the "endogenous" parameters that are adjusted so that model outcomes correspond to observed or assumed economic data.

We employ a functional form for the utility of consuming miles that yields a constant elasticity demand function. For gasoline miles we have

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

and for electric miles we have

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

Using these equations, $-\frac{1}{\gamma}$ turns out to be the elasticity of demand for miles. We assume the elasticity is the same for gas and electric miles. Because prices for miles are different, this assumption would imply different number of lifetime miles for the two vehicles at business as usual (no policy intervention). Because we want lifetime miles to be the same, we include the endogenous parameters k_g and k_e. We also include the endogenous parameter H, which is the intercept of $h(e)$. This allows us to incorporate a non-stochastic taste for driving electric vehicles. This is in contrast to the parameter μ which describes the standard deviation of the random variables in the discrete choice model.

As in the main text, we compared the Ford Focus with the Ford Focus Electric. The

Table F: State electric vehicle policies

State	Full Damage Subsidy	Native Damage Subsidy	Actual Subsidy	Significant Incentives	All incentives and regulations	All incentives
Alabama	-1747	44	0	1	3	1
Arizona	889	276	0	5	14	6
Arkansas	-1747	-37	0	0	2	0
California	2785	1547	2500	9	42	21
Colorado	902	312	6000	1	11	5
Connecticut	-1933	-126	0	0	5	1
Delaware	-2688	-27	0	0	3	1
District of Columbia	-1017	441	0	2	4	3
Florida	-1049	293	0	1	7	3
Georgia	-1166	595	5000	4	7	7
Idaho	499	46	0	0	1	1
Illinois	-2345	1000	4000	3	13	7
Indiana	-3448	255	0	2	9	6
Iowa	-4394	-109	0	0	4	2
Kansas	-1133	118	0	0	1	0
Kentucky	-1957	76	0	0	4	1
Louisiana	-1735	-9	3000	1	4	3
Maine	-2811	-393	0	0	4	1
Maryland	-2199	439	3000	6	12	7
Massachusetts	-1713	220	2500	1	5	2
Michigan	-3720	279	0	3	5	5
Minnesota	-4145	306	0	1	7	1
Mississippi	-1992	-54	0	0	2	1
Missouri	-2957	127	0	0	4	1
Montana	-32	-41	0	0	1	1
Nebraska	-3927	-14	0	0	2	1
Nevada	728	137	0	2	9	3
New Hampshire	-2450	-324	0	0	3	0
New Jersey	-1598	717	2461	2	4	2
New Mexico	521	74	0	0	6	3
New York	-1371	616	0	1	6	4
North Carolina	-1611	204	0	1	11	6
North Dakota	-4964	-213	0	0	1	0
Ohio	-2640	414	0	1	4	1
Oklahoma	-1021	201	0	0	7	3
Oregon	648	149	0	1	12	5
Pennsylvania	-2675	322	0	0	4	3
Rhode Island	-1962	-132	0	0	5	1
South Carolina	-1711	48	0	0	2	1
South Dakota	-3992	-174	0	0	0	0
Tennessee	-1729	55	0	1	3	1
Texas	505	380	2500	2	7	6
Utah	1089	544	605	2	8	4
Vermont	-3034	-431	0	0	7	1
Virginia	-1807	69	0	2	14	6
Washington	865	295	2321	1	19	5
West Virginia	-3168	-91	0	0	4	0
Wisconsin	-4180	76	0	0	6	2
Wyoming	205	-42	0	0	0	0
Correlation with full damage subsidy			0.30	0.40	0.50	0.49
Correlation with native damage subsidy			0.52	0.76	0.68	0.79

Notes: New Jersey and Washington give a sales tax exemption for electric vehicles. Sales tax rates are 6.5% in Washington and 7% in New Jersey. The value for the subsidy in these states is calculated for the Ford Focus electric.

exogenous parameters are shown in Table G.[74] This leaves us with the task of specifying the endogenous parameters k_g, k_e, H and μ. To pin down values of k_g and k_e, we follow Michalek et al (2011) and assume that both gasoline vehicles and electric vehicles would be driven 150,000 lifetime miles at business as usual. Using the functions $f(g)$ and $h(e)$ in the consumer's optimization problems, and then solving these problems at business as usual, gives the demand for miles

$$g = \left(\frac{k_g}{p_g}\right)^{\frac{1}{\gamma}}$$

and

$$e = \left(\frac{k_e}{p_e}\right)^{\frac{1}{\gamma}}.$$

Setting $e = 150,000$ and $g = 150,000$, substituting the values for γ, p_g, and p_e from Table G, and solving for k_e and k_g gives $k_g = 2.58 \times 10^9$ and $k_e = 8.93 \times 10^8$.

The values for μ and H were determined such that model outcomes matched two pieces of economic data. First, at business as usual, the consumer would select the gasoline vehicle with some given probability $\hat{\pi}$. Second, consistent Li et al (2015)'s observation, when the federal subsidy is \$7500, half of all electric vehicles sales are due to the subsidy. These conditions give us two equations, from which the values for μ and H can be determined. For example, suppose that, at business as usual, ninety nine percent of the vehicles sold would be gasoline, so that $\hat{\pi} = 0.99$. Using Li et al (2015)'s observation, this implies that, when the subsidy is \$7500, ninety eight percent of vehicles sold would be gasoline. So we have two equations

$$\pi|_{s=0} = 0.99$$

and

$$\pi|_{s=7500} = 0.98.$$

Because all of the other parameters have been specified, the two left-hand-sides of these equations are a function of H and μ only. Solving these equations numerically for H and μ gives the values in the first row of Table H. The other rows correspond to different assumptions about $\hat{\pi}$.

[74]Values in the table are in 2013 dollars. We convert to 2014 dollars when making calculations.

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

Table G: Exogenous Calibration Parameters : Ford Focus and Ford Focus Electric

Param.	Value	Economic Interpretation	Source/Notes
I	430040	Income over 10 year vehicle lifetime	US BLS : $827 week
p_e	0.0389	Price of electric miles ($ per mile)	EIA : 0.1212 $ per kWh * 0.321 kWh/mile
p_g	0.1126	Price of gasoline miles ($ per mile)	CNN : 3.49 $ per gallon / 31 miles/gallon
p_Ω	35170	Price of electric vehicle ($)	Ford Motors
p_G	16810	Price of gasoline vehicle ($)	Ford Motors
γ	2	Gives elasticity for miles of -0.5	Espey 1998, Davis and Kilian 2011

Notes: www.bls.gov/emp/ep_chart_001.htm,
http://www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_5_3,
http://money.cnn.com/2013/12/31/news/economy/gas-prices/, www.Ford.com. All accessed May 20, 2014.

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

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

$\hat{\pi}$	H	μ
0.99	1688947865	10664
0.98	1688955973	10508
0.95	1688967313	10037

We conducted a final sensitivity analysis with respect to the price of gasoline and electric miles. Up to now, we have assumed (in both the theoretical model and the empirical calculations) that these prices are the same across locations. In this final sensitivity analysis, we

Table I: Sensitivity of Exogenous Calibration Parameters

Parameter	Welfare Loss Subsidy		Welfare Loss Tax		Gain from Differentiation	
	Federal	State	Federal	State	Subsidy	Tax
Baseline	1782.8	1758.5	162.1	89.1	24.3	72.9
Gas Miles Elasticity + 33%	1232.3	1208.0	120.9	62.5	24.3	58.5
Gas Miles Elasticity 33%	2322.2	2297.9	200.8	113.9	24.3	86.9
Electric Miles Elasticity + 33%	1760.9	1736.6	161.4	89.1	24.3	72.3
Electric Miles Elasticity 33%	1803.7	1779.4	162.6	89.1	24.3	73.4
Lifetime Miles Electric 16.6%	1795.5	1765.4	167.2	89.2	30.2	78.0
Lifetime Miles Electric - 16.6%	1769.1	1750.3	157.1	89.0	18.8	68.1
Lifetime Miles Gas +16.6%	2069.5	2042.9	187.6	104.7	26.6	82.9
Lifetime Miles Gas -16.6%	1496.5	1474.2	137.0	73.8	22.3	63.2
Purchases due to subsidy +10%	1787.8	1756.2	168.5	90.4	31.6	78.1
Purchases due to subsidy - 10%	1778.7	1760.6	156.8	88.1	18.1	68.7
Price of Electric Vehicle +16.6%	1782.8	1758.5	162.1	89.1	24.3	72.9
Price of Electric Vehicle -16.6%	1782.8	1758.5	162.1	89.1	24.3	72.9
Price of Gas Vehicle + 16.6%	1782.8	1758.5	162.1	89.1	24.3	72.9
Price of Gas Vehicle -16.6%	1782.8	1758.5	162.1	89.1	24.3	72.9
Price of Electric Miles +16.6%	1775.0	1750.7	162.0	89.1	24.3	72.9
Price of Electric Miles -16.6%	1792.9	1768.6	162.0	89.1	24.3	72.9
Price of Gas Miles + 16.6%	1558.7	1534.4	147.2	79.6	24.3	67.5
Price of Gas Miles 16.6%	2084.6	2060.3	181.0	101.2	24.3	79.9
Income + 16%	1782.8	1758.5	162.1	89.1	24.3	72.9
Income -16%	1782.8	1758.5	162.1	89.1	24.3	72.9

Note: $ Million/year

drop this assumption and employ state-specific prices for electric miles and region-specific prices for gasoline miles (using data from EIA.gov). In this analysis, the second best uniform federal subsidy is no longer given by the expression in Proposition 2, and in fact does not have a closed form expression. Likewise for the second best uniform federal taxes. So we determine the these quantities numerically. The benefits of differentiated subsidies, state vs. federal, is \$24.3 million (compared to a baseline of \$24.3 million) and the benefits of differentiated taxes is \$68.5 million (compared to a baseline of \$72.9 million).

L Single tax policies

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

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

Proposition 5. *The optimal tax on gasoline miles alone in location i is given by*

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

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

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

Proof of Proposition 5.

Throughout the proof we can drop the subscript i. The first-order condition for t_g is the same as (A-13):

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

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

$$R = t_g \pi g,$$

and hence

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

Using this in the first-order condition gives

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

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

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

Solving for t_g gives

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

Now from (A-2), (A-3), and (A-4), we have

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

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

and

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

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

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

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

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

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

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

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

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

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

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

■

M Large scale electric vehicle adoption

This paper measures the marginal emissions from an increase in electricity consumption. In this supplementary appendix, we consider two questions about this procedure related to the current electricity grid. First, is it reasonable to use marginal emissions for our policy analyses (e.g. considering a 5 percent electric vehicle adoption rate)? Second, does the relationship between load and marginal emissions vary between high and low load conditions?

A simple way of approaching the first question is to compare the load due to electric vehicle adoption with the total electricity consumption in the country. The entire light duty vehicle fleet is approximately 250 million vehicles. Suppose 5 percent of this fleet consisted of electric vehicles. This is the steady state version of the 5 percent adoption rate discussed in the main paper. The charging need for these vehicles corresponds to 60 TWh per year, which is approximately 1.6% of total U.S. electricity consumption per year.[75] Another approach is based on the hourly load from electric cars relative to the random component of hourly electricity load (after controlling for fixed effects by hour-of-day times month-of-sample). If the electric vehicles were charged uniformly across the day, the electricity demand would be 6.8 GW (GWh per hour). The standard deviation of the random component of electricity load in the country is 30.8 GW. So electric cars, at 5 percent of the entire fleet, would add a load shock equal to approximately 22 percent of the standard deviation of load variation.

For the second question, we broke our load sample into two sub-samples, corresponding to high and low load conditions. Note that our main regression includes fixed effects by hour-of-day times month-of-sample. For each of these groups, there are about 30 observations. We split each group based on the median to define "low demand" and"high demand" hours. Using the aggregated data (all emissions within an interconnection), we regressed emissions on load and fixed effects for just the high demand hours and then for just the low demand hours. We then took the coefficients from these regressions as data and pooled them to include all NERC regions and all hours for high/low demand levels (9*24*2=432 obsevations). We regressed them on an indicator of whether they came from the high demand sample. Periods with high demands have greater marginal emissions than periods with low demands, but the effect varies by pollutant. For SO_2 the increase is 68 percent, for CO_2 the increase is 12 percent, for NO_X the increase is 46 percent, and for generation (which we use for $PM_{2.5}$) it is 80 percent. Although some of these percentages are large, none of the effects are statistically significant when clustering by NERC region.

Our final analysis considers the implications of a large scale adoption of electric vehicles on the future of the electricity grid. A full model would need to account for entry and exit of power plants and transmission capacity, which is beyond the scope of this paper. However, we can discuss how our approach could be modified to examine discrete changes in load levels. Suppose the investment in new power plants to build grid capacity mimics the existing grid. Under this assumption, we can use the average emission rates as an

[75] We have 12.5 million electric vehicles driven 15,000 miles per year using 0.32 KWh per mile.

approximation for emission rates that result under grid expansion to service electric vehicles. On average, the average emission rates are comparable to the marginal emission rates we used in the main paper. But there is variation across interconnections and pollutants. See Table J. For example, in Texas (ERCOT), average SO_2 emission rates are 187% larger than marginal rates, but average NO_X rates are only 5% larger than marginal rates. In the Eastern interconnection (EAST), both average SO_2 and NO_X emissions rates about 18% smaller than marginal rates.

Table J: Average emission rates relative to marginal

Interconnection	SO_2	CO_2	NO_X	$PM_{2.5}$
ERCOT	187%	19%	5%	-10%
WECC	72%	-4%	54%	-28%
EAST	-18%	-10%	-19%	-22%

N CAFE standards

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

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

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

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

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

$$\frac{\frac{n_a+1}{f_a} + \frac{n_b-1}{f_b} + \frac{n_g-1}{f_g} + \frac{1}{f_e}}{n_a + n_b + n_g} \leq \frac{1}{k}. \tag{A-24}$$

Using the initial condition this becomes

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

and so the condition becomes

$$\frac{1}{f_a} - \frac{1}{f_b} \leq \frac{1}{f_g} - \frac{1}{f_e}. \tag{A-25}$$

The right-hand-side of (A-25) specifies the maximum feasible increase in gallons per mile that may occur from the swap of a for b due to the sale of an electric vehicle. If the CAFE constraint binds after this swap (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 due to damages from emissions.

We see that CAFE regulation induces an additional environmental cost from electric vehicles due to the substitution of a low MPG vehicle for a high MPG vehicle . We can sketch a back-of-the-envelope calculation for the magnitude of this CAFE induced environmental cost and its effect on the second-best subsidy on electric vehicles as follows. Assume that vehicle a and vehicle b are in the same Tier 2 "bin". For vehicles in the same bin, the vast majority of environmental damages are due to emissions of CO_2. In addition, without a explicit model of the new vehicle market, we don't know in which location the vehicle a will be driven. So we calculate the CAFE induced environmental cost due to CO_2 emissions only. Let δ_a and δ_b be the damage (in \$ per mile) due to CO_2 emissions from vehicle a and b, respectively.[76] It follows that the additional environmental cost is given by $(\delta_a - \delta_b)g$.

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

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

We see that if the consumer selects the gasoline vehicle, then the fleet consists of this gasoline vehicle in conjunction with vehicle b. But if the consumer selects the electric vehicle, then the fleet consists of the electric vehicle in conjunction with vehicle a. (We are ignoring the utility benefit generated by the switch from b to a.) Following similar arguments as in the proof of Proposition 1, the optimal subsidy is determined to be

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

We see that the optimal subsidy is decreased by the amount equal to the CAFE induced environmental cost $(\delta_a - \delta_b)g$. Using our Ford Focus baseline numbers, the CAFE induced environmental cost turns out to be \$1555.[77]

[76] We have $\delta_a = \frac{\$0.3644}{f_a}$, where the numerator is the CO_2 damages per gallon in our model. (There are 0.008887 metric tons of CO_2 per gallon of gasoline and the social cost of carbon is \$41 per metric ton in 2014 dollars. Multiplying these two numbers gives 0.3644)

[77] There are two complications in this calculation. First, for a given vehicle, the MPG for CAFE purposes is not equal to the EPA posted MPG number. On average, the EPA number is eighty percent of the CAFE number. Second, for electric cars, the CAFE MPG is calculated as 82049 watt hours per gallon divided by the EPA determined electricity consumption in watt hours per mile. So the CAFE MPG for a electric Ford Focus is 82049/321 = 255.6 MPG. The EPA MPG for a gasoline Ford Focus is 30, dividing by 0.8 gives a CAFE MPG of 37.5. We want to use the EPA MPG in the equation for the additional environmental cost because it more accurately reflects real world gasoline consumption, but we must use the CAFE MPG in the constraint (A-25). Let the EPA MPG be denoted with the superscript E and the CAFE MPG be denoted

In addition to CAFE regulations, vehicle manufacturers must also satisfy EPA CO_2 regulations. In theory, these regulations have been harmonized, so that the CO_2 constraint is equivalent to the CAFE constraint. In practice, there may be differences between the two constraints. See Jenn et al (2016) for details.

O Calculation of upstream externalities from data in Michalek et al (2011).

Table K: Damages Due To Upstream Externalities (Source: Michalek et al 2011)

	GHG	Local	Other	Total
Gasoline Vehicle (CV)				
Vehicle production	316	535	78	929
Battery production	12	17	2	31
Gasoline production	290	289	18	597
Total				**1557**
Electric Vehicle (BEV 240)				
Vehicle production	291	566	69	926
Battery production	532	1272	103	1907
Upstream electricity production	63	47	2	111
Total				**2944**

Michalek et al (2011) present data on damages due to upstream externalities from both gasoline vehicles and electric vehicles. These data (in 2010 dollars) are presented in Table K. Local corresponds to the damages from the local pollutants analyzed in our study (SO_2, NO_X, $PM_{2.5}$, and VOCs). Other corresponds to CO and PM_{10}. All data except the upstream electricity production row are taken directly from table S-25 in Michalek et al (2011). Upstream electricity production is calculated from electricity production in table S-25 assuming 6.3% percent of emissions from electricity production occur upstream (a number

with the superscript C. We have

$$(\delta_a - \delta_b)g = 0.3644\left(\frac{1}{f_a^E} - \frac{1}{f_b^E}\right)g = 0.3644\left(\frac{1}{0.8f_a^C} - \frac{1}{0.8f_b^C}\right)g = \frac{0.3644}{0.8}\left(\frac{1}{f_a^C} - \frac{1}{f_b^C}\right)g = \frac{0.3644}{0.8}\left(\frac{1}{f_g^C} - \frac{1}{f_e^C}\right)g,$$

where the last equality follows from the assumption that (A-25) is binding. Substituting 37.5 for f_g^C, 255.6 for f_e^C, and $150,000$ for g gives \$1555.

which is calculated from Table S-15).

The electric vehicle total upstream costs are \$2944 and the gasoline vehicle total upstream costs are \$1557, for a difference of \$1387 in 2010 dollars, which is approximately \$1500 in 2014 dollars.

We can also compare our calculation of the average environmental benefits of an electric vehicle over the lifetime of driving the vehicle with the corresponding value from Michalek et al (2011). Recall we found the average environmental benefits are be equal to -\$1095. The corresponding value for Michalek et al is -\$181.[78]

P Cap and Trade Programs

If electric power plants are subject to a binding cap on total emissions of some pollutants, then this will have an effect on the calculation of the environmental benefits of electric cars. A complete analysis of this issue would require a model of the cap and trade market, because permit trade would shift the location of emissions, even though the total level is capped. In this Appendix, we approximate the effect of a binding cap by zeroing out marginal damages from power plants that are subject to cap and trade markets.

There are several cap and trade markets that are relevant for our analysis of 2010-2012 (these are described in EPA's eGRID, see http://www.epa.gov/energy/egrid). Markets regulating SO2 emissions include the Acid Rain Program and the Clean Air Interstate Rule (CAIR) annual SO_2 market. Markets for NO_X emissions include both the CAIR seasonal NOx market and the CAIR annual NO_X market. The Regional Greenhouse Gas Initiative regulates CO_2 in the Northeast. As noted in the main text, during the period of analysis, permit prices were low and the stock of banked permits was increasing.[79] We set a power plant's marginal emissions for a given pollutant to zero if it is regulated for even part of the year by one of these programs.

[78]According to table S-25 in Michalek et al (2011), the environmental externality from driving an electric vehicle is electricity production (1762) plus vehicle operation (75) less PM_{10} (22) which equals 1815. For gasoline cars is it vehicle operation (3246) less military (120) less monopsony (829) less disruption (335) less CO (292) less PM_{10} (22) which equals 1648. This gives a difference of -\$167 in 2010 dollars, which is -\$181 in 2014 dollars.

[79]See the EPAs progress reports on emission, compliance, and market analyses (e.g., https://www.epa.gov/sites/production/files/2015-08/documents/arpcair10_analyses.pdf).

The results are given in Table L. First we consider caps on pollutants in isolation. The effect is largest for caps on SO_2 (the environmental benefits shift from -0.73 to 0.79 cents per mile). We also consider simultaneous caps on NO_X, SO_2, and CO_2 (the environmental benefits become 0.92 cents per mile.)

Table L: Effects of binding caps on environmental benefits (cents/mile for 2014 electric and gasoline Ford Focus)

	Electric Vehicle			Gasoline Vehicle			Environmental Benefits		
	mean	min	max	mean	min	max	mean	min	max
Baseline	2.59	0.67	4.72	1.86	1.03	4.32	-0.73	-3.63	3.16
NO_X only	2.54	0.67	4.60	1.86	1.03	4.32	-0.68	-3.51	3.16
SO_2 only	1.07	0.70	1.54	1.86	1.03	4.32	0.79	-0.47	3.40
CO_2 only	2.50	0.67	4.73	1.86	1.03	4.32	-0.65	-3.63	3.16
NO_X, SO_2, and CO_2	0.94	0.29	1.42	1.86	1.03	4.32	0.92	-0.35	4.04

Q Full Size Color Figures

Here we reproduce the figures from the main paper in color and at full size.

Figure 1a: Marginal Damages for Gas Vehicles by County

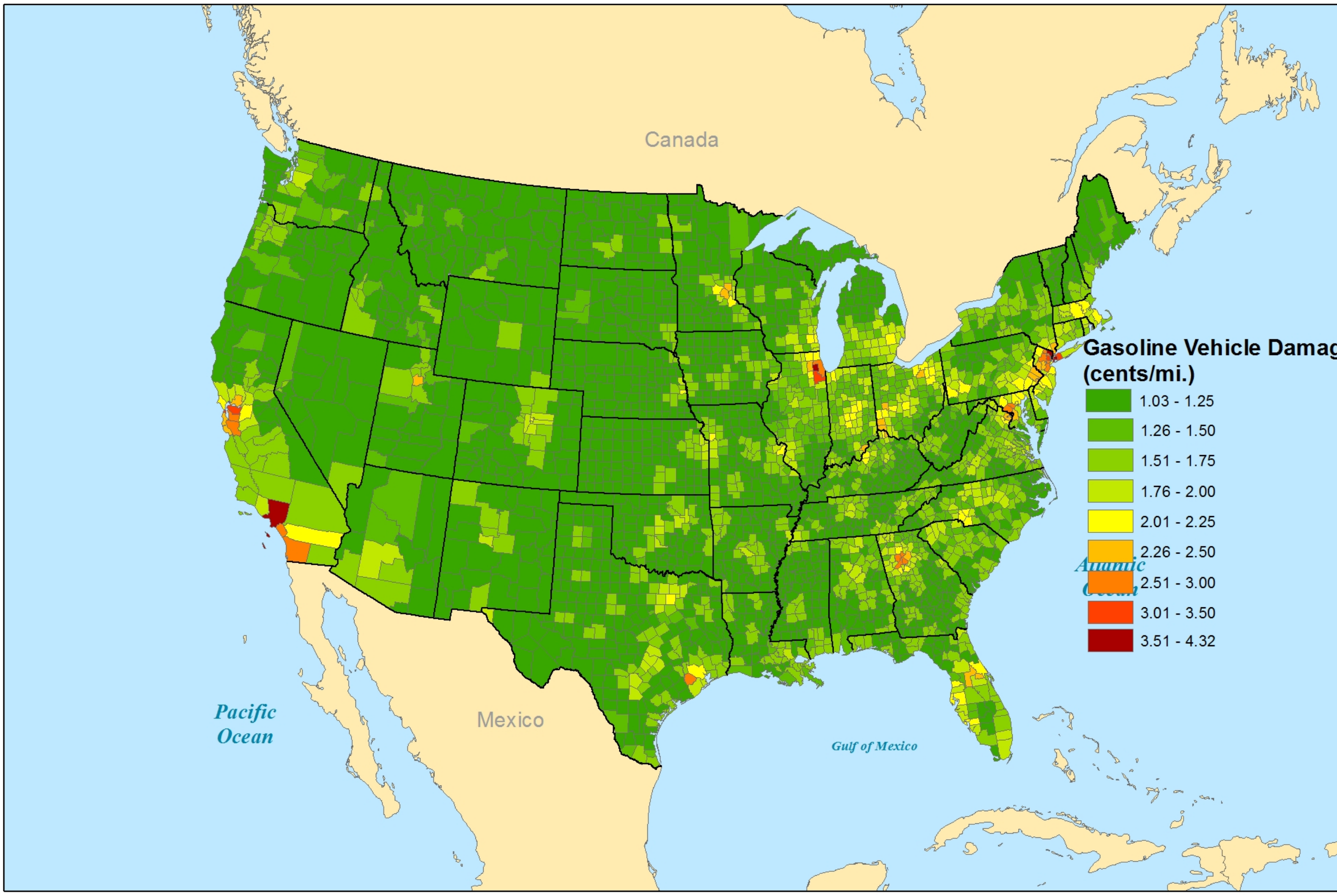


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Figure 1b: Marginal Damages for Electric Vehicles by County

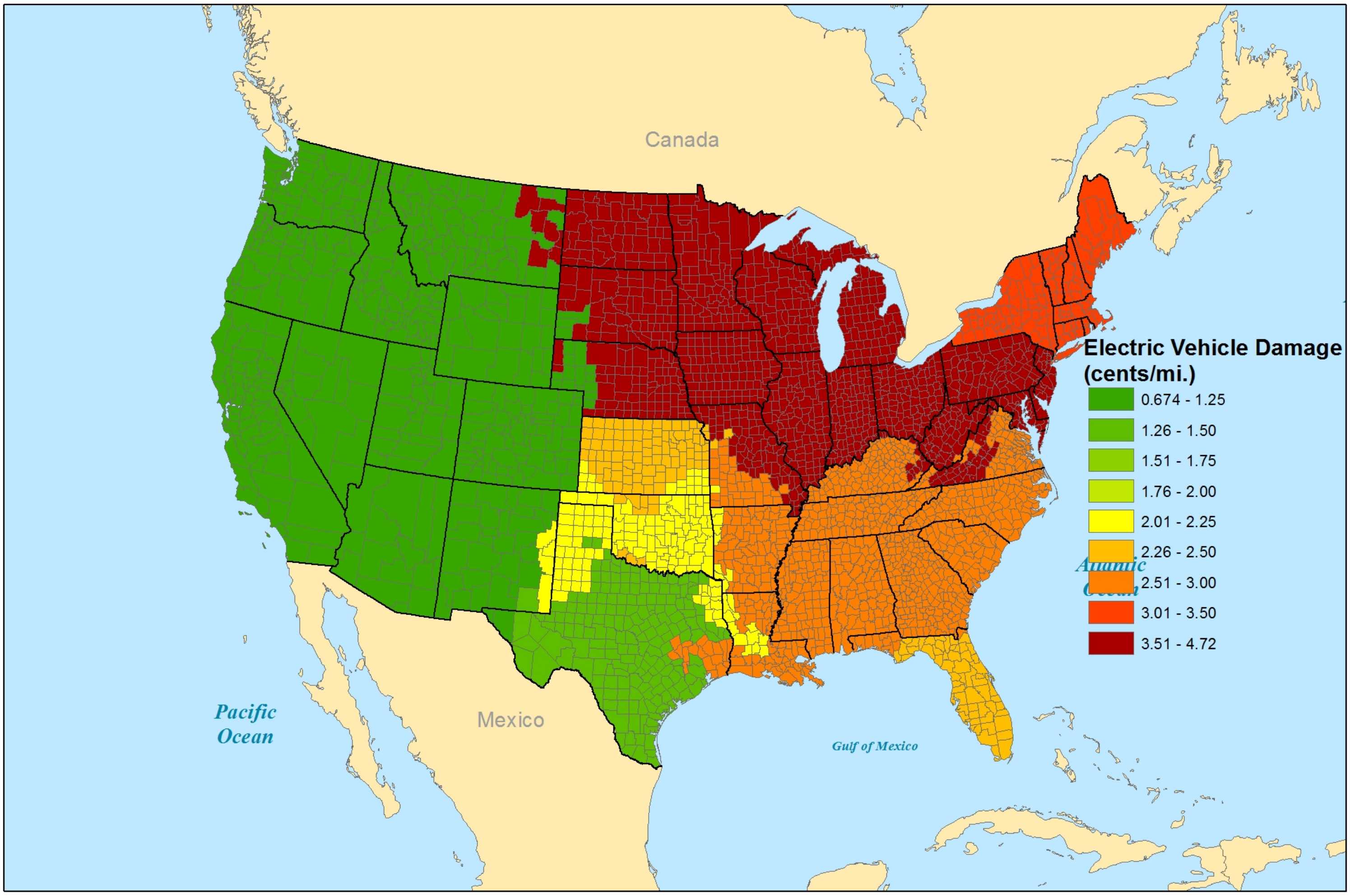

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Figure 2: Second-Best Electric Vehicle Subsidy by County

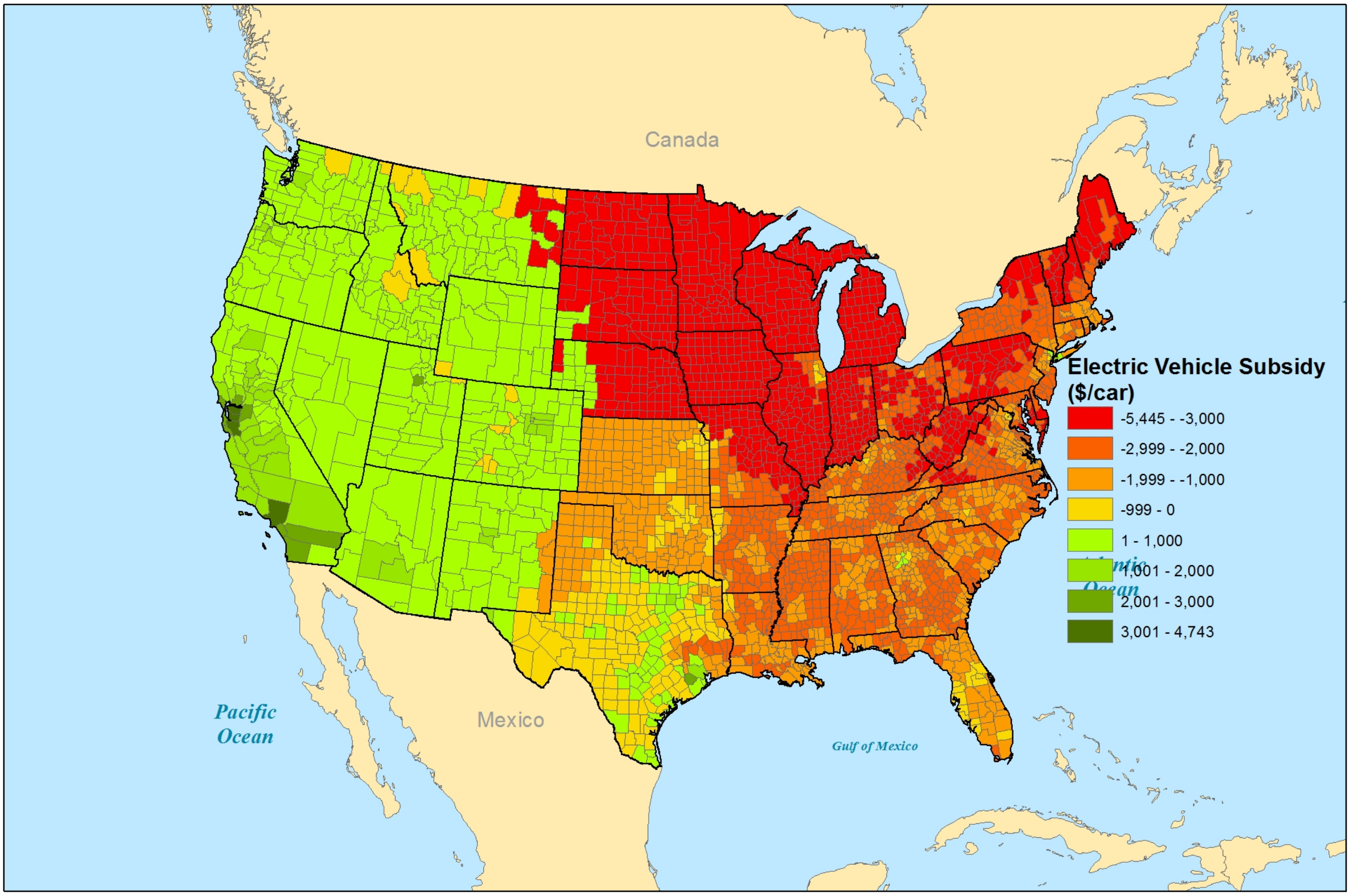

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Figure 3a: Second-Best Electric Vehicle Subsidy by State (Full Damages)

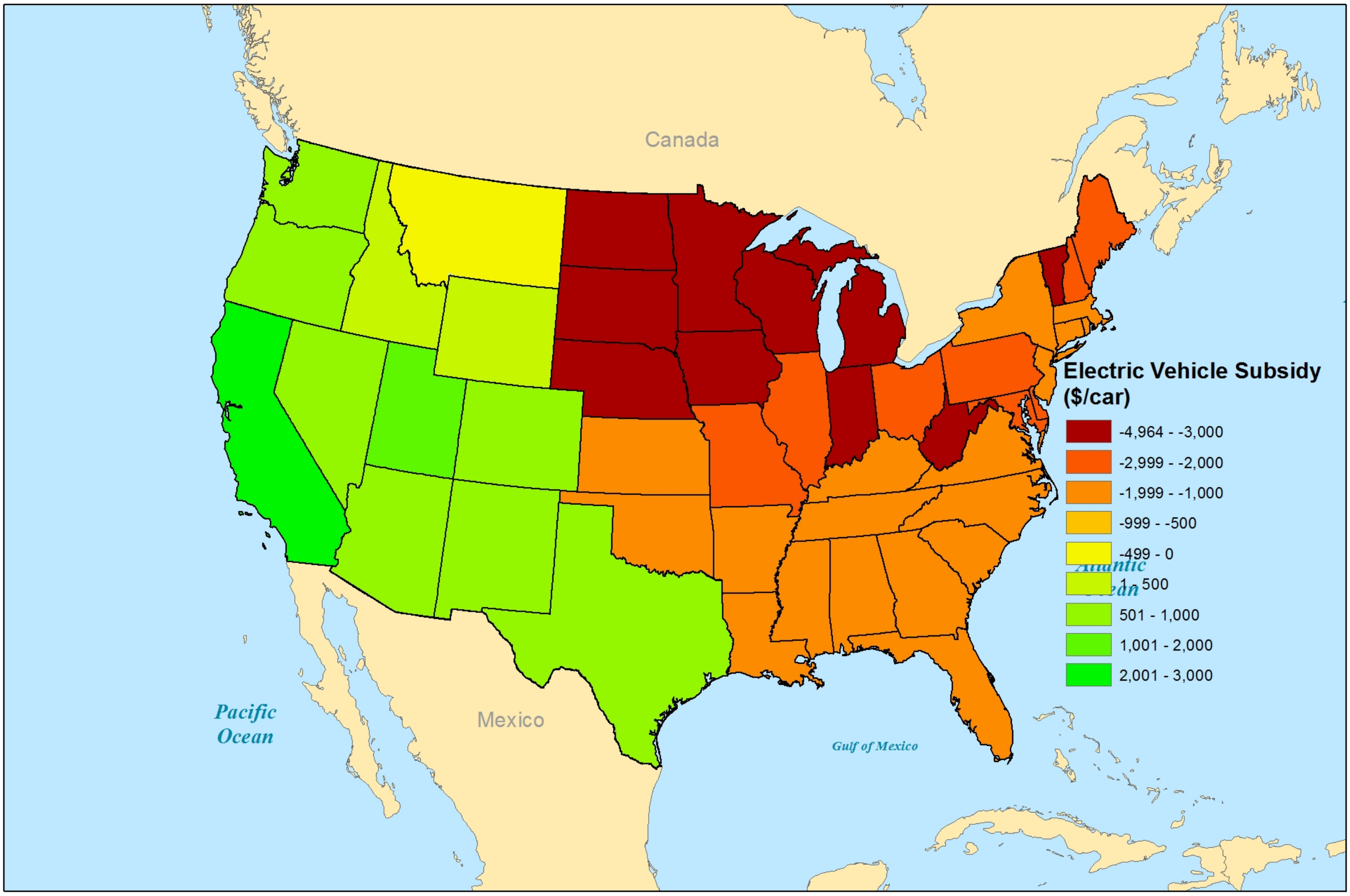

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Figure 3b: Second-Best Electric Vehicle Subsidy by State (Native Damages)

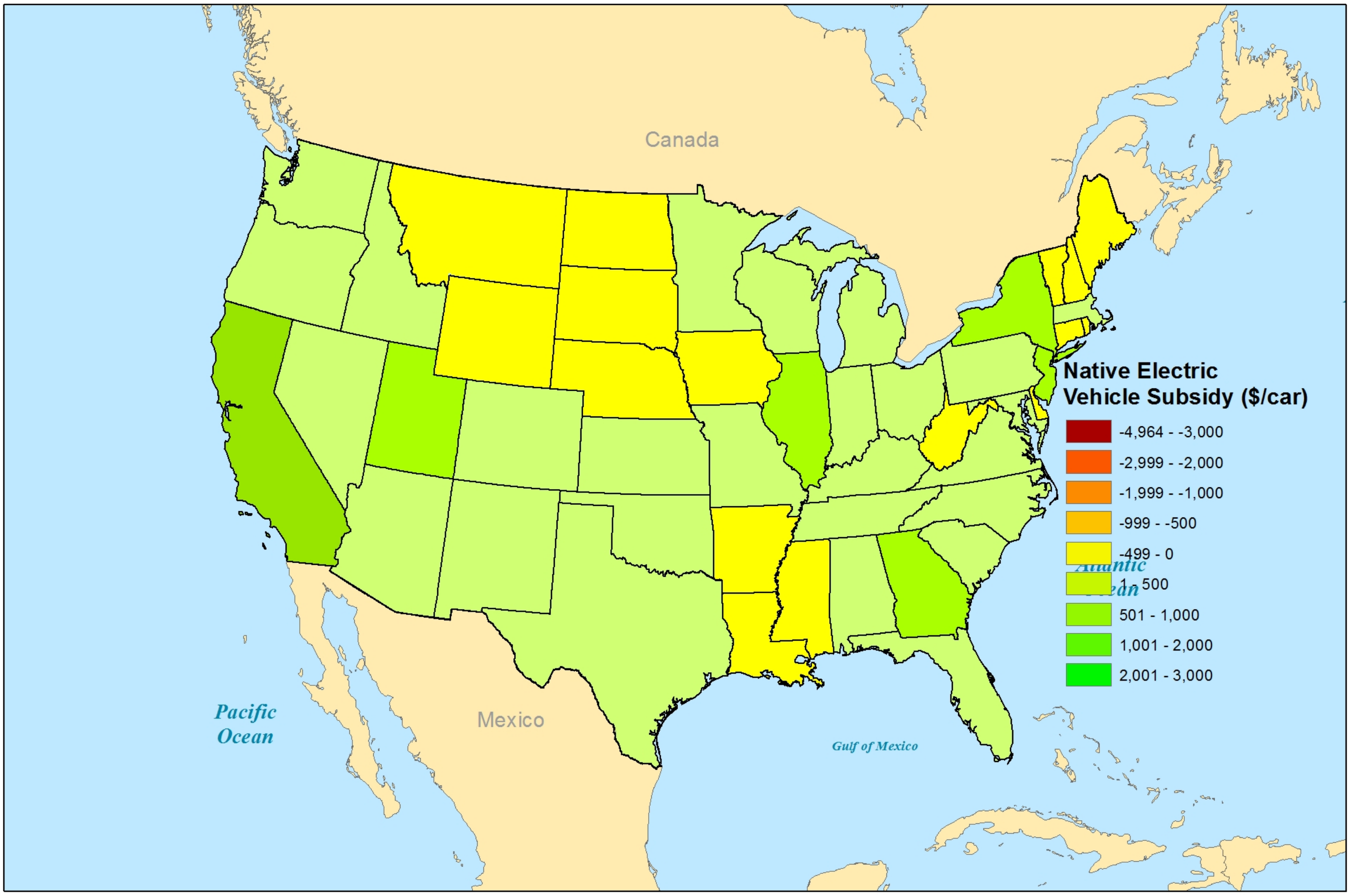

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Figure 4a: Change in $PM_{2.5}$ from Gasoline Vehicle in Fulton County, Georgia

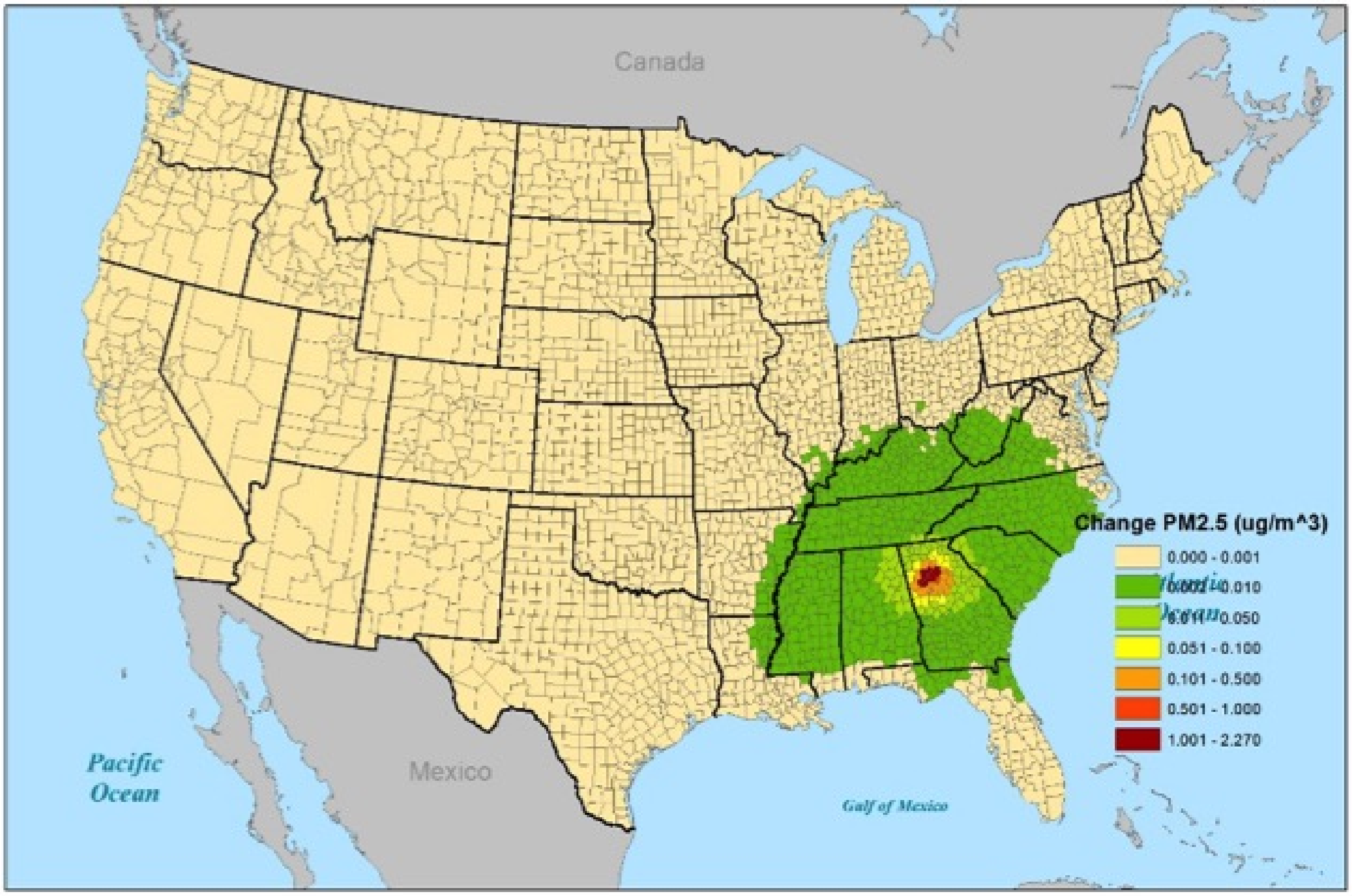

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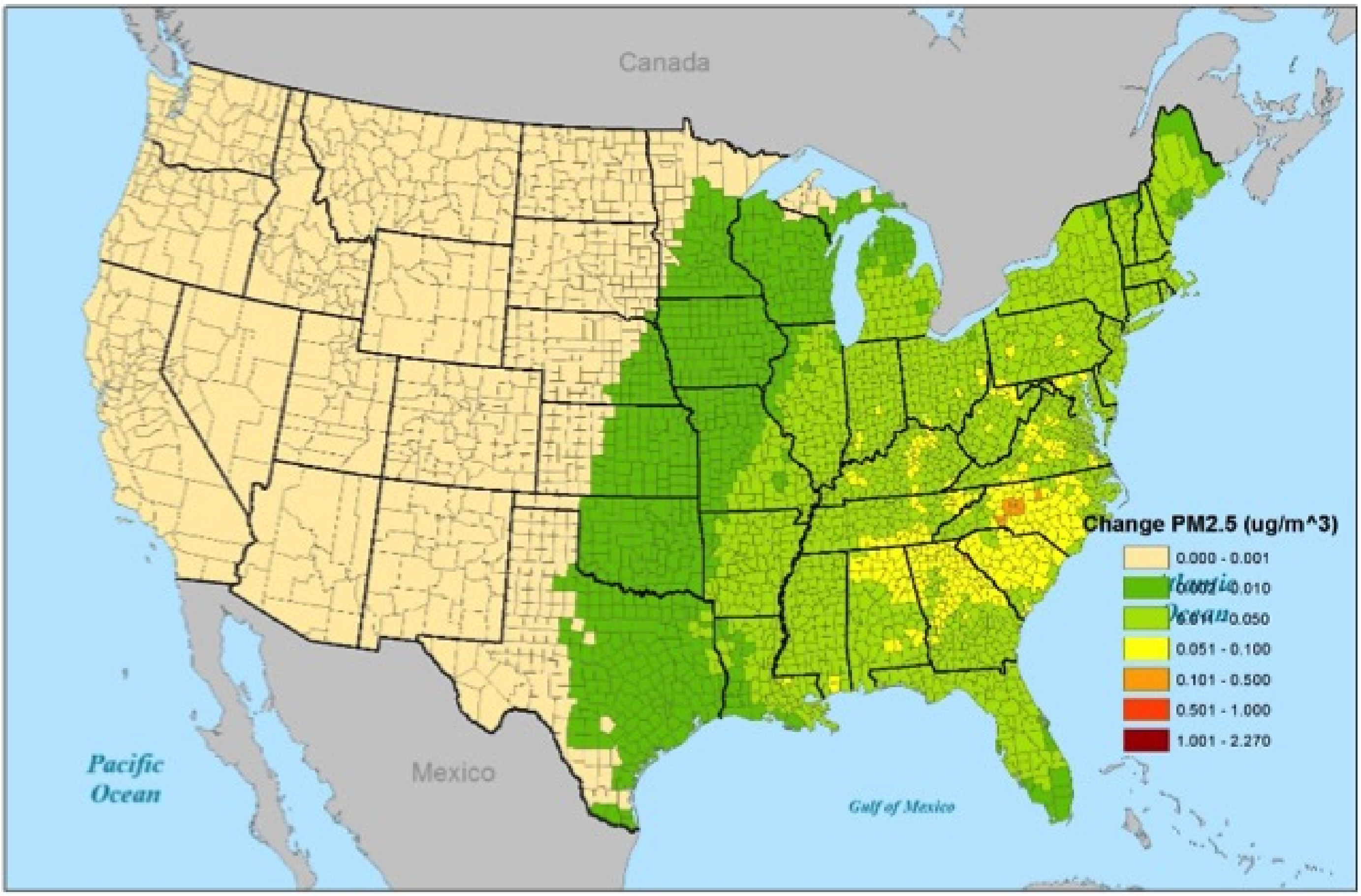
Figure 4b: Change in $PM_{2.5}$ from Electric Vehicle in Fulton County, Georgia



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Supplementary Appendix References

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