NBER WORKING PAPER SERIES

ENVIRONMENTAL BENEFITS FROM DRIVING ELECTRIC VEHICLES?

Stephen P. Holland
Erin T. Mansur
Nicholas Z. Muller
Andrew J. Yates

Working Paper 21291
http://www.nber.org/papers/w21291

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2015

We thank Gregory Grissom for his research assistance. We thank Joseph Aldy, Matthew Kahn, Joseph Shapiro, and seminar participants at POWER, NBER, and ASSA conferences for helpful comments and suggestions. Special thanks to Gloria Helfand and David Brzezinski for data. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Environmental Benefits from Driving Electric Vehicles?
Stephen P. Holland, Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates
NBER Working Paper No. 21291
June 2015
JEL No. D62,H23,Q53,Q54

ABSTRACT

Electric vehicles offer the promise of reduced environmental externalities relative to their gasoline counterparts. We combine a theoretical discrete-choice model of new vehicle purchases, an econometric analysis of the marginal emissions from electricity, and the AP2 air pollution model to estimate the environmental benefit of electric vehicles. First, we find considerable variation in the environmental benefit, implying a range of second-best electric vehicle purchase subsidies from $3025 in California to -$4773 in North Dakota, with a mean of -$742. Second, over ninety percent of local environmental externalities from driving an electric vehicle in one state are exported to others, implying that electric vehicles may be subsidized locally, even though they may lead to negative environmental benefits overall. Third, geographically differentiated subsidies can reduce deadweight loss, but only modestly. Fourth, the current federal purchase subsidy of $7500 has greater deadweight loss than a no-subsidy policy.

Stephen P. Holland
Bryan School of Business and Economics
University of North Carolina, Greensboro
P.O. Box 26165
Greensboro, NC 27402-6165
and NBER
sphollan@uncg.edu

Erin T. Mansur
Dartmouth College
100 Tuck Hall
Hanover, NH 03755
and NBER
erin.mansur@dartmouth.edu

Nicholas Z. Muller
Department of Economics
Warner Hall, 305D
Middlebury College
303 College Street
Middlebury, VT 05753
and NBER
nicholas.muller74@gmail.com

Andrew J. Yates
Department of Economics
and Curriculum for the
Environment and Ecology
University of North Carolina at Chapel Hill
CB 3305
Chapel Hill, NC 27599
ajyates@email.unc.edu

A supplemental appendix is available at:
http://www.nber.org/data-appendix/w21291

1 Introduction

Due to a combination of factors, 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 consumer vehicle choice set. Almost all major manufacturers are bringing new models to the market. The Federal Government is encouraging these developments by providing a significant subsidy for the purchase of an electric vehicle, and some states augment the federal subsidy with their own additional subsidy.

The subsidies reflect beliefs that electric vehicles generate a range of benefits including: decreased reliance on imported oil, insulation from oil price shocks, and a reduction in environmental impacts.[2] This paper explores the latter with a particular focus on the air pollution emissions generated by driving a vehicle, including both greenhouse gasses (GHGs) and local pollutants. Rather than simply accepting the assertion of environmental benefits from electric vehicle use, we conduct a rigorous comparison of the environmental consequences of gasoline and electric vehicles by extending and integrating existing modeling tools.

There are two factors that motivate our exploration of the ex ante claims of environmental benefits from electric vehicles. First, and most obvious, despite being treated by regulators as "zero emission vehicles", electric vehicles are not necessarily emissions free. In 2014, the U.S. 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 in the country, 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. It is well-known that coal has higher emissions than oil which has higher emissions than natural gas. Thus, the relative emissions intensity per vehicle mile traveled is not immediately clear, despite strong beliefs otherwise.

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

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

Second, there are significant physical differences between emissions from gasoline and electric vehicles. This is due to the distributed nature of the electricity grid as well as the height at which emissions occur. Charging an electric vehicle increases electricity demand which is met by (potentially) several power plants that may be quite distant from where the vehicle is driven. In contrast, emissions from a gasoline vehicle occur where the vehicle is driven. Even if the two vehicle types are driven in the same location, their emission patterns will be spatially distinct. Because air pollution damages depend on the location of emissions (Muller and Mendelsohn, 2009), the damages associated with driving the vehicles in one place may differ greatly from the damages associated with driving the vehicles in another place. As for emissions height, gasoline vehicles emit pollutants at or near the ground while power plant discharges occur hundreds of feet above the ground, leading to additional heterogeneity in the damages produced by the two vehicle types (Muller, Tong, and Mendelsohn, 2009). Evaluating these sources of heterogeneity requires careful attention to the complex interactions among the underlying economic and physical systems.

These factors generate critical questions as to the merits of the federal subsidy. The first factor questions the policy in terms of its sign: is it better to subsidize or tax electric vehicle purchases? The second factor raises concerns regarding the one-size-fits-all design of the subsidy. With heterogeneity in the environmental benefits of electric vehicles, what are the welfare benefits of differentiated policy (i.e., allowing policy to vary by location)?

Our analysis addresses these questions. We determine the environmental benefit of electric vehicles relative to comparable gasoline vehicles accounting for heterogeneity in the externalities from both types of vehicles. We analyze the welfare associated with policies that target these externalities, such as subsidies on the purchase of an electric vehicle and taxes on electric and/or gasoline miles, and we consider the welfare benefits of differentiated policy.

To accomplish these tasks, we extend and integrate three component models. The first component uses a theoretical discrete choice transportation model to analyze consumer choice between electric and gasoline vehicles and welfare issues.[3] The second component builds on

[3]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), Stavins (1996), Banzhaf and Chupp (2012), Muller and Mendelsohn (2009), and Fowlie

the econometric analysis of the relationship between electricity generation and air pollution emissions to analyze the effects of changes in electricity load due to charging electric vehicles on emissions from individual electric power plants.[4] The third component builds on air pollution integrated assessment models to describe the relationship between emissions from a given smokestack or tailpipe and damages at a given location.[5] Combining the components together yields a powerful and unprecedented modeling framework for analyzing electric vehicle policy.[6]

Our first set of results documents the considerable heterogeneity in the environmental benefit of an electric vehicle relative to a gasoline vehicle. This benefit 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 a large positive environmental benefit of an electric vehicle. These conditions are reversed in North Dakota. In New York City and rural Nevada, the environmental benefit is negligible. Using the environmental benefit, we calculate the welfare maximizing (second-best) subsidies on electric vehicle purchases. Even in locations like California, subsidy values are significantly less than the current federal subsidy. And in North Dakota the subsidy is negative, implying a tax on the purchase an electric vehicle. The national average subsidy for the purchase of an electric vehicle is estimated to be -$742. Thus, on average in the U.S. for our study period, the second-best purchase policy is a tax, not a subsidy.[7]

Our second set of results shows the remarkable degree to which electric vehicles driven in one location lead to environmental externalities in other locations. For example, at the

and Muller (2013).

[4]See Graff Zivin et al (2014) and Holland and Mansur (2008).

[5]Previous works includes Mendelsohn (1980), Burtraw et al. (1998), Mauzerall et al. (2005), Tong et al. (2006), Fann et al. (2009), Levy et al. (2009), Muller and Mendelsohn (2009), Henry et al. (2011), and Mauzerall et al. (2005). In our application of integrated assessment, 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).

[6]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. 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 consumer choice model to evaluate welfare.

[7]Our electricity grid data are from the period 2010-2012 and the emissions inventory used by AP2 is from 2011. These are the latest years for which data are available.

state level, ninety-one percent 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 eighteen percent of local pollution damages from driving a gasoline vehicle are exported to other states. This discrepancy has interesting political economy implications. Suppose that a given state is considering whether or not to implement a subsidy on the purchase of an electric vehicle. It is not obvious whether the state will consider 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. Central aspects of federal air pollution policy, namely the National Ambient Air Quality Standards (NAAQS) established by Title I of the Clean Air Act, 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. All else equal this would lead state regulators to focus on in-state damage. 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 12 states. Accounting for only native damages, the second-best subsidy is positive in 34 states.

The final set of results assesses the deadweight loss of various second-best policies as well as the welfare gains from differentiated policy. The theoretical analysis of our discrete choice model 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. We also evaluate the current federal policy of a \$7500 subsidy on the purchase of an electric vehicle relative to a default policy in which there is no subsidy at all. Because electric vehicles, on average, generate greater environmental externalities than gasoline vehicles, the current federal policy has greater deadweight loss than the no-subsidy policy. Moreover, the welfare difference between these two policies increases substantially as the electric vehicle adoption rate increases, rising from \$200 million at recent adoption rates to \$3.7 billion at adoption rates that are foreseeable in the near future (i.e., five percent of sales).

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) large, or economically significant outcomes. The federal policy which encourages the purchase of electric vehicles exhibits each of these traits. As such, the present study is warranted and should be of broad interest to economists, policymakers, consumers, and the environmental community.

In Section 2 we develop a simple general equilibrium model that includes discrete choice over vehicle type as well as environmental externalities from driving. We derive several theoretical results about second-best policy choices and the welfare benefits from differentiated policies. In Section 3 we describe the methods by which we determine emissions and damages from electric and gasoline vehicles. Section 4 presents the results. In Section 5 we consider how the interaction with the Corporate Average Fuel Economy (CAFE) standards may effect the second-best subsidies on electric vehicles and we discuss several important 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.[8] 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. We hold fuel and vehicle prices fixed.[9]

[8] Examples of general discrete choice models are Anderson et al. (1992) and Small and Rosen (1981). Examples of theoretical discrete choice 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.

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

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

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

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. Because the objective function in these optimization problems is quasi-linear, there are no income effects.[10]

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.[11] Accordingly, we define the conditional utility, given that a consumer elects the gasoline vehicle, as

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

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

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

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

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

where μ is proportional to the standard deviation of the extreme value random variables.

[10] The marginal utility of income is constant, the number of miles driven does not depend on income, and the choice of vehicle does not depend on income.

[11] The extreme value distribution (or double exponential distribution) has two parameters, η and μ. The expected value is $\mu\gamma + \eta$ where γ is Euler's constant (0.577). The variance is $\mu^2(3.14159)^2/6$.

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.

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.[12] 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.[13]

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 gen-

[12]Prior research on the damages from local air pollutants has found strong evidence of constant marginal damages. See Muller and Mendelsohn (2009); Fowlie and Muller (2013). Constant marginal damages is also consistent with the EPA's social cost of carbon calculations.

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

erated by the purchase of a new vehicle in location i.[14] 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 the location, defined as the sum of expected utility and expected revenue less expected pollution damage:[15]

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

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

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

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

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.[16] Even if the electric vehicle emits less pollution per mile than the gasoline vehicle, the sign of the subsidy is ambiguous, because the number of miles driven may be different. If the miles driven are indeed the same, and the electric vehicle emits less pollution per mile than the gasoline vehicle, then the subsidy is positive. We refer to the difference $\delta_{gi} - \delta_{ei}$ as the *environmental benefit* of an electric 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

[14] 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.

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

[16] The simple structure for the second-best subsidy is due to the fact that we only have two vehicles in the choice set. If there are two or more gasoline vehicles in the choice set, then the second-best subsidy will depend on the various cross-price elasticities (see Supplementary Appendix A).

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, 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.

Proposition 2 is most easily interpreted in the special case in which the population of new vehicle buyers in the same in each location ($\alpha_i = \frac{1}{n}$) and the electric vehicle and gasoline vehicle are driven the same number of miles ($g = e$). Here the second-best uniform subsidy $\tilde{s}$ is equal to the average environmental benefit 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. This provides a point of comparison to previous work on differentiated regulation.[17] 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

[17]Mendelsohn (1986) finds the exact welfare improvement from differentiation to be a function of the second moment of the distribution of the relevant environmental parameter. The reasons for this difference are discussed in Supplementary Appendix C. See also Jacobsen et al (2015).

approximation.

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 benefit 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 air 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.[18] Our set of electric vehicles includes each of the eleven pure electric vehicles in the EPA fuel efficiency database for the 2014 model year. Our set of gasoline vehicles is meant to capture the closest substitute in terms of non-price attributes to each electric vehicle. Wherever possible, we use the gasoline-powered version of the identical vehicle, e.g., the gasoline-powered Ford Focus for the electric Ford Focus.

To determine the emissions per mile for each gasoline vehicle, we integrate data from several sources. 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.[19] We differentiate urban and non-urban counties by using EPA's city and highway mileage.[20] 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 mile for each gasoline vehicle only differ across urban and non-urban counties.[21]

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).[22] We adjust this

[18] A more complete analysis would also include assessment of emissions from CO and toxics.

[19] 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.

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

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

[22] We use the combined city/highway EPA figure and do not differentiate electric vehicles by urban and

figure to account for the temperature profile of each county, because electric vehicles use more electricity per mile in cold and hot weather.[23] 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.[24] 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.[25] 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, 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 Simulator (MOVES).[26]

---

rural since regenerative braking leads to smaller differences in city and highway efficiencies.

[23]This is due to both the decreased performance of the battery and the increased demand for climate control (Yuksel and Michalek, forthcoming, 2015). Temperature also effects the performance of gasoline vehicles, but the effects are much smaller, 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 E. We explore how sensitive our findings are to this assumption, as well as others, in Section 4.4.

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

[25]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.

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

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.[27] 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.[28]

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.[29] 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.

The dependent variable in our analysis, y_{it}, is power plant i's hourly emissions (CO_2,

[27] See http://www.nerc.com for a description of NERC regions. We model the Eastern interconnection as the six NERC regions (FRCC, MRO, NPCC, RFC, SERC, and SPP). We define the MRO region to include all of the Midwest Independent Transmission System (MISO) territory (circa 2012), even those parts in other regions. We split the Western interconnection between California and the rest of the WECC. The Texas interconnection is simply the coterminous ERCOT.

[28] 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.

[29] 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 F.

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:

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

where $J(i)$ equals the number of regions in the interconnection in which power plant i is located, $HOUR_h$ is an indicator variable for hour of the day h, $REGION_j$ indicates electricity region j, $MONTH_m$ indicates month of the sample m, and $LOAD_{jt}$ is the electricity consumed in region j at time t. The 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.[30] 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

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

of total damage (Muller, Mendelsohn, Nordhaus, 2011)

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.[31] 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, Mendelsohn, and Nordhaus, 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.

[31] In our sensitivity analysis, we show the effects of using a more recent concentration response functions from Roman et al., 2008.

4 Results

4.1 Environmental benefit of electric vehicles

The environmental benefit of an electric vehicle 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. 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.[32] In the baseline EPRI profile, mean damages are 2.5 cents per mile (the equivalent of 7.5 cents per kWh) but range from less than one cent per mile in California and the West (WECC) to over four cents per mile in the Midwest (MRO). 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. It is widely assumed, as in the EPRI charging profile, that most electric vehicle charging will occur at night. However, damages could be reduced in the Midwest (MRO) 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 2 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 2.5 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 the damages (in cents per mile) for the gasoline Ford Focus by county. The counties with

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

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 2. For the gasoline Ford Focus, mean damages are two cents per mile (the equivalent of $0.60 per gallon) but range from about a cent per mile to over four cents per mile.[33]

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 benefit of an electric vehicle would be small in most counties. In fact, the damages are not highly correlated (the correlation is 0.06). As a result, the environmental benefit varies substantially, as shown in the right columns of Table 2. 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 benefit is 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 benefit of an electric vehicle is *negative*, and is almost equal to the electric vehicle damages. Overall, the environmental benefit is negative on average for each of the electric vehicles in Table 2.[34] The electric Ford Focus is the median electric vehicle in terms of environmental benefit, and we focus on it throughout the results section.

Using Proposition 2, we can convert the environmental benefit into the second-best purchase subsidy by assuming that both the electric vehicle and the gasoline vehicle are driven 150,000 miles.[35] Figure 2 shows the second-best subsidies by county. Except for a few coun-

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

[34]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).

[35]We are assuming that both types of vehicles have 10 year lifetimes, regardless of the number of miles driven, and that both types of vehicles 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.

ties 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 benefit 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 benefit 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 subsidy 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 12 states in which the environmental benefit is positive, and Texas is the only high VMT state outside the Western interconnection in which the environmental benefit is 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 $724 more environmental damages over its driving lifetime than the equivalent gasoline Ford Focus.

Despite these modest (or negative) environmental benefits of electric vehicles, the current federal subsidy for electric vehicles is $7500. Many states have additional policies designed to encourage the adoption of electric vehicles.

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). To illustrate this discrepancy, we first analyze transport of a specific pollutant from a specific county. Panel A in Figure 4 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 Georgia. Most of the increase in $PM_{2.5}$ is centered within a few nearby counties. Panel B in Figure 4 shows the change in $PM_{2.5}$ associated with the same number of miles driven by electric powered Ford Focus vehicles that are charged in Fulton County, thereby increasing the consumption of electricity in the Southeast (SERC). 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 1.6 cents per mile on average. Native state damages are only 0.15 cents per mile, and native county damages are only 0.02 cents per mile. Thus on average 91% of electric vehicle damages 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 18% of these damages are exported from a state and only 57% are exported from a county.

Using native damages rather than full damages changes the environmental benefit 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 benefit moves from approximately -3.5 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 benefit.

On average, the environmental benefit 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 33 out of 48 states.

Do state policymakers place greater emphasis on full or native damages when considering electric vehicle subsidies? Eight states have implemented subsidies for the adoption of electric vehicles, above and beyond the federal subsidy: California (\$2500), Colorado (\$6000), Georgia (\$5000), Illinois (\$4000), Maryland (\$3000), Massachusetts (\$2500), Texas (\$2500) and Utah (\$1500). In addition, some states offer a variety of other incentives, including carpool lane access, electricity discounts, and parking benefits.[36] As shown in supplementary Appendix G, 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.[37] In addition to electric 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

[36] The Department of Energy maintains a database of alternative fuels policies by state: http://www.afdc.energy.gov/laws/matrix?sort_by=tech. A small number of states impose a special registration fee for electric vehicles. State policies change frequently. Our data accounts for policies in place on January 1, 2015.

[37] See Supplementary Appendix H for more details.

is no subsidy at all (or business as usual.) If the share would be 5%, we refer to this as the 5% BAU EV share case. Given a 5% BAU EV share, state-specific taxes have a deadweight loss of $102 million per year, and uniform federal taxes has a deadweight loss of $273 million per year.[38] This implies a gain from differentiation of $171 million (moving from federal to state) and of $273 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 I). For single tax policies, the gains from differentiation are on the order of $150-$200 million. However, the deadweight losses are large ($2 billion) particularly for taxes on electric miles only. 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 ($1-$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 $20-$40 million at 5% BAU EV share. These gains are much smaller than the gains from differentiation of VMT taxes. In addition to small gains from differentiation, deadweight losses from electric vehicle subsidies are large: over $2 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-subsidy policy. The deadweight loss from the current federal subsidy is $6 billion per year at 5% BAU EV share. This exceeds the deadweight loss from the no-subsidy policy by $3.7 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%.[39] The deadweight loss from the current federal subsidy is $2.2 Billion and the deadweight loss

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

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

from the no-subsidy policy is \$2 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 critical 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.[40]

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 benefit is 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 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 benefit. 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

[40] Additional sensitivity for the welfare analysis is in Supplementary Appendix H.

response parameter leads to higher damages for both vehicles which widens the distribution of environmental benefits.

The final sensitivity 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. 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.[41] 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 benefit 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 benefit of 0.64 cents per mile implies an electric vehicle subsidy of $960, which is still substantially less than current subsidies.

5 Extensions and caveats

5.1 Effects of CAFE standards

We have analyzed the environmental benefit of electric vehicles in isolation from other environmental regulations. In practice, other regulations may impact the electricity market and/or the market for vehicles, and hence have an effect on the environmental benefit of electric vehicles.

One important regulatory interaction is with the Corporate Average Fuel Economy

[41] 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.

(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 equivalent for this calculation. These values are generally much larger than any existing gasoline vehicle. Assuming that the CAFE requirement is initially binding, selling an electric vehicle enables manufacturers to meet a lower standard for the rest of their fleet. Starting in 2017, this effect will be exacerbated, as the CAFE standards will treat electric vehicles even more generously. An electric vehicle sale will receive a multiplier, starting at two and then declining over time. When a manufacturer sells an electric vehicle, it will get credit in the CAFE calculation as if it sold two electric vehicles. This will enable the firm to decrease the fuel economy of the rest of its fleet even more while remaining in compliance with CAFE.

We give a preliminary analysis of this interaction that is consistent with our model.[42] 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 J we show that the CAFE-induced environmental cost is the difference in damages due to the substitution of a low MPG vehicle for a high MPG vehicle.[43] We also 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 under current CAFE standards is $1439 per vehicle. The magnitude of this CAFE-induced environmental cost is significant in comparison with even the largest second-best subsidy for an electric vehicle found in our study ($3025, in California).

5.2 Caveats

There are several important caveats that affect the calculation and interpretation of our environmental benefit of an electric vehicle due to decreased air pollution emissions.

First, it is important to stress that we have only considered the externalities from air

[42] A more thorough analysis would require a complete model of both supply and demand for the entire new vehicle market and relax our assumption of constant prices.

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

pollution emissions associated with driving the vehicles. There are several other externalities associated with electric and gasoline vehicles. For example, there are pollution emissions associated with manufacturing and disposing of both types of vehicles. There are emissions associated with extracting oil, refining gasoline, and transporting the gasoline to the retail stations. There are emissions associated with mining coal and natural gas and transporting these resources to electric power plants. In addition to these "life-cycle" externalities, there may be a geo-political externality from oil consumption. It is unlikely, however, that these externalities have the same degree of heterogeneity found in air pollution emissions. 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. Moreover, previous research on life-cycle externalities has shown that the differences between electric vehicles and gasoline vehicles are relatively small (Michalek et al. 2011).

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.

Third, an additional argument put forth in favor of electric vehicle subsidies involves the dynamics of network externalities. Subsidizing electric vehicles today helps boost demand, which in turn increases incentives to provide electric vehicle charging infrastructure.[44] This results in a larger network in the future, at which point electric vehicle adoption will presumably be more 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 the foundation for an estimate of these costs.

Fourth, electric power plants may be subject to cap-and-trade emission permit markets.

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

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, the permit prices in these markets were low, which suggests that the constraints due to the cap were not severe.[45]

Finally, there are three important caveats to our calculation of the environmental benefit. First, it 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 benefit of electric vehicles will depend on the relative rates of changes of these two factors. Table 7 makes a preliminary 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. Second, 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. The effects of large scale adoption of electric vehicles would require analysis beyond the scope of this paper. Third, our results depend critically on the AP2 model, so our analysis inherits any of its limitations.

6 Conclusion

The Federal Government encourages the adoption of electric vehicles by providing a $7,500 subsidy for the purchase of an electric vehicle. Some states add to the federal subsidy with their own financial inducements. These public sector interventions embody a conventional wisdom that electric vehicles generate a range of benefits. Perhaps chief among these is a reduction in environmental impacts relative to gasoline vehicles. Rather than simply accepting the assertion of environmental benefits from electric vehicle use, this paper conducts

[45] A complete analysis of this issue would also require evaluating the increase in abatement costs to meet the cap following the increase in emissions from electric vehicles.

a rigorous comparison of the environmental consequences of gasoline and electric powered vehicles, specifically by quantifying the externalities (both greenhouse gases and local air pollution) generated by driving these vehicles.

On average, electric vehicles generate a negative environmental benefit of about -0.5 cents per mile relative to comparable gasoline vehicles (-1.5 cents per mile for vehicles driven outside metropolitan areas). We find considerable variation around this central result; electric vehicles used in Los Angeles, California produce a benefit of 3.3 cents per mile while those used in Grand Forks, North Dakota, produce a cost of 3 cents per mile. One implication of these findings is the dependence of policy orientation (whether a policy encourages or discourages electric vehicle adoption) on the policymaker's jurisdiction. Our distinction between full and native damages reveals another policy implication. In the vast majority of states, when a consumer opts for an electric vehicle rather than a gasoline vehicle, they reduce air pollution in their state. However, in all but twelve states, this purchase makes society as a whole worse off because electric vehicles tend to export air pollution to other states more than gasoline vehicles. Given this, we would not be surprised to see a proliferation of state-specific subsidies for electric vehicles. Hence there may be a need for federal policy to account for exported damages.

Of course, given the heterogeneity in the magnitude and the sign of the environmental benefit of an electric vehicle, differentiated policy is in fact appropriate, provided it accounts for full damages, not just native damages. 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 preliminary analysis suggests that the interaction of these policies may have significant unintended consequences. It seems worthwhile to devote additional study to this issue.

In summary, our findings generate critical questions as to the merits of the federal subsidy in the U.S. and may provide guidance to other governments considering interventions in the electric vehicle market. We evaluate concerns regarding the sign, the magnitude, and the one-size-fits-all nature of the subsidy. We find that both sign and magnitude of the federal subsidy are significantly different from those indicated by our model. Differentiated policy can lead to welfare improvements relative to one-size-fits all, but greater gains are realized by using differentiated taxes on electric and gasoline miles rather than differentiated purchase subsidies. As a general point, the paper argues that public policy evaluation is especially important in contexts characterized by: economically significant outcomes with complicated interactions among economic and physical systems, where stakeholders possess strong prior beliefs among as to the merits of the policy. The federal subsidy 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.

Appendix

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

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

From the definition of π we have

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

which simplifies to

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

Using this result we can derive the following

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

and

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

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

Proof of Proposition 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 (2) 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

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

So the optimal s is given by

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

From (4) and (5), we have
$$\frac{\partial G}{\partial s} = \frac{\partial g}{\partial s}\pi + g\frac{\partial \pi}{\partial s} = g\frac{\partial \pi}{\partial s},$$
and
$$\frac{\partial E}{\partial s} = \frac{\partial e}{\partial s}(1-\pi) - e\frac{\partial \pi}{\partial s} = -e\frac{\partial \pi}{\partial s},$$
where the second equality in both equations follows from the fact that there are no income effects, so $\frac{\partial g}{\partial s}$ and $\frac{\partial e}{\partial s}$ are equal to zero. Substituting these into the first-order condition for s and simplifying gives
$$s = (\delta_g g - \delta_e e)\,.$$

■

Proof of Proposition 2.

Let $\mathcal{W}(S)$ denote the weighted average of per capita welfare across regions as a function of an arbitrary vector of subsidies $S = (s_1, s_2, \ldots, s_n)$. We have
$$\mathcal{W}(S) = \sum \alpha_i \mathcal{W}_i(s_i) = \sum \alpha_i \left(\mu \left(\ln(\exp(V_{ei}/\mu) + \exp(V_{gi}/\mu))\right) + R_i - (\delta_{gi}G_i + \delta_{ei}E_i)\right).$$

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 $\tilde{s}$
$$\tilde{s} = \frac{1}{\frac{\partial \pi}{\partial s}}\left(\sum \alpha_i \delta_{gi}\frac{\partial G}{\partial s} + \sum \alpha_i \delta_{ei}\frac{\partial E}{\partial s}\right). \tag{8}$$

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 $\tilde{S} = (\tilde{s}, \tilde{s}, \ldots, \tilde{s})$. 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
$$\frac{\partial \mathcal{W}}{\partial s_i} = \alpha_i s_i \frac{\partial \pi_i}{\partial s_i} - \alpha_i \left(\delta_{gi}\frac{\partial G_i}{\partial s_i} + \delta_{ei}\frac{\partial E_i}{\partial s_i}\right)$$
From (3), (4), and (5) we have: $\frac{\partial \pi_i}{\partial s_i} = -\frac{\pi_i(1-\pi_i)}{\mu}$, $\frac{\partial G_i}{\partial s_i} = -\frac{\pi_i(1-\pi_i)}{\mu}g_i$ 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

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

and

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

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

$$\left.\frac{\partial \mathcal{W}}{\partial s_i}\right|_{\tilde{S}} = \frac{\alpha_i}{\mu}\pi(1-\pi)(s_i^* - \tilde{s}). \tag{11}$$

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 (10) and (11) 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. ■

References

[1] Anderson, S., A. de Palma, and J. Thisse (1992), *Discrete choice theory of product differentiation*, Cambridge: MIT Press.

[2] Babaee, S., A. Nagpure, and J. DeCarolis (2014), "How much do electric drive vehicles matter to future U.S. emissions", *Environmental Science and Technology*, forthcoming.

[3] Banzhaf, H., and B. Chupp (2012), "Fiscal federalism and interjurisdictional externalities: New results and an application to US air pollution", *Journal of Public Economics*, 96: 449-464.

[4] Bell, M.L., A. McDermott, S. L. Zeger, J. M. Samet, and F. Domenici. (2004), "Ozone and Short-Term Mortality in 95 US Urban Communities, 1987-2000." *J. of the Amer. Medical Association*, 17: 2372-2378.

[5] Burtraw, D., A. Krupnick, D. Austin, D. Farrel, and E. Mansure (1998), "Costs and benefits of reducing air pollutants related to acid rain," *Contemporary Economic Policy*, 16: 379-400.

[6] De Borger, B. (2001), "Discrete choice models and optimal two-part tariffs in the presence of externalities: optimal taxation of cars," *Regional Science and Urban Economics*, 31: 471-504.

[7] De Borger, B. and I. Mayeres (2007), "Optimal taxation of car ownership, car use and public transport: Insights derived from a discrete choice numerical optimization model," *European Economic Review*, 51: 1177-1204.

[8] Dubin, J. and D. McFadden (1984), "An econometric analysis of residential electric appliance holdings and consumption," *Econometrica*, 52: 345-362.

[9] Fann, N., C. Fulcher, and B. Hubbell (2009), "The Influence of location, source, and emission, type in estimates of the human health benefits of reducing a ton of air pollution," *Air Quality, Atmosphere and Health*, 2: 169-176.

[10] Fowlie, M. and N. Muller (2013), "Market-based emissions regulation when damages vary across sources: What are the gains from differentiation?" EI@Haas WP 237.

[11] Graff Zivin, J., M. Kotchen, and E. Mansur (2014), "Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies", *Journal of Economic Behavior and Organization*, 107(A): 248-268.

[12] Grissom, G. (2013), "Determining the optimal subsidy for plug-in electric vehicles in the United States by county", Honors Thesis in Economics, The University of North Carolina at Chapel Hill.

[13] Henry, D., N. Muller, and R, Mendelsohn (2011), "The social cost of trading: measuring the increased damages from Sulfur Dioxide trading in the United States," *Journal of Policy Analysis and Management*, 30(3): 598-612.

[14] Holland, S., and E. Mansur (2008), "Is real-time pricing green? The environmental impacts of electricity demand variance", *Review of Economics and Statistics*, 90(3): 550-561.

[15] Jacobsen, M., C. Knittel, J. Sallee, and A. van Benthem (2015), "Correcting externalities from durable goods in the presence of herterogeneity", working paper.

[16] Levy, J., L. Baxter, and J. Schwartz (2009),"Uncertainty and Variability in Health Related Damages from Coal-fired Power Plants in the United States, *Risk Analysis*, DOI: 10.1111/j.1539-6924.2009.01227.x

[17] Li, S., L. Tong, J. Xing, and Y. Zhou (2015), "The market for electric vehicles: Indirect network effects and policy impacts", working paper, Cornell University.

[18] Mauzerall, D., B. Sultan, N. Kim, and D. Bradford (2005), "NOx Emissions from Large Point Sources: Variability in Ozone Production, Resulting Health Damages and Economic Costs," *Atmospheric Environment*, 39: 2851-66.

[19] Mendelsohn, R. (1980), "An Economic Analysis of Air Pollution from Coal-Fired Power Plants," *Journal of Environmental Economics and Management*, 7(1): 30-43.

[20] Mendelsohn, R. (1986), "Regulating heterogeneous emissions," *Journal of Environmental Economics and Management*, 13: 301-312.

[21] Michalek, J., M. Chester, P. Jaramillo, C. Samaras, C. Shiau, and L. Lave (2011), "Valuation of plug-in vehicle life-cycle air emissions and oil displacement benefits", *Proceedings of the National Academy of Sciences*, 108: 16554-16558.

[22] Muller, N. (2011), "Linking Policy to Statistical Uncertainty in Air Pollution Damages." *The B.E. Press Journal of Economic Analysis and Policy.* 11(1), Contributions, Article 32.

[23] Muller, N. (2012), "The Design of Optimal Climate Policy with Air Pollution Co-Benefits." *Resource and Energy Economics.* http://dx.doi.org/10.1016/j.reseneeco.2012.07.002

[24] Muller, N. (2014), "Boosting GDP growth by accounting for the environment: Including air pollution and greenhouse gas damages increases estimated U.S. growth." *Science.* August 22nd, Vol. 345 no. 6199 pp. 873-874: DOI:10.1126/science.1253506.

[25] Muller, N. and R. Mendelsohn (2007), "Measuring the Damages of Air Pollution in the United States" *J. of Environmental Economics and Management,* 54: 1-14.

[26] Muller, N. and R. Mendelsohn (2009), "Efficient pollution regulation: getting the prices right," *American Economic Review*, 99: 1714-1739.

[27] Muller, N. and R. Mendelsohn (2012), *Using Marginal Damages in Environmental policy: A Study of Air Pollution in the United States*, The American Enterprise Institute Press. Washington, D.C., USA.

[28] Muller, N., R. Mendelsohn, W. Nordhaus (2011), "Environmental Accounting for Pollution in the United States Economy." *American Economic Review*. 101: 1649-1675.

[29] Muller, N., D. Tong, R. Mendelsohn, (2009) "Regulating NO_x and SO_2 in Atlanta." *The B.E. Journal of Economic Analysis & Policy*: Vol. 9 : Iss. 2 (Contributions), Article 3.

[30] National Academy of Sciences, National Research Council. (NAS NRC) 2010. *Hidden Costs of Energy: unpriced consequences of energy production and use.* National Academy Press, Washington, D.C., USA.

[31] Parry, I. and K. Small (2005), "Does Britain or the United States have the right gasoline tax?" *American Economic Review*, 95: 1276-1289.

[32] Pope, C. A., R. T. Burnett, M. J. Thun, E. E. Calle, D. Krewski, K. Ito, G. D. Thurston. (2002). "Lung Cancer, Cardiopulmonary Mortality, and Long-Term Exposure to Fine Particulate Air Pollution." *J. of the Amer. Medical Association*, 287 (9): 1132-1141.

[33] Roman, H.A. K.D. Walker, T.L. Walsh, L. Conner, H.M. Richmond, B.J. Hubbell, P.L. Kinney. (2008). "Expert Judgment Assessment of the Mortality Impact of Changes in Ambient Fine Particulate Matter in the U.S." *Environmental Science and Technology.* 42:2268 – 2274.

[34] Small, K. and H. Rosen (1981), "Applied welfare economics with discrete choice models," *Econometrica*, 49: 105-130.

[35] Stavins, R. (1996), "Correlated Uncertainty and Policy Instrument Choice," *Journal of Environmental Economics and Managemetn*, 30: 218-232.

[36] Tessum, C., J. Hill, and J. Marshall (2014), "Life cycle air quality impacts of conventional and alternative light duty transportation in the United States," *Proceedings of the National Academy of Sciences*, 111: 18490-18495.

[37] Tong, D., N. Muller, D. Mauzerall, and R. Mendelsohn (2006), "Integrated Assessment of the Spatial Variability of Ozone Impacts from Emissions of Nitrogen Oxides," *Environmental Science and Technology*, 40(5): 1395-1400.

[38] USEPA (2014) National Emissions Inventory (NEI), 2011. Washington, DC: Office of Air Quality Planning and Standards, Emissions Inventory Group; Emissions, Monitoring, and Analysis Division.

[39] Weitzman, M. (1974), "Prices vs. Quantities," *Review of Economic Studies*m 41: 477-491.

[40] Yuksel, T. and J. Michalek (2015), "Effects of regional temperature on electric vehicle efficiency, range, and emissions in the United States", forthcoming, *Environmental Science and Technology.*

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

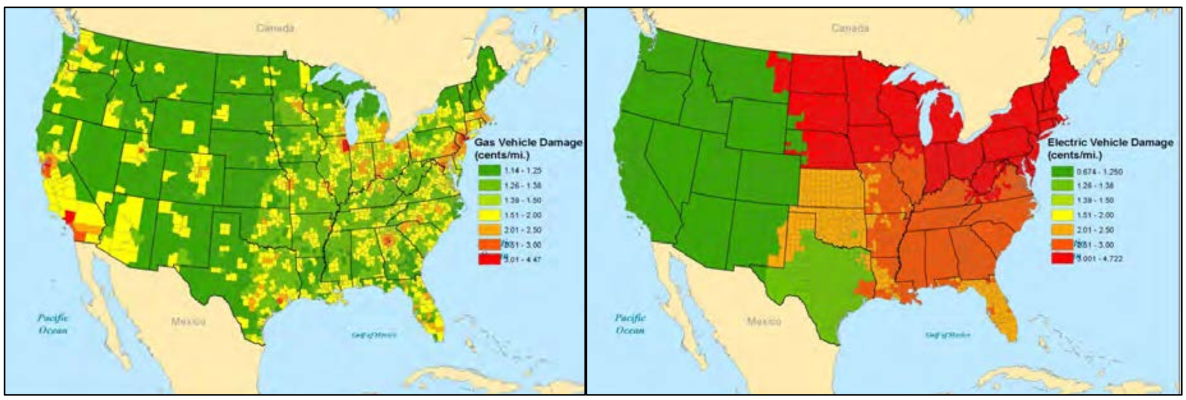


Figure 2: Second-Best Electric Vehicle Subsidy by County

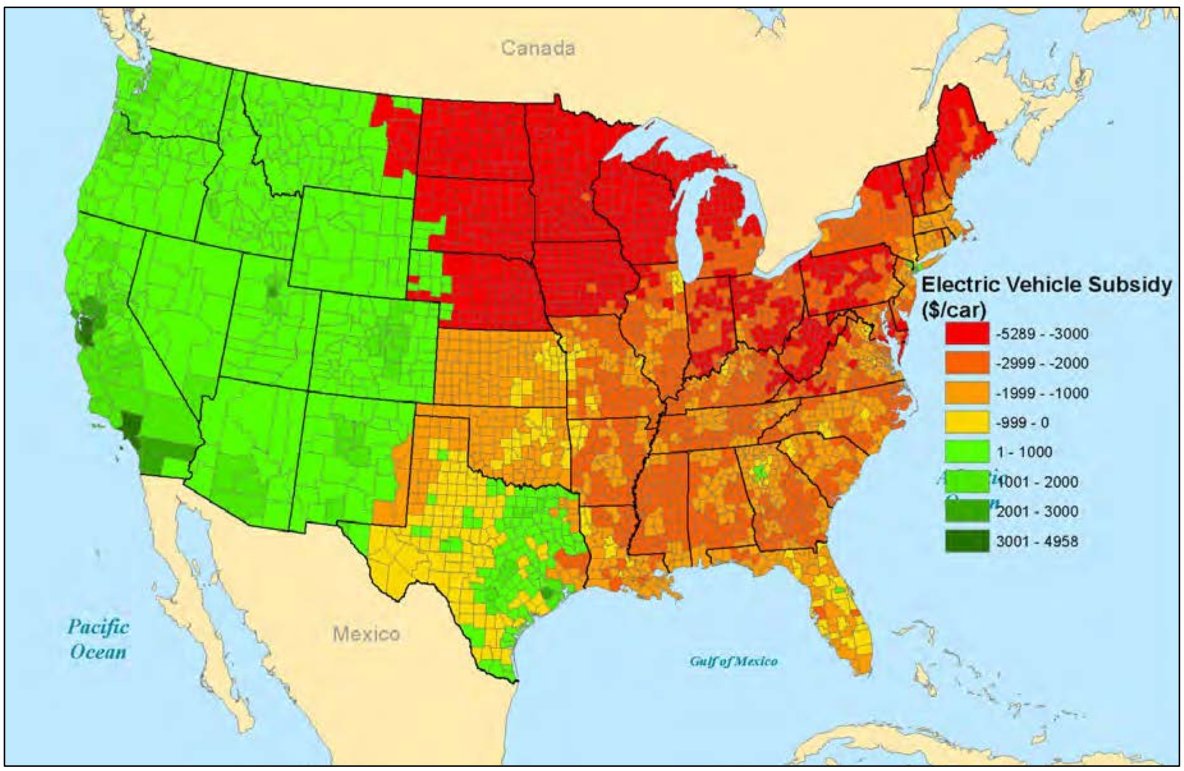


Figure 3: Second-Best Electric Vehicle Subsidy by State (Full and Native Damages)

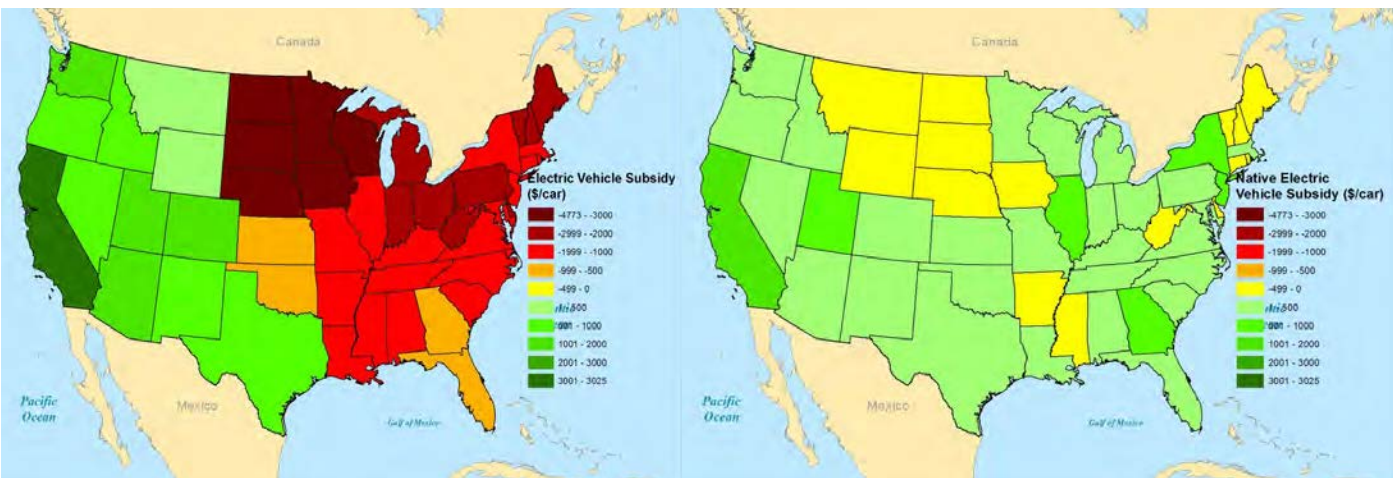


Figure 4 Panel A: Change in $PM_{2.5}$ Preliminary Fulton County:
1000 ICE Focus

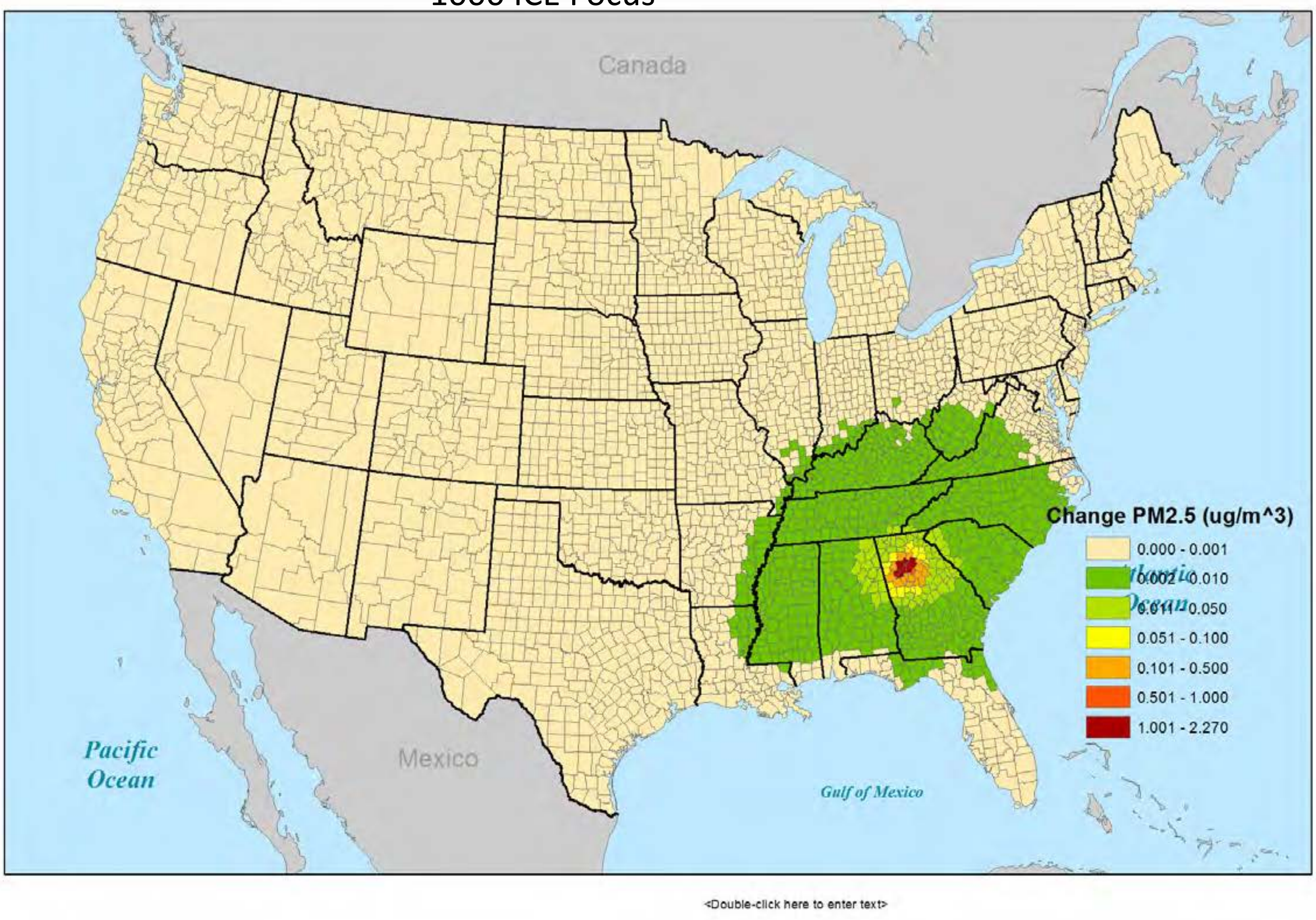
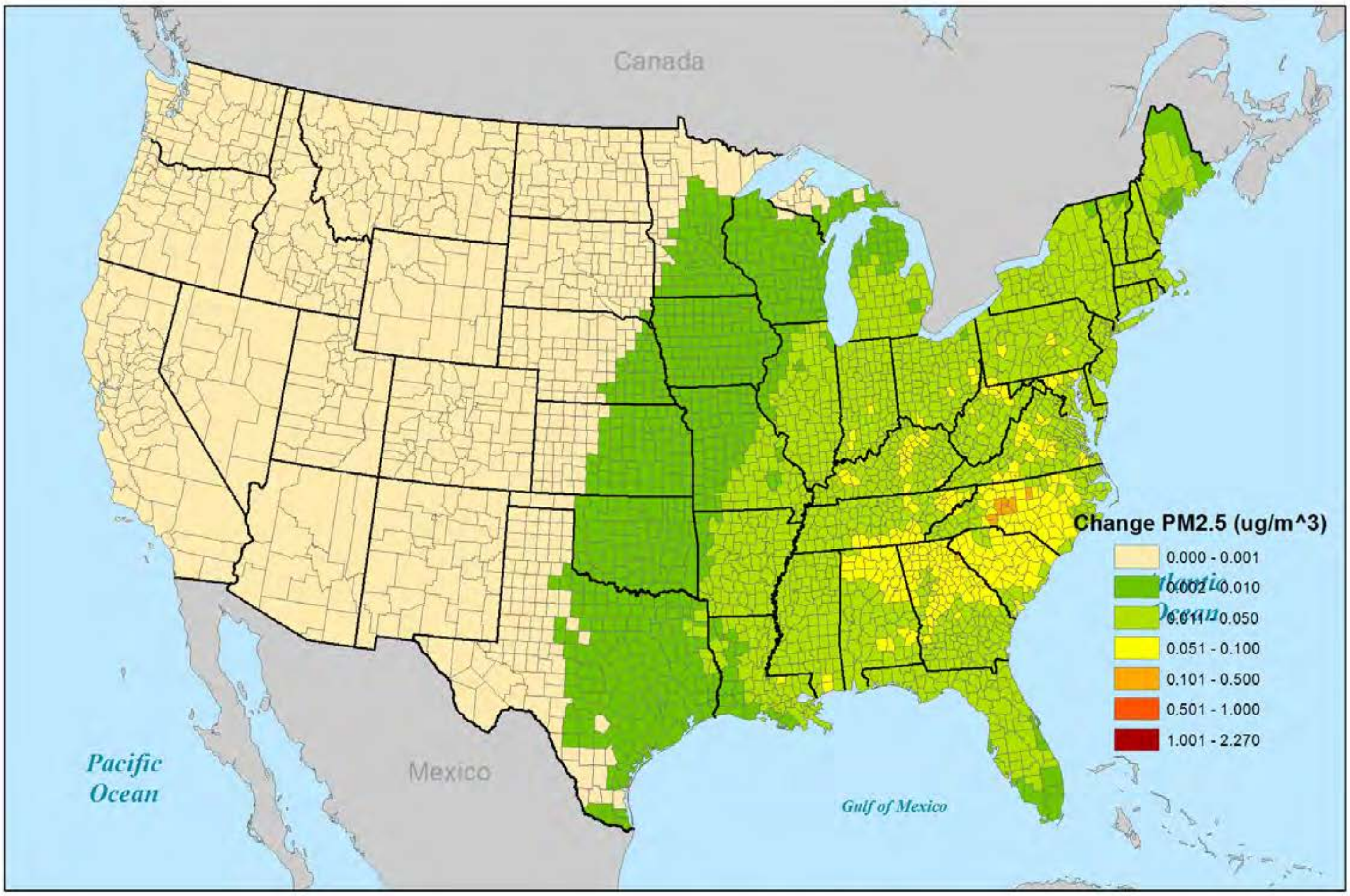


Figure 4 Panel B: Change in $PM_{2.5}$: 1000 EV Focus in SERC Region



<Double-click here to enter text>

Table 1: Mean damages in cents per mile by NERC electricity 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	12%
WECC w/o CA	1.03	0.92	1.18	0.98	0.84	0.76	0.73	0.99	10%
ERCOT	1.28	1.21	1.50	1.41	1.10	1.07	1.05	1.16	8%
FRCC	2.48	2.14	3.21	2.36	2.25	1.39	1.53	2.11	7%
SERC	2.75	2.68	2.76	2.26	2.73	2.97	2.64	2.72	24%
SPP	2.24	2.74	2.07	4.91	2.30	2.89	2.39	1.89	4%
NPCC	3.11	2.75	4.19	3.75	1.61	2.12	2.49	2.35	9%
RFC	3.65	3.56	3.44	3.39	3.85	3.07	3.44	4.17	22%
MRO	4.39	3.61	5.77	4.01	3.11	2.63	2.37	3.78	5%
Total	2.50	2.38	2.69	2.49	2.30	2.18	2.18	2.44	100%

Notes: The regions are listed by the damage per mile under the "Flat" charging profile. The "EPRI" charging profile is illustrated in Appendix Figure 1. The flat charging profile assumes charging is equally likely across hours. Other profiles assume charging occurs only in the indicated hours. Damages (in cents per mile) are weighted across counties by passenger vehicle VMT. "WECC w/o CA" is the Western US excluding California; "ERCOT" is Texas; "FRCC" is Florida; "SERC" is the Southeast; "SPP" is Kansas and Oklahoma; "NPCC" is the Northeast; "RFC" is the Mid-Atlantic and Midwest; and "MRO" is the upper Midwest including all of MISO. See http://www.nerc.com for a map of the regions.

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

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

Notes: Damages are from power plant emissions or tailpipe emissions of NOx, VOCs, PM2.5, SO2, and CO2e. Electric vehicles assume the EPRI charging profile. Equivalent vehicles are defined as the identical make where possible. The equivalent 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 benefit in cents per mile by Metropolitan Statistical Areas for a 2014 Ford Focus (electric v. gasoline)

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

Notes: The environmental benefit is the difference in damages between the gasoline-powered Ford Focus and the electric Ford Focus. Environmental benefit is weighted by 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 benefit in cents per mile by state for a 2014 Ford Focus (electric v. gasoline)

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

Notes: The environmental benefit is the difference in damages between the gasoline-powered Ford Focus and the electric Ford Focus. Environmental benefit is weighted by gasoline-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	2.50	2.74	1.11	0.67	4.72
	Non-GHG	1.62	1.86	0.95	0.16	3.50
	State	0.15	0.16	0.07	0.04	0.33
	Export %	91%	91%			91%
	County	0.02	0.02	0.01	0.00	0.06
	Export %	99%	99%			98%
Gasoline	All	2.00	1.91	0.60	1.13	4.47
	Non-GHG	0.54	0.37	0.53	0.01	2.92
	State	0.44	0.27	0.51	0.00	2.76
	Export %	18%	27%			5%
	County	0.23	0.11	0.38	0.00	2.03
	Export %	57%	71%			30%
Environmental Benefit	All	-0.49	-0.81	1.34	-3.53	3.31
	Non-GHG	-1.08	-1.44	1.14	-3.43	2.28
	State	0.29	0.12	0.51	-0.32	2.46
	County	0.21	0.09	0.37	-0.06	2.00

Note: Damages in cents per mile. "All" reports damages from all pollutants at all receptors. "Non-GHG" reports damages from local pollutants (i.e., excluding CO_2) at all receptors. "State" reports damages from local pollutants from receptors within the same state as the source. "County" reports damages from local pollutants from receptors within the same county as the source. "State Export %" reports the share of non-GHG damages which occur at receptors outside the state. "County Export %" reports the share of non-GHG damages which occur at receptors outside the county. Electric damages assume the EPRI charging profile. Damages are weighted by 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%	5%	10%	1%	5%	10%	1%	5%	10%
County policies	0	0	0	192	863	1543	1958	1994	2042
State policies	90	102	118	281	962	1688	1960	2005	2064
Federal policy	163	273	415	336	1004	1830	1983	2121	2303
County (Native)	1158	1445	1808						
State (Native)	1234	1531	1906						
Federal (Native)	911	1034	1194						

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

	BAU EV Share		
	1%	5%	10%
County policies	1996	2182	2411
State policies	2000	2205	2458
Federal policy (-$742 subsidy)	2024	2324	2703
County policies (native damages)	2022	2315	2686
State policies (native damages)	2026	2333	2723
Federal policy (native damages, -$1553 subsidy)	2028	2344	2744
Current Federal Policy ($7500 subsidy)	2765	6009	10015
BAU Federal Policy (Zero subsidy)	2027	2343	2742

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 (10735.3, 16753.7, 22451.1) which is proportional to the standard deviation of the unobserved relative preference shock. In Table 6a, federal taxes in the joint tax case are 2.0 cents per mile on gasoline miles and 2.5 cents per mile on electric miles.

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

	Electric Vehicle			Gasoline Vehicle			Environmental Benefit		
	mean	min	max	mean	min	max	mean	min	max
Baseline	2.50	0.67	4.72	2.00	1.13	4.47	-0.49	-3.53	3.31
Carbon cost									
SCC=$51	2.71	0.80	5.02	2.36	1.41	4.84	-0.35	-3.55	3.56
SCC=$31	2.28	0.55	4.42	1.65	0.86	4.09	-0.64	-3.50	3.06
No temperature adjustment	2.35	0.67	3.90	2.00	1.13	4.47	-0.35	-2.74	3.32
Flat charging profile	2.38	0.74	3.88	2.00	1.13	4.47	-0.38	-2.69	3.24
Average MPG	2.50	0.67	4.72	1.87	1.36	4.23	-0.63	-3.30	3.02
Double gasoline emissions rates	2.50	0.67	4.72	2.54	1.15	7.38	0.04	-3.48	5.75
$2 Million VSL	1.57	0.71	2.64	1.68	1.13	2.69	0.12	-1.49	1.78
PM dose response	3.59	1.25	6.89	2.31	1.14	6.10	-1.28	-5.65	4.05
Future grid & vehicle	0.66	0.37	1.39	1.31	0.81	3.60	0.64	-0.50	2.81

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. Damages are in cents per mile and are weighted across counties by VMT.

Notes: "Carbon cost" uses a social cost of carbon of $51 or $31. "No temperature adjustment" assumes electric vehicles have no range degradation at low temperatures. "Flat charging profile" assumes electric vehicle charging occurs equally in all hours instead of following the estimated EPRI charging profile. "Average MPG" uses the average MPG for gasoline vehicles instead of using the city MPG in urban counties and the highway MPG in non-urban counties. "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 the higher PM2.5 adult-mortality dose-response from Roman etal 2008 instead of the baseline dose response. "Future grid & vehicle" assumes all coal-fired power plants are replaced by clean natural gas plants which are dispatched identically and the gasoline vehicle is a Toyota Prius.