Online Appendices for "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors."

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

Proof of propositions

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

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

which simplifies to

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

From the definition of π we have

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

which simplifies to

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

Using this result we can derive the following

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

and

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

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

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

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

Expected tax revenue is $R = -s(1-\pi)$. So we have $\frac{\partial R}{\partial s} = -(1-\pi) + s\frac{\partial \pi}{\partial s}$. Substituting this into the first-order condition and simplifying gives

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

So the optimal s is given by

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

From (A-3) and (A-4), we have

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

and

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

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

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

■

Proof of Proposition 2.

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

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

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 $\tilde{s}$

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

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

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

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

Now take the second derivative. We have

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

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

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

and

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

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

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

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

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

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

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

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

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

Choice over several gasoline and electric vehicles

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

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

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

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

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

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

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

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

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

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

The probability of selecting the electric vehicle j is

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

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

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

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

Differentiated subsidies on purchase of electric vehicle

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

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

From the Envelope Theorem, we have

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

and, for $j \neq k$,

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

For $j = k$ we have

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

Substituting these expressions into the first-order condition gives

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

Now

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

Substituting this into the first-order condition gives

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

Because there are no income effects,

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

and

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

Substituting these derivatives into the first-order condition gives

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

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

Uniform subsidy on the purchase of an electric vehicle

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

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

Solving for s gives

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

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

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

Using this gives

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

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

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

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

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

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

From the definition of π_i it follows that

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

Substituting into the expression for s gives

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

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

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

It follows that

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

We can use (A-12) to describe the likely effect of including an additional gasoline vehicle in the consumers choice set on the welfare gains from differentiated regulation. Consider a baseline two-vehicle case in which the electric vehicle pollutes more than gasoline cars, so that the optimal uniform policy is a tax on electric vehicle purchase. Starting at this baseline, we consider an expanded choice set with an additional gasoline vehicle. Suppose initially that the original gasoline vehicle and the additional gasoline vehicle are exactly the same (they have the same purchase price, price for miles, and external costs). Then, of course, adding the additional gasoline vehicle to the choice set will not have any welfare consequences. Now suppose that in each region, the external costs from the additional gasoline vehicle are D units less than the external costs from the original gasoline vehicle. Thus the additional vehicle lowers the mean of the distribution of environmental benefits, but does not change the variance or skewness. We now make two observations. First, because the purchase price and price for miles are still the same we have $\pi_1 = \pi_2$. Second, the additional vehicle leads to lower average environmental damages from gasoline vehicles in each region. Combining these two observations with (A-12) implies that the tax on electric vehicle purchases increases in each region. Because the gasoline vehicles are the same from the point of view of the consumer, Proposition 2 still applies. Thus the additional gasoline vehicle lowers the welfare gain from differentiation.[1] This result is reversed if the additional vehicle raises the mean of the distribution of environmental benefits.

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

Here there are taxes on both gasoline and electric miles. We know that location specific Pigovian taxes are first-best, but it is useful to derive this result in our model before turning

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

to other welfare results. For the moment we can drop the location subscript i.

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

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

and

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

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

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

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

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

Using this in the first-order condition gives

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

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

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

Similar calculations with respect to t_e gives

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

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

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

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

We have

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

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

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

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

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

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

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

and

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

At $\tilde{T}$, taxes equal in each location, so the gasoline miles and electric miles will be the same each each location. Thus we can drop the subscripts from g, e, G, E and π. From (A-3) we have

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

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

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

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

This gives

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

and

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

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

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

Using the expressions above gives

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

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

Which can be written as

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

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

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

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

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

which can be written as

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

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

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

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

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

C Continuous Choice Model

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

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

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

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

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

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

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

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

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

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

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

Uniform vs. differentiated regulation

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

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

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

Optimizing the welfare function gives the the following Proposition.

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

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

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

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

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

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

So welfare is

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

The first-order condition is

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

We have

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

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

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

Solving for s_i gives (A-14).

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

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

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

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

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

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

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

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

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

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

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

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

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

Solving for s gives

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

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

Next we want to determine a second-order Taylor series approximation to $\mathcal{W}(S)$ at the point $\tilde{S} = (\tilde{s}, \tilde{s}, \ldots, \tilde{s})$. First we take the derivatives at an arbitrary point. Because $\frac{\partial \mathcal{W}}{\partial s_i}$ does not depend on s_j, the cross-partial derivative terms will all be equal to zero. We have

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

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

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

Now take the second derivative. We have

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

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

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

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

and

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

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

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

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

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

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

It follows that

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

□

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

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

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

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

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

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

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

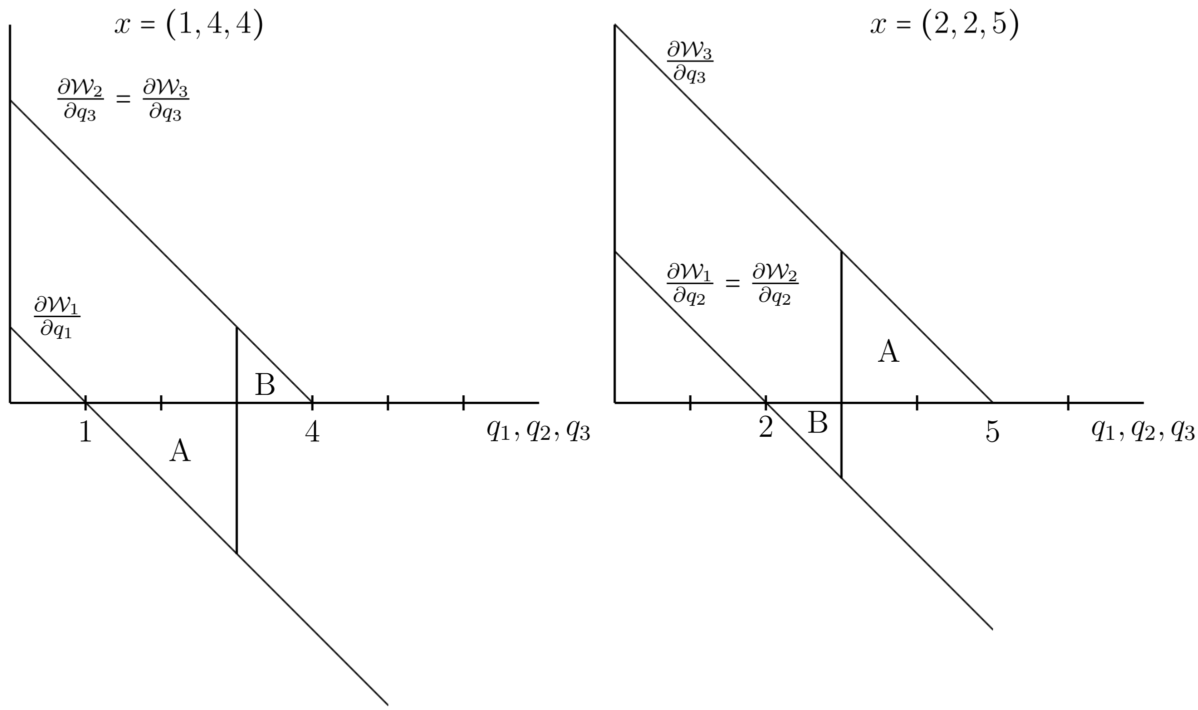
$$\frac{\partial \mathcal{W}_i}{\partial q_i} = a + x_i - bq_i. \tag{A-20}$$

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

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

A graphical illustration of these ideas for a three region example is given in Figure A. Here we use Mendelsohn's notation with units normalized such that the optimal differentiated policy variable is equal to the environmental variable (thus, for example, in (A-20), $a = b = 1$). Assume for the moment that marginal welfare is a linear function of the policy variable q_i. We have superimposed all the marginal welfare functions for all three regions on the same coordinate axis. In the first case, shown on the left-hand-side, the environmental variable x takes on the values (1,4,4) in the three regions. Notice that regions two and three have the same marginal welfare. Under differentiated regulation, the optimal values are $(q_1^*, q_2^*, q_3^*) = (1, 4, 4)$. Under uniform regulation, the optimal value for $\tilde{q}$ is three, which

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



is simply the average of the x_i's. The welfare loss from uniform regulation is equal to the area A plus two times the area B. In the second case, shown on the right-hand-side, the environmental variable takes on the values (2,2,5) and region one and two now have the same marginal welfare. Notice that the two cases have the same mean and variance for the distribution of x, but the third moment is different. The welfare loss from uniform regulation in the second case is equal to the area A plus two times the area B. Because these triangles have the same area in both cases, the welfare loss from uniform regulation is the same in both cases. Thus the third moment does not effect the welfare loss, provided that marginal welfare is linear in the policy variable. If we relax this assumption, however, then the welfare loss will no longer be the same across the two cases, and hence will depend on the third moment.

As a final point, our welfare approximation was defined relative to the reference point of uniform regulation. Suppose instead we define the reference point to be the second-best differentiated regulation. In this case we are measuring the welfare loss of using uniform regulation rather than differentiated regulation.[2] Modifying (A-8) to evaluate the derivative at S^* rather than $\tilde{S}$ gives

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

As we would expect, the first derivative of the welfare function is equal to zero at the second-best differentiated regulation. Similar modifications of (A-9) gives

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

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

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

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

E Substitute gasoline vehicles and their emissions

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

To test to see if our choices were reasonable, we obtained data from the market research company MaritzCX. They conduct a new vehicle customer survey in which participants are asked: "When shopping for your new vehicle, did you consider any OTHER cars or trucks?"

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

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

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

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

(emphasis in original). If the participants responded yes, then they were asked to state the "model most seriously considered". We obtained data on responses from participants who purchased one of the electric vehicles listed in Table 2 during the years 2013-2015.

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

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

Most of the results in the main paper are based on the comparison of the Ford Focus EV with the gasoline Ford Focus. Changing the substitute gasoline vehicle to one of the other gasoline vehicles identified in Table B would affect these results. For example, the Toyota Prius is substantially cleaner than the gasoline Ford Focus. Using the Toyota Prius as the substitute gasoline vehicle would shift the distribution of environmental benefits of the Ford Focus EV downward. Using the numbers in Table 2a, mean environmental benefits would decrease from -0.73 to -1.36 cents per mile. Conversely, using the Audi A3 or Volkswagen Golf (dirtier cars than the gasoline Ford Focus) would shift the distribution of environmental benefits of the Ford Focus EV upward. Thus our choice of the gasoline Ford Focus as the substitute vehicle can be viewed as a moderate one given the alternatives.

As an additional robustness check, we created "composite" substitute gasoline vehicles by taking the weighted average of emissions of the top 10 gasoline substitute vehicles for each electric vehicle, where the weights correspond to the response frequencies. Table E compares the environmental benefits with respect to our original substitute vehicle and the environmental benefits with respect to the composite substitute vehicle.[3] In about half of the cases the composite substitute vehicle is cleaner than the original substitute vehicle and in about half the cases it is dirtier.

F EPRI charging profile

The EPRI charging profile is given in Figure B.

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

Table B: Ford Focus EV: Model most seriously considered

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

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

Table C: Nissan Leaf EV: Model most seriously considered

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

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

Table D: Tesla S EV: Model most seriously considered

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

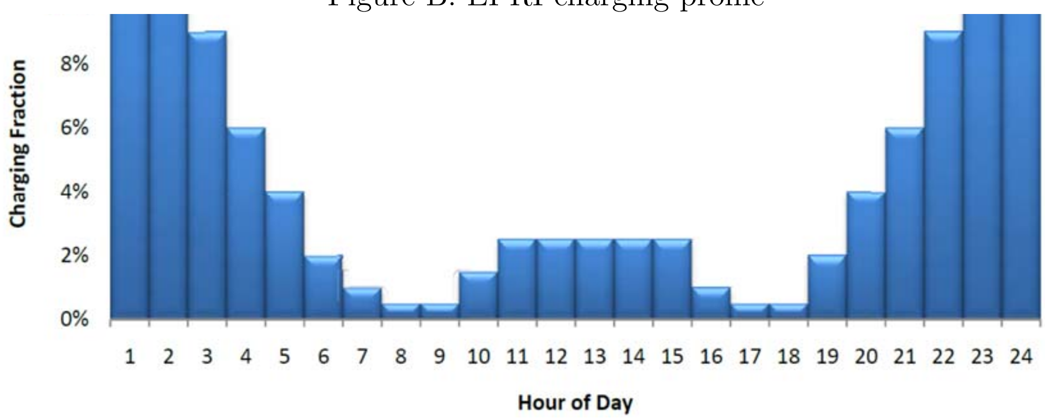
Notes: The survey has 92,437 responses from Tesla S EV purchasers. * indicates plug-in vehicles.

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

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

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

Figure B: EPRI charging profile



Source: Electric Power Research Institute (2007).

G The effect of temperature on electric vehicle energy use

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

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

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

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

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

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

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

There is clear evidence in these studies that significant range loss in electric vehicles occurs both at low and high temperatures.[4] We use a Gaussian function to describe this range loss

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

where R_{68} is the range at the baseline temperature of 68°F and y is a parameter to be fitted from the range loss data. The transport Canada study indicates a 20 percent range loss at 19.4°F with the heat off and a 45 percent range loss at 19.4°F with the heat on. We took the average of these figures and assumed a 33 percent range loss. This gives[5]

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

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

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

Temperature data was obtained from the CDC website.[6] This gave us the average monthly temperature in each county for the years 1979-2011. In a given month j with temperature T_j, the energy usage per mile in that month is given by

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

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

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

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

H Procedure for assigning counties to electricity regions

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

Given this set of NERC regions, we assign each county to specific region using the following procedure. The EPA power profiler (http://www.epa.gov/energy/power-profiler, year 2010 data) provides a mapping from zip code to eGrid subregion. More specifically,

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

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

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

The overall result is shown in Figure C

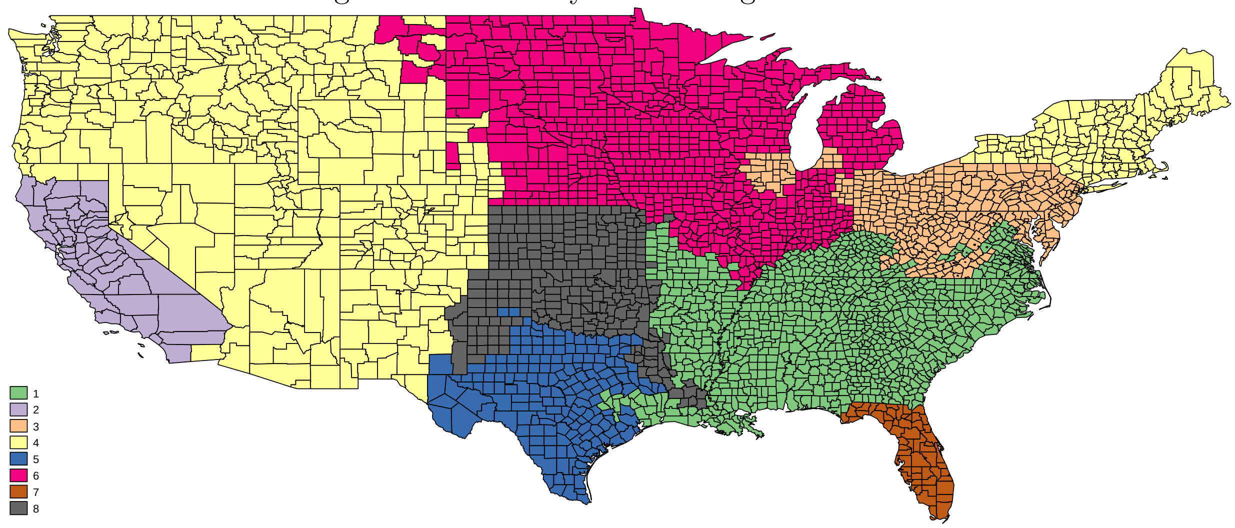
I Methods details

Data sources for emissions of gasoline vehicles

The emissions of SO_2 and CO_2 follow directly from the sulfur or carbon content of the fuels. Since emissions per gallon of gasoline does not vary across vehicles, emissions per mile can be simply calculated by the efficiency of the vehicle.[7] For emissions of NO_X, VOCs and $PM_{2.5}$, we use the Tier 2 standards for NO_X, VOCs (NMOG) and PM. We augment the VOC emissions standard with GREET's estimate of evaporative emissions of VOCs and augment the PM emissions standard with GREET's estimate of $PM_{2.5}$ emissions from tires

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

Figure C: Electricity demand regions



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

and brake wear. Electric vehicles are likely to emit far less $PM_{2.5}$ from brake wear because they employ regenerative braking. We had no way of separating emissions into tires and brake wear separately, so we elected to ignore both of these emissions from electric vehicles. This gives a small downward bias to emissions of electric vehicles.

Data sources for the electricity demand regressions

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

of VOC emissions, but 75% of SO_2 emissions and 20% of NO_X emissions. In contrast, the transportation sector accounted for about 40% of VOC emissions.

The hourly electricity load data are from the Federal Energy Regulatory Commission's (FERC) Form 714. Weekends are excluded to focus on commuting days. See Graff Zivin et al (2014) for more details on the CEMS and FERC data.

Details of the AP2 model

AP2 is a standard integrated assessment model in that it links emissions to damages.[8]

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

The inputs to the air quality module are the emissions of ammonia (NH_3), fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), nitrogen oxides (NO_X), and volatile organic compounds (VOC)—from all of the sources in the contiguous U.S. that report emissions to the USEPA.[9] The outputs from the air quality module are predicted ambient concentrations of the three pollutants—SO_2, O_3, and $PM_{2.5}$— at each of the 3,110 counties in the contiguous U.S. The relationship between inputs and outputs captures the complex chemical and physical processes that operate on the pollutants in the atmosphere. For example, emissions of ammonia interact with emissions of NO_X, and SO_2 to form concentrations of ammonium nitrate and ammonium sulfate, which are two significant (in terms of mass) constituents of

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

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

$PM_{2.5}$. And emissions of NO_X and VOCs are linked to the formation of ground-level ozone, O_3. The predicted ambient concentrations from the air quality module give good agreement with the actual monitor readings at receptor locations (Muller 2011).

The inputs to the economic valuation module are the ambient concentrations of SO_2, O_3, and $PM_{2.5}$ and the outputs are the monetary damages associated with the physical effects of exposure to these concentrations. The majority of the damages are associated with human health effects due to O_3 and $PM_{2.5}$, but AP2 also considers crop and timber losses due to O_3, degradation of buildings and material due to SO_2, and reduced visibility and recreation due to $PM_{2.5}$. For human health, ambient concentrations are mapped into increased mortality risk and then increased mortality risks are mapped into monetary damages.[10] AP2 uses the value of a statistical life (or VSL) approach to monetize an increase in mortality risk (see Viscusi and Aldy 2003). In this paper we use the USEPA's value of approximately \$600 per 0.0001 change in annual mortality risk.[11] This value of an incremental change in mortality risk yields a VSL of $\$6 \text{ x } 10^6 = \$600/0.0001$.

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

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

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

case and the add-one-ton case is the marginal damage of emitting NO_X from the power plant in Western Pennsylvania.[12] This routine is repeated for all pollutants and all sources in the model, first for full damages, and then second for native damages (which only looks at receptors in the state or county of interest).

To assess the statistical uncertainty associated with the marginal damages produced by AP2 for both gas and electric vehicles, we use results from Muller (2011) that executes a Monte Carlo simulation for each marginal damage for the data year 2005 (by source and pollutant). We use these simulation results in the following way. First, we compute the coefficient of variation for each pollutant-source marginal damage (standard deviation/arithmetic mean). We then multiply these coefficients times the matching 2011 marginal damages. This yields an estimate of the standard deviation for each source-pollutant marginal damage. We then estimate confidence intervals in order to estimate the 5th and 95th percentiles for the damages from gas and electric vehicles. These are used to calculate the environmental benefits reported in Table 7.

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

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

J State electric vehicle incentives

The Department of Energy maintains a database of alternative fuels policies by state.[13] Using this information, we determined four measures of state electric vehicle policy. (These data reflect policies in place on July 28, 2014.) The first measure is the actual subsidies for the purchase of an electric vehicle. The second measure is equal to the total number of electric vehicle policies (including both incentives and regulations). The third measure is equal to the number of policies that were classified by the Department of Energy as incentives. The fourth measure is equal to the number of incentives that were deemed by us to be significant (thus excluding, for example, an incentive that would only apply to the first 100 consumers to install electric vehicle charging equipment).

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

K Calibration and welfare sensitivity

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

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

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

and for electric miles we have

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

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

Table F: State electric vehicle policies

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

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

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

As in the main text, we compared the Ford Focus with the Ford Focus Electric. The exogenous parameters are shown in Table G.[14] This leaves us with the task of specifying the endogenous parameters k_g, k_e, H and μ. To pin down values of k_g and k_e, we follow Michalek et al (2011) and assume that both gasoline vehicles and electric vehicles would be driven 150,000 lifetime miles at business as usual. Using the functions $f(g)$ and $h(e)$ in the consumer's optimization problems, and then solving these problems at business as usual, gives the demand for miles

$$g = \left(\frac{k_g}{p_g}\right)^{\frac{1}{\gamma}} \tag{A-24}$$

and

$$e = \left(\frac{k_e}{p_e}\right)^{\frac{1}{\gamma}}. \tag{A-25}$$

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

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

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

equations

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

and

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

Because all of the other parameters have been specified, the two left-hand-sides of these equations are a function of H and μ only. Using the definition of π, we can write these equations as

$$V_e\big|_{s=0} - V_g\big|_{s=0} = \mu \ln\left(\frac{1-0.99}{0.99}\right)$$

and

$$V_e\big|_{s=7500} - V_g\big|_{s=7500} = \mu \ln\left(\frac{1-0.98}{0.98}\right).$$

From the definition of V_g and V_e we have

$$H - A = \mu \ln\left(\frac{1-0.99}{0.99}\right)$$

and

$$H - A + 7500 = \mu \ln\left(\frac{1-0.98}{0.98}\right),$$

where

$$A = \left(k_g \frac{g^{1-\gamma}-1}{1-\gamma} - p_g g - p_G\right) - \left(k_e \frac{e^{1-\gamma}-1}{1-\gamma} - p_e e - p_\Omega\right)$$

and g and e are the demand functions described in (A-24) and (A-25). We interpret $\left(k_g \frac{g^{1-\gamma}-1}{1-\gamma} - p_g g - p_G\right)$ as the "surplus" of driving a gasoline vehicle (the indirect utility from miles minus the purchase cost and cost of miles). Thus A is the difference in the surplus of driving an electric vehicle and a gasoline vehicle. Eliminating H from these equations gives the solution for μ:

$$\mu = \frac{7500}{\ln\left(\frac{1-0.98}{0.98}\right) - \ln\left(\frac{1-0.99}{0.99}\right)}.$$

It follows that the solution for H is

$$H = A + \frac{7500 \ln\left(\frac{1-0.99}{0.99}\right)}{\ln\left(\frac{1-0.98}{0.98}\right) - \ln\left(\frac{1-0.99}{0.99}\right)}.$$

We see that the non-stochastic taste for electric vehicles H is smaller than the difference in the surplus between the two vehicles. The exact degree to which it is smaller depends on the assumed probabilities and subsidy used for calibration. Evaluating these expressions for H and μ gives the values in the first row of Table H. The other rows correspond to different assumptions about $\hat{\pi}$.

The large values for H are due to the fact that we are integrating under the entire constant elasticity demand curve to get indirect utility. In practice, there is likely a choke price such that above this price, demand goes to zero. Implementing demand curves with such a choke price would significantly lower the surplus of driving both vehicles, significantly lower the the value for A, and significantly lower the values for H. But, as long as the choke price was well above the range of prices we consider, including it would not have any effect on our welfare calculations because they are all defined as differences from the first best outcome.

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

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

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

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

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

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

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

We conducted a final sensitivity analysis with respect to the price of gasoline and electric miles. Up to now, we have assumed (in both the theoretical model and the empirical calculations) that these prices are the same across locations. In this final sensitivity analysis, we drop this assumption and employ state-specific prices for electric miles and region-specific prices for gasoline miles (using data from EIA.gov). In this analysis, the second best uniform federal subsidy is no longer given by the expression in Proposition 2, and in fact does not have a closed form expression. Likewise for the second best uniform federal taxes. So we determine the these quantities numerically. The benefits of differentiated subsidies, state vs. federal, is \$24.3 million (compared to a baseline of \$24.3 million) and the benefits of differentiated taxes is \$68.5 million (compared to a baseline of \$72.9 million).

L Single tax policies

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

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

Table I: Sensitivity of Exogenous Calibration Parameters

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

Note: $ Million/year

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

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

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

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

Proof of Proposition 5.

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

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

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

$$R = t_g \pi g,$$

and hence

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

Using this in the first-order condition gives

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

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

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

Solving for t_g gives

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

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

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

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

and

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

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

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

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

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

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

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

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

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

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

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

■

M Large scale electric vehicle adoption

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

A simple way of approaching the first question is to compare the load due to electric vehicle adoption with the total electricity consumption in the country. The entire light duty vehicle fleet is approximately 250 million vehicles. Suppose 5 percent of this fleet consisted of electric vehicles. This is the steady state version of the 5 percent adoption rate discussed in the main paper. The charging need for these vehicles corresponds to 60 TWh per year, which is approximately 1.6% of total U.S. electricity consumption per year.[15] Another approach is based on the hourly load from electric cars relative to the random component of hourly electricity load (after controlling for fixed effects by hour-of-day times month-of-sample). If the electric vehicles were charged uniformly across the day, the electricity demand would be 6.8 GW (GWh per hour). The standard deviation of the random component of electricity load in the country is 30.8 GW. So electric cars, at 5 percent of the entire fleet, would add a load shock equal to approximately 22 percent of the standard deviation of load variation.

For the second question, we broke our load sample into two sub-samples, corresponding to high and low load conditions. Note that our main regression includes fixed effects by hour-of-day times month-of-sample. For each of these groups, there are about 30 observations. We split each group based on the median to define "low demand" and"high demand" hours. Using the aggregated data (all emissions within an interconnection), we regressed emissions on load and fixed effects for just the high demand hours and then for just the low demand hours. We then took the coefficients from these regressions as data and pooled them to include all NERC regions and all hours for high/low demand levels (9*24*2=432 obsevations). We regressed them on an indicator of whether they came from the high demand sample. Periods with high demands have greater marginal emissions than periods with low demands,

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

but the effect varies by pollutant. For SO_2 the increase is 68 percent, for CO_2 the increase is 12 percent, for NO_X the increase is 46 percent, and for generation (which we use for $PM_{2.5}$) it is 80 percent. Although some of these percentages are large, none of the effects are statistically significant when clustering by NERC region.

Our final analysis considers the implications of a large scale adoption of electric vehicles on the future of the electricity grid. A full model would need to account for entry and exit of power plants and transmission capacity, which is beyond the scope of this paper. However, we can discuss how our approach could be modified to examine discrete changes in load levels. Suppose the investment in new power plants to build grid capacity mimics the existing grid. Under this assumption, we can use the average emission rates as an approximation for emission rates that result under grid expansion to service electric vehicles. On average, the average emission rates are comparable to the marginal emission rates we used in the main paper. But there is variation across interconnections and pollutants. See Table J. For example, in Texas (ERCOT), average SO_2 emission rates are 187% larger than marginal rates, but average NO_X rates are only 5% larger than marginal rates. In the Eastern interconnection (EAST), both average SO_2 and NO_X emissions rates about 18% smaller than marginal rates.

Table J: Average emission rates relative to marginal

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

N CAFE standards

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

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

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

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

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

$$\frac{\frac{n_a+1}{f_a} + \frac{n_b-1}{f_b} + \frac{n_g-1}{f_g} + \frac{1}{f_e}}{n_a + n_b + n_g} \leq \frac{1}{k}. \tag{A-26}$$

Using the initial condition this becomes

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

and so the condition becomes

$$\frac{1}{f_a} - \frac{1}{f_b} \leq \frac{1}{f_g} - \frac{1}{f_e}. \tag{A-27}$$

The right-hand-side of (A-27) specifies the maximum feasible increase in gallons per mile that may occur from the swap of a for b due to the sale of an electric vehicle. If the CAFE constraint binds after this swap (which we would generally expect to be the case), then this maximum will be obtained. And of course this increase in gallons per mile has an associated cost to society due to damages from emissions.

We see that CAFE regulation induces an additional environmental cost from electric vehicles due to the substitution of a low MPG vehicle for a high MPG vehicle . We can sketch a back-of-the-envelope calculation for the magnitude of this CAFE induced environmental cost and its effect on the second-best subsidy on electric vehicles as follows. Assume that vehicle a and vehicle b are in the same Tier 2 "bin". For vehicles in the same bin, the vast majority of environmental damages are due to emissions of CO_2. In addition, without a explicit model of the new vehicle market, we don't know in which location the vehicle a will be driven. So we calculate the CAFE induced environmental cost due to CO_2 emissions only. Let δ_a and δ_b be the damage (in \$ per mile) due to CO_2 emissions from vehicle a and b, respectively.[16] It follows that the additional environmental cost is given by $(\delta_a - \delta_b)g$.

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

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

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

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

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

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

We see that the optimal subsidy is decreased by the amount equal to the CAFE induced environmental cost $(\delta_a - \delta_b)g$. Using our Ford Focus baseline numbers, the CAFE induced environmental cost turns out to be \$1555.[17]

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

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

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

[17] There are two complications in this calculation. First, for a given vehicle, the MPG for CAFE purposes is not equal to the EPA posted MPG number. On average, the EPA number is eighty percent of the CAFE number. Second, for electric cars, the CAFE MPG is calculated as 82049 watt hours per gallon divided by the EPA determined electricity consumption in watt hours per mile. So the CAFE MPG for a electric Ford Focus is 82049/321 = 255.6 MPG. The EPA MPG for a gasoline Ford Focus is 30, dividing by 0.8 gives a CAFE MPG of 37.5. We want to use the EPA MPG in the equation for the additional environmental cost because it more accurately reflects real world gasoline consumption, but we must use the CAFE MPG in the constraint (A-27). Let the EPA MPG be denoted with the superscript E and the CAFE MPG be denoted with the superscript C. We have

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

where the last equality follows from the assumption that (A-27) is binding. Substituting 37.5 for f_g^C, 255.6 for f_e^C, and $150,000$ for g gives \$1555.

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

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

suming 6.3% percent of emissions from electricity production occur upstream (a number which is calculated from Table S-15).

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

We can also compare our calculation of the average environmental benefits of an electric vehicle over the lifetime of driving the vehicle with the corresponding value from Michalek et al (2011). Recall we found the average environmental benefits are be equal to -\$1095. The corresponding value for Michalek et al is -\$181.[18]

P Cap and Trade Programs

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

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

from power plants that are subject to cap and trade markets.

There are several cap and trade markets that are relevant for our analysis of 2010-2012 (these are described in EPA's eGRID, see http://www.epa.gov/energy/egrid). Markets regulating SO2 emissions include the Acid Rain Program and the Clean Air Interstate Rule (CAIR) annual SO_2 market. Markets for NO_X emissions include both the CAIR seasonal NOx market and the CAIR annual NO_X market. The Regional Greenhouse Gas Initiative regulates CO_2 in the Northeast. As noted in the main text, during the period of analysis, permit prices were low and the stock of banked permits was increasing.[19] We set a power plant's marginal emissions for a given pollutant to zero if it is regulated for even part of the year by one of these programs.

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

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

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

Q Full Size Color Figures

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

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

Figure 1a: Marginal Damages for Gas Vehicles by County

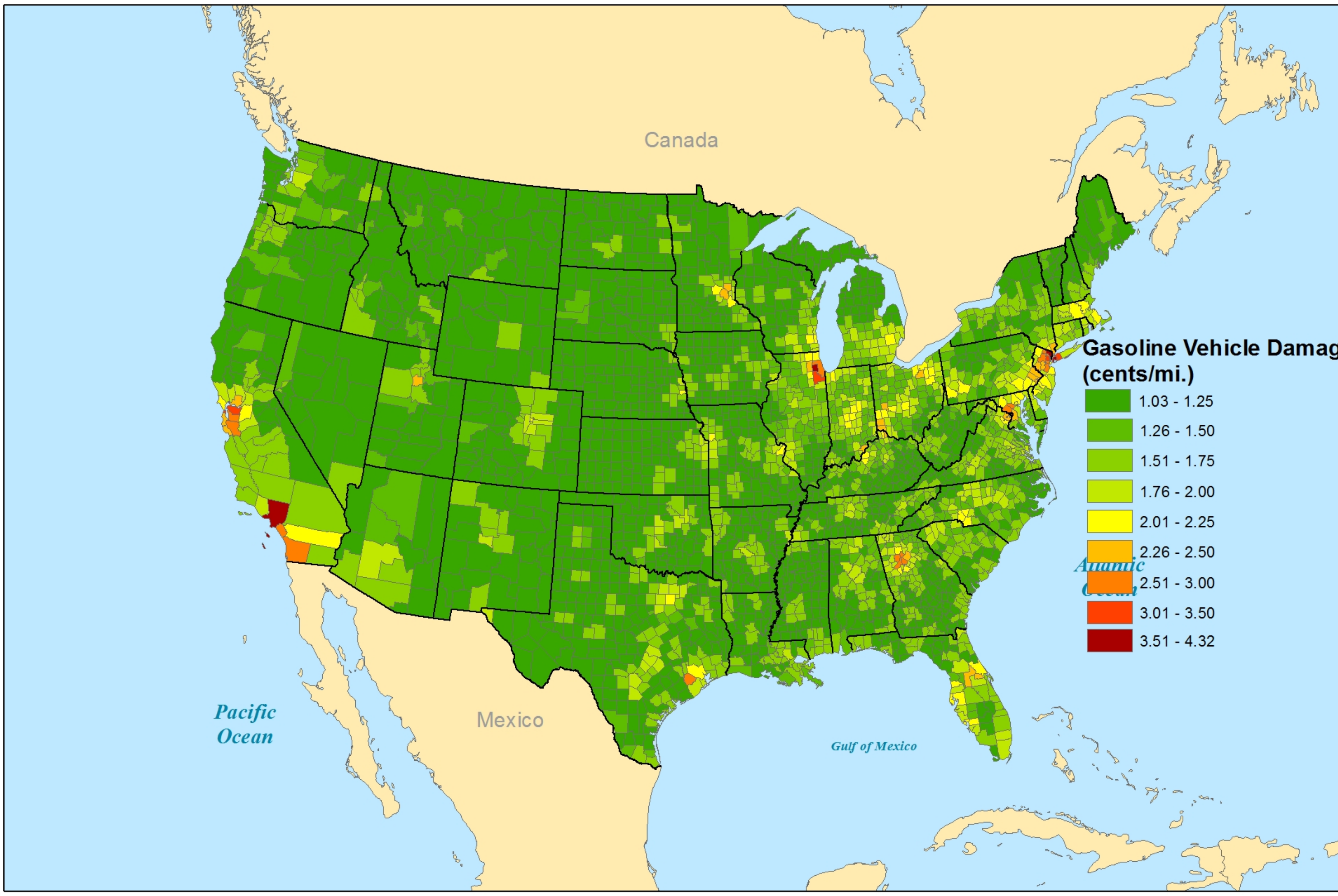


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Figure 1b: Marginal Damages for Electric Vehicles by County

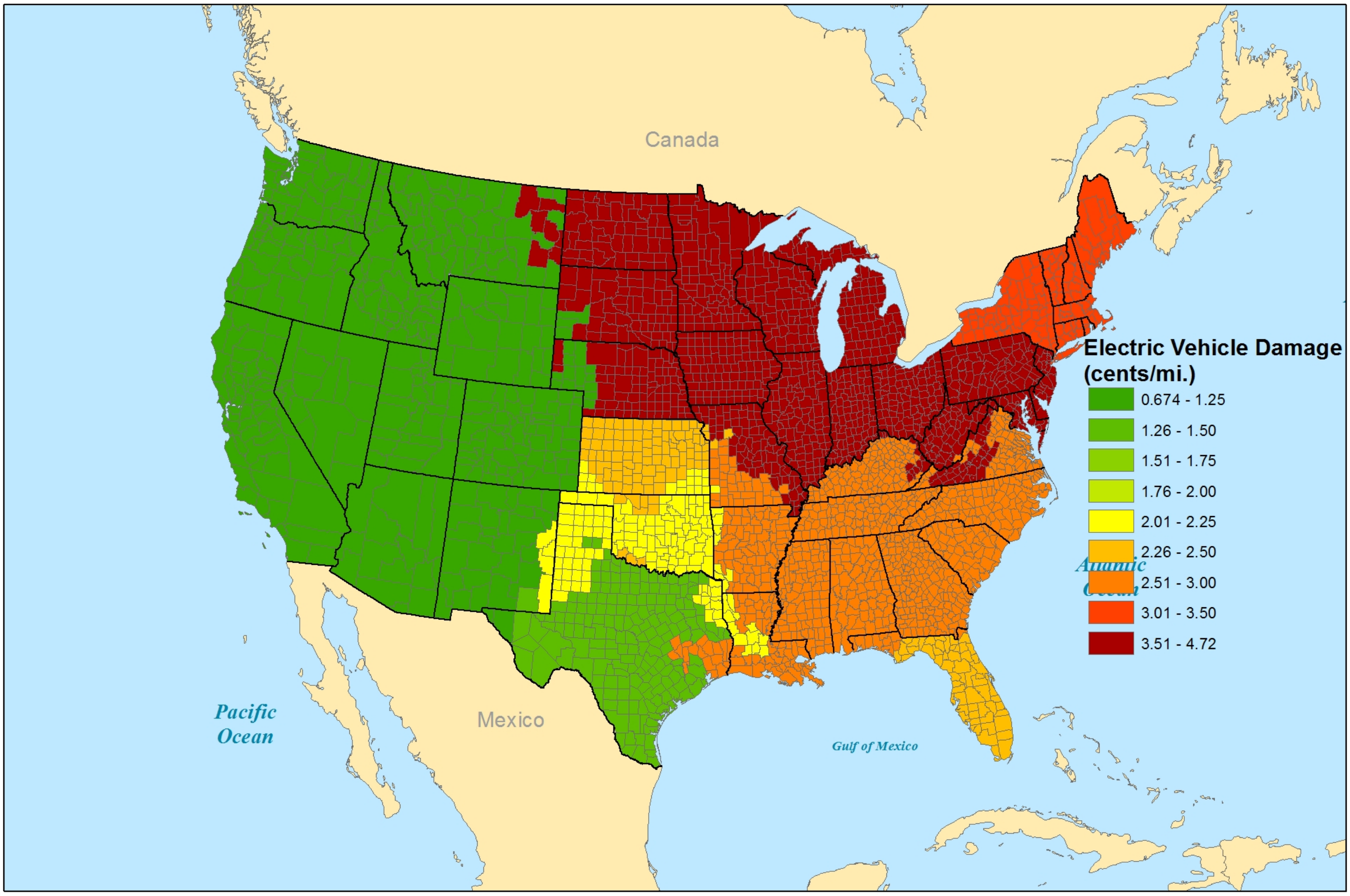

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Figure 2: Second-Best Electric Vehicle Subsidy by County

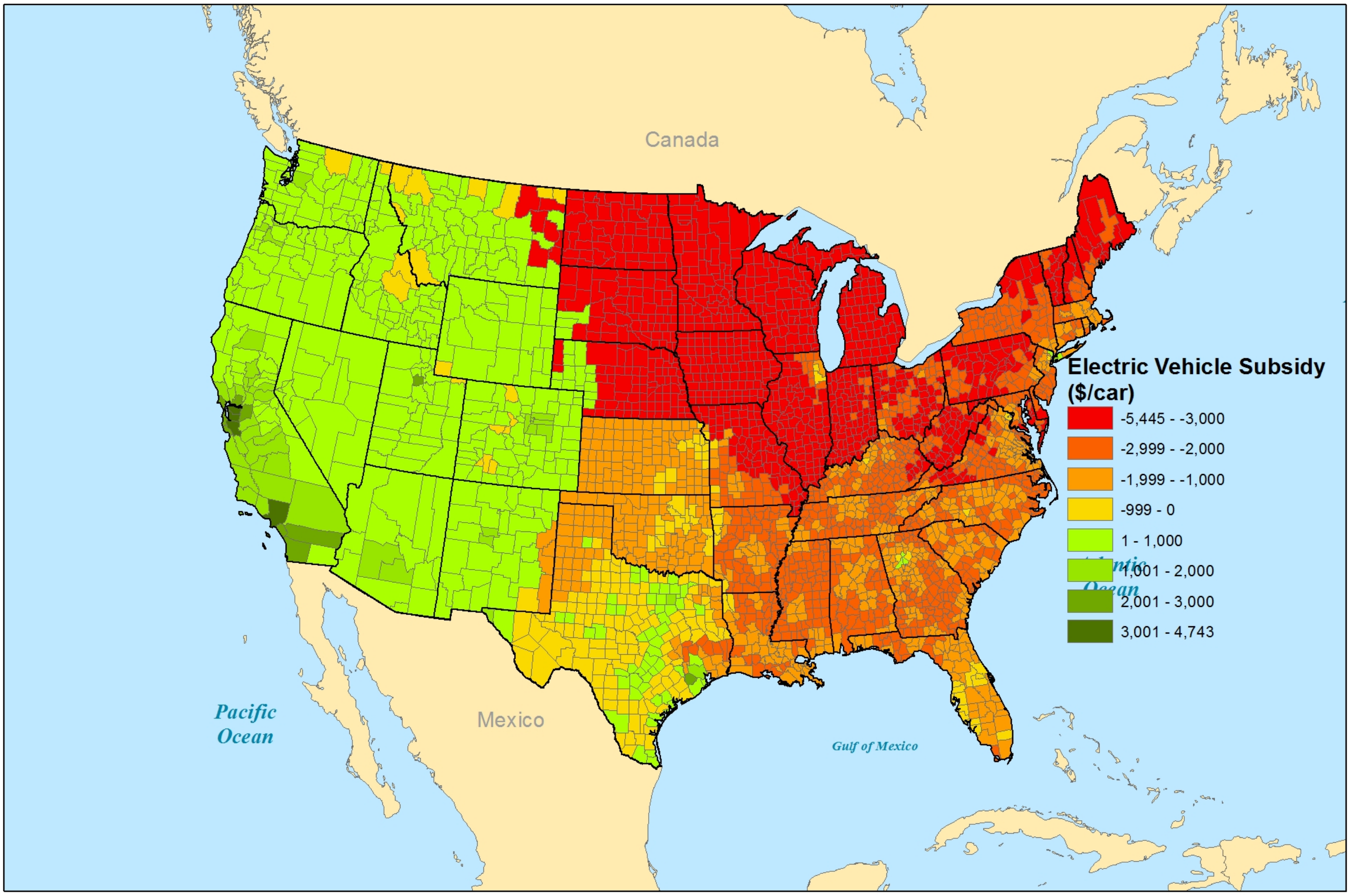

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Figure 3a: Second-Best Electric Vehicle Subsidy by State (Full Damages)

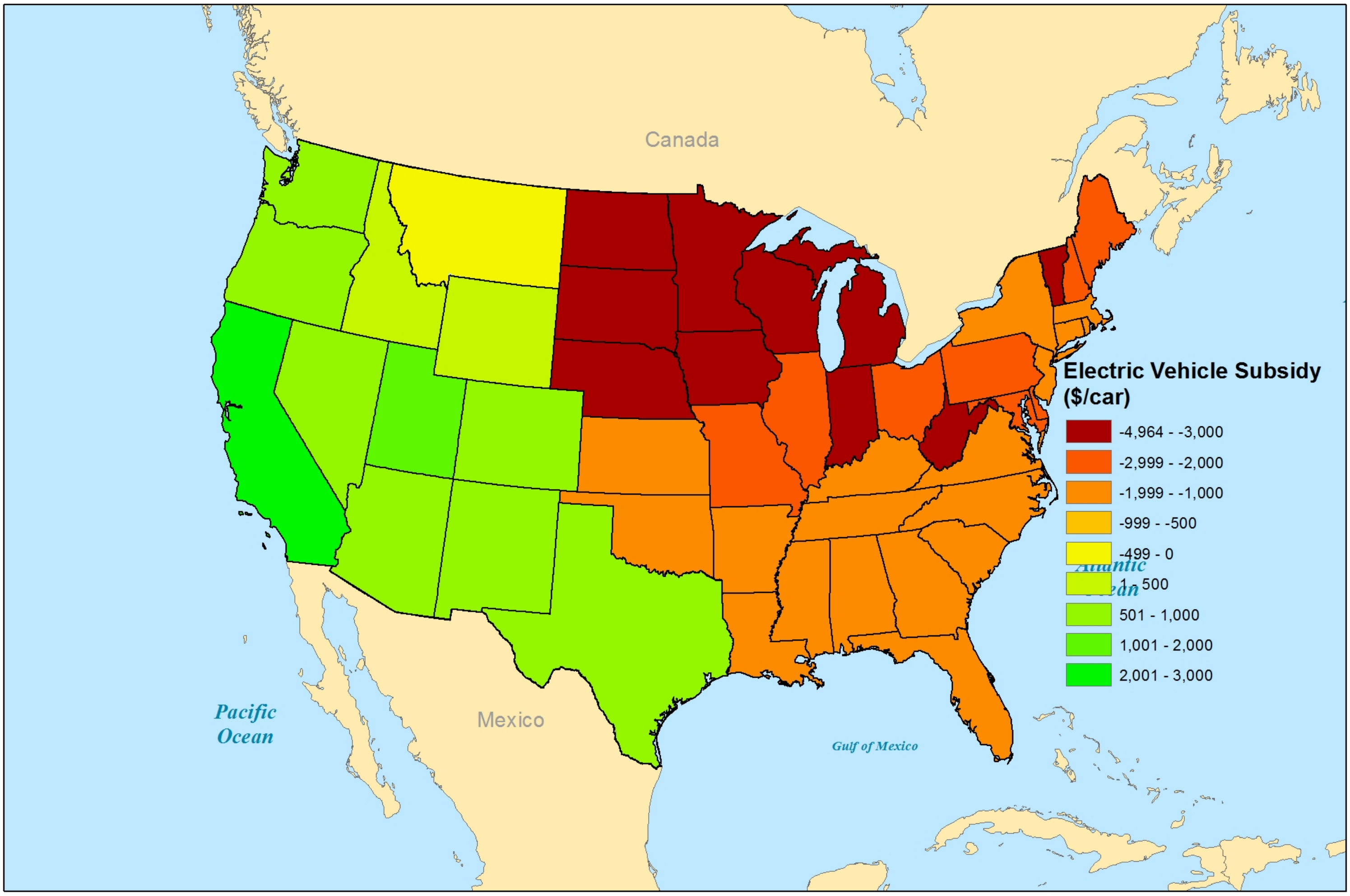

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Figure 3b: Second-Best Electric Vehicle Subsidy by State (Native Damages)

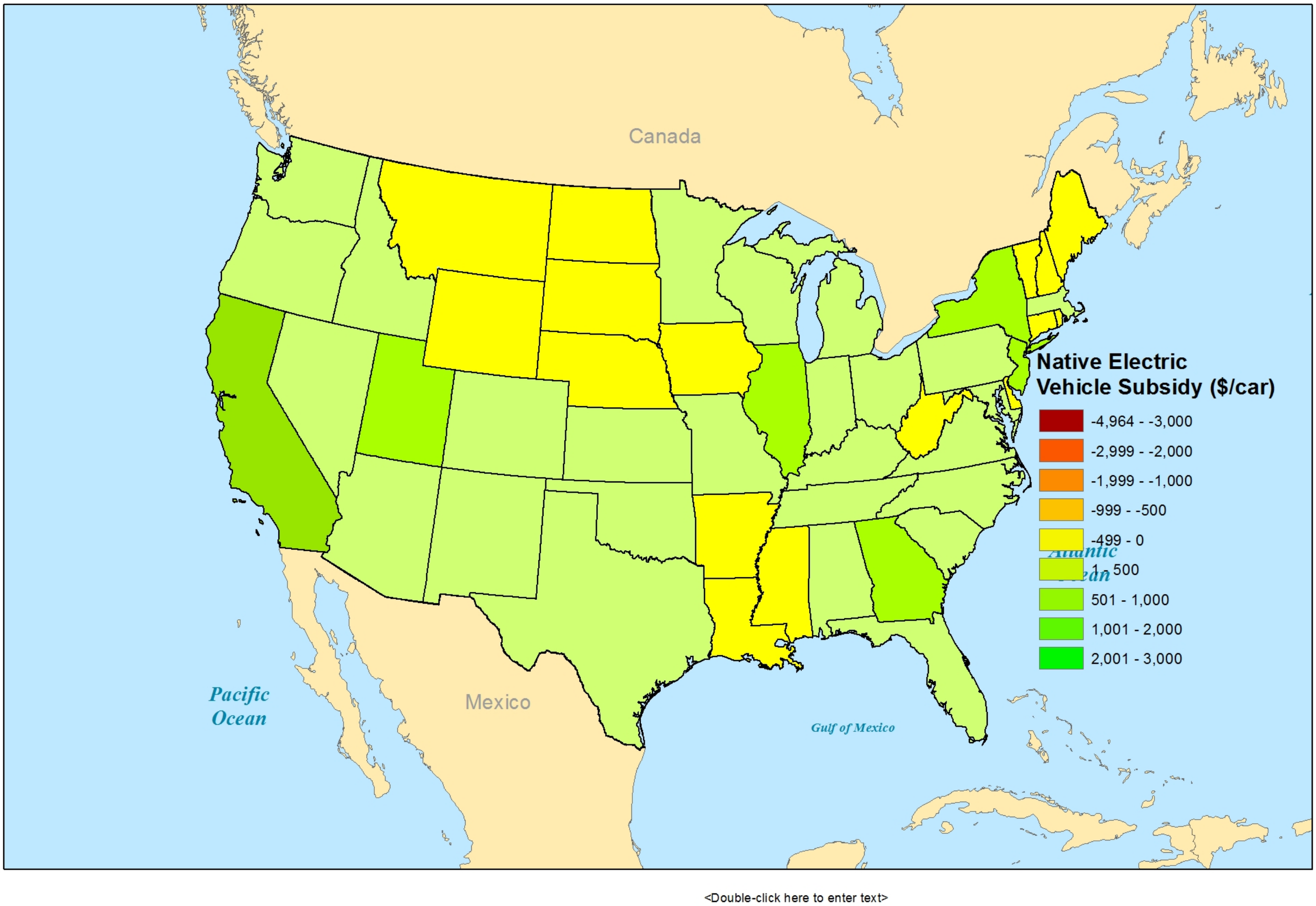

Figure 4a: Change in $PM_{2.5}$ from Gasoline Vehicle in Fulton County, Georgia

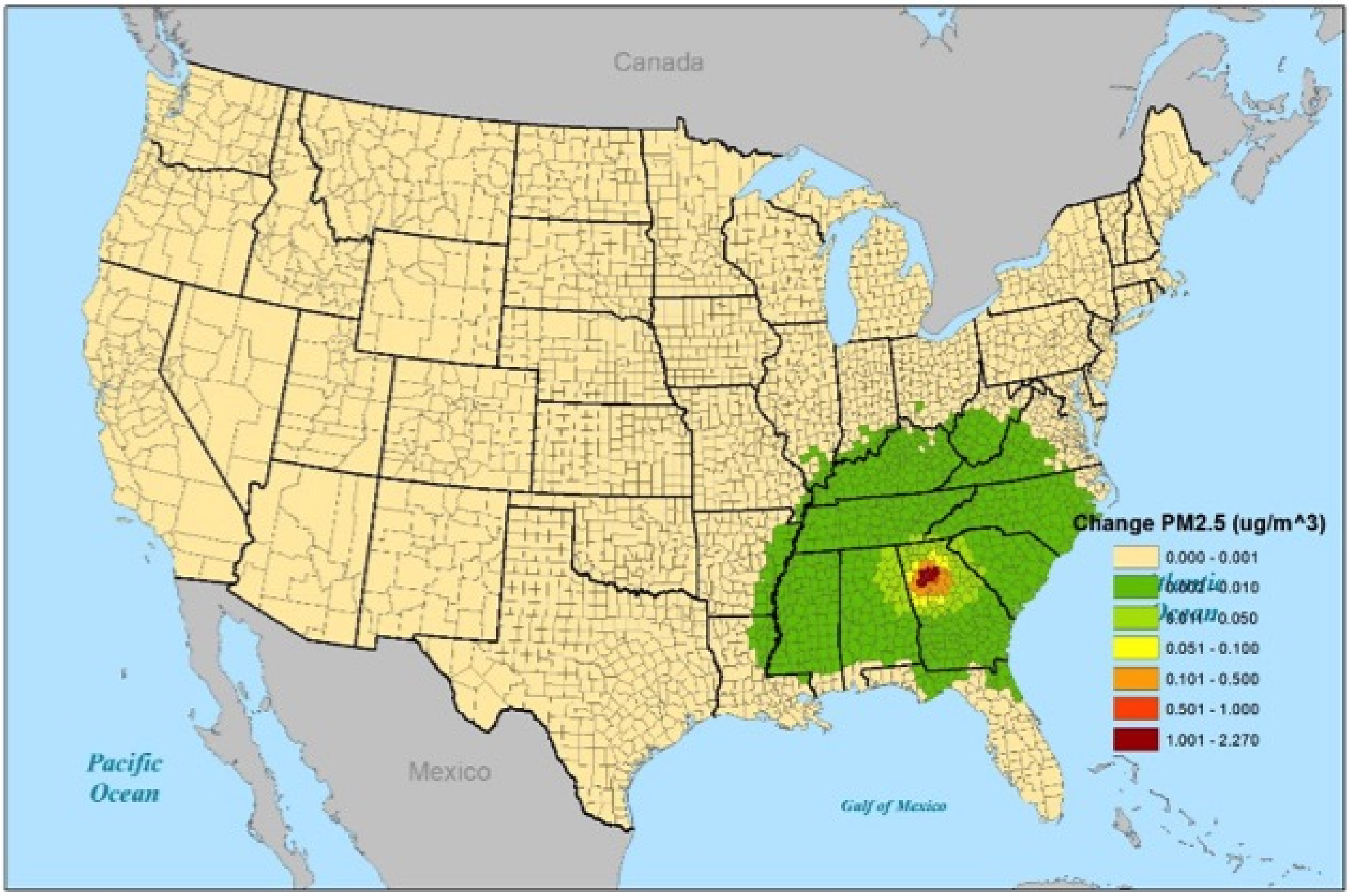

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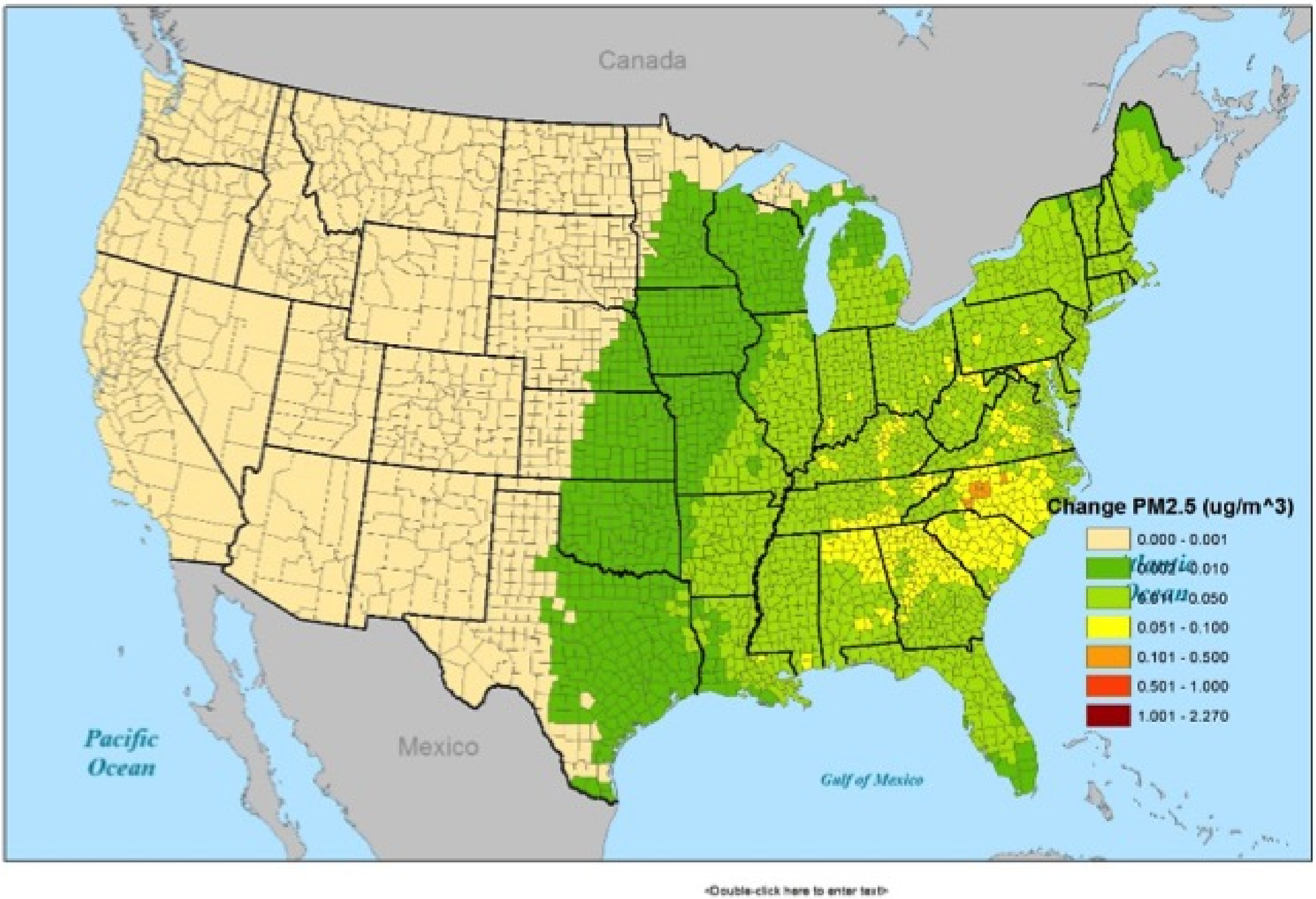
Figure 4b: Change in $PM_{2.5}$ from Electric Vehicle in Fulton County, Georgia



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Supplementary Local Pollution Maps for "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors"[1]

Stephen P. Holland[2] Erin T. Mansur[3] Nicholas Z. Muller[4]

Andrew J. Yates[5]

June 4, 2016

[1]We would like to thank Jonathan Hughes for providing the STATA map-making code.

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Contents

1 Description

These supplementary maps illustrate the environmental effects from local pollution due to driving a Ford Focus EV and gasoline Ford Focus in each of the 20 largest Metropolitan Statistical Areas (MSAs) in the United States. The methodology for generating the maps is described in our paper entitled "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors." For all maps, we assume that the vehicles are driven 150,000 miles over their lifetime. We also assume the vehicles are driven exclusively within the county that has the largest population of all the counties in the MSA. Damages are determined from the emissions of four local pollutants (NO_X, SO_2, VOC, $PM_{2.5}$) from the tailpipe of the gasoline Ford Focus and the smokestacks of electric power plants that charge the Ford Focus EV.

For each MSA we give three maps. One shows the damages that accrue to various counties from the plume of pollution generated by driving the gasoline Ford Focus in the given county. One shows the damages that accrue to various counties from the plumes of pollution that are generated by the power plants that increase emissions when a Ford Focus EV is charged in the given county. And one shows the environmental benefits that accrue to various counties from driving the Ford Focus EV in the given county (defined as the damages from the gasoline Ford Focus minus the damages from the Ford Focus EV.)

This maps illustrate the the importance of pollution export and native damages. The damages from gasoline vehicles are highly concentrated in a few counties surrounding the county in which the vehicle is driven. In contrast, the damages from electric vehicles are largely exported to other counties and states. Thus native damages from electric vehicles are generally much smaller than native damages from gasoline vehicles. Correspondingly, driving an electric vehicle generally leads to a positive environmental benefit within the given county, but also tends to create a negative environmental benefit in other places.

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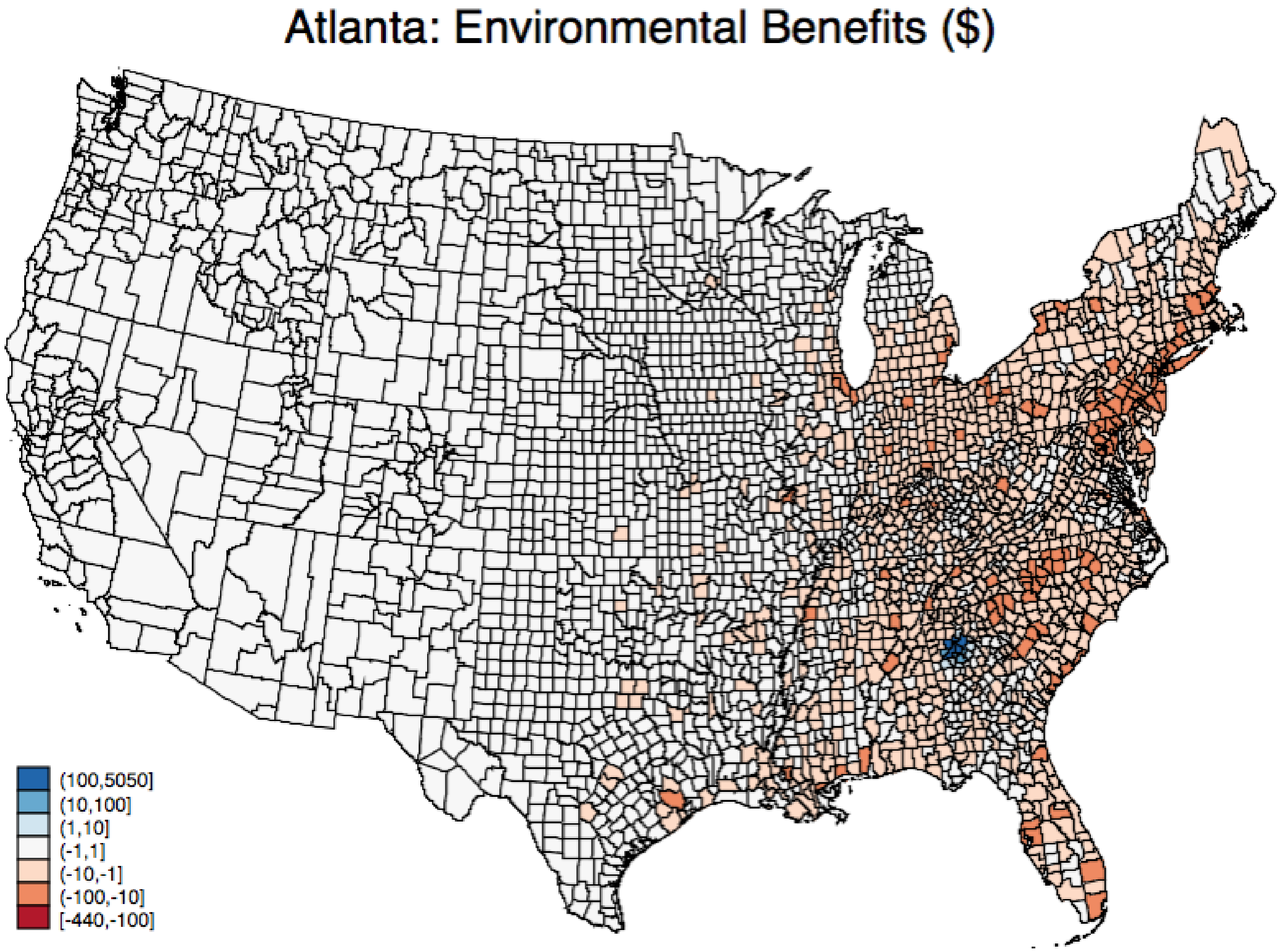
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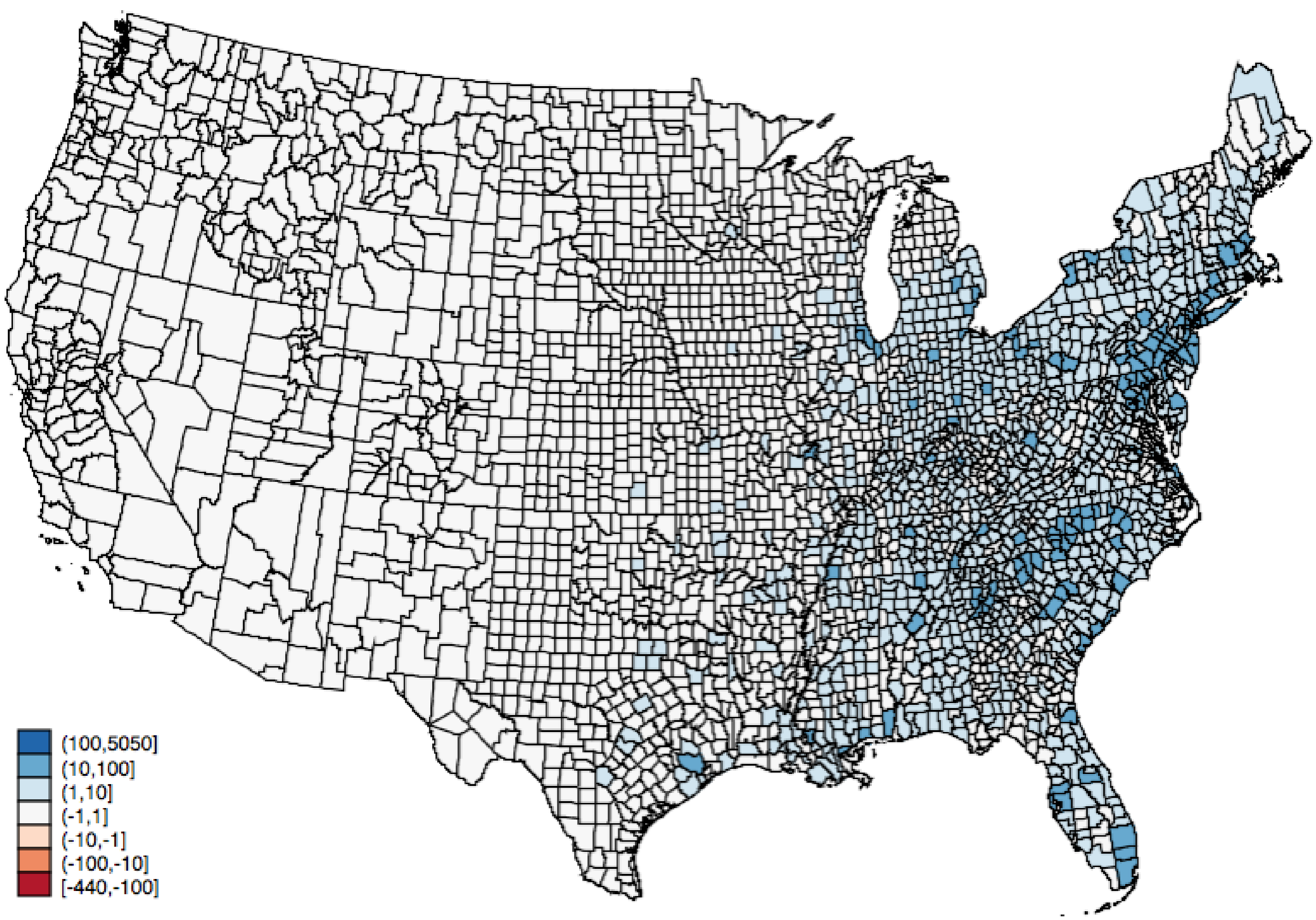

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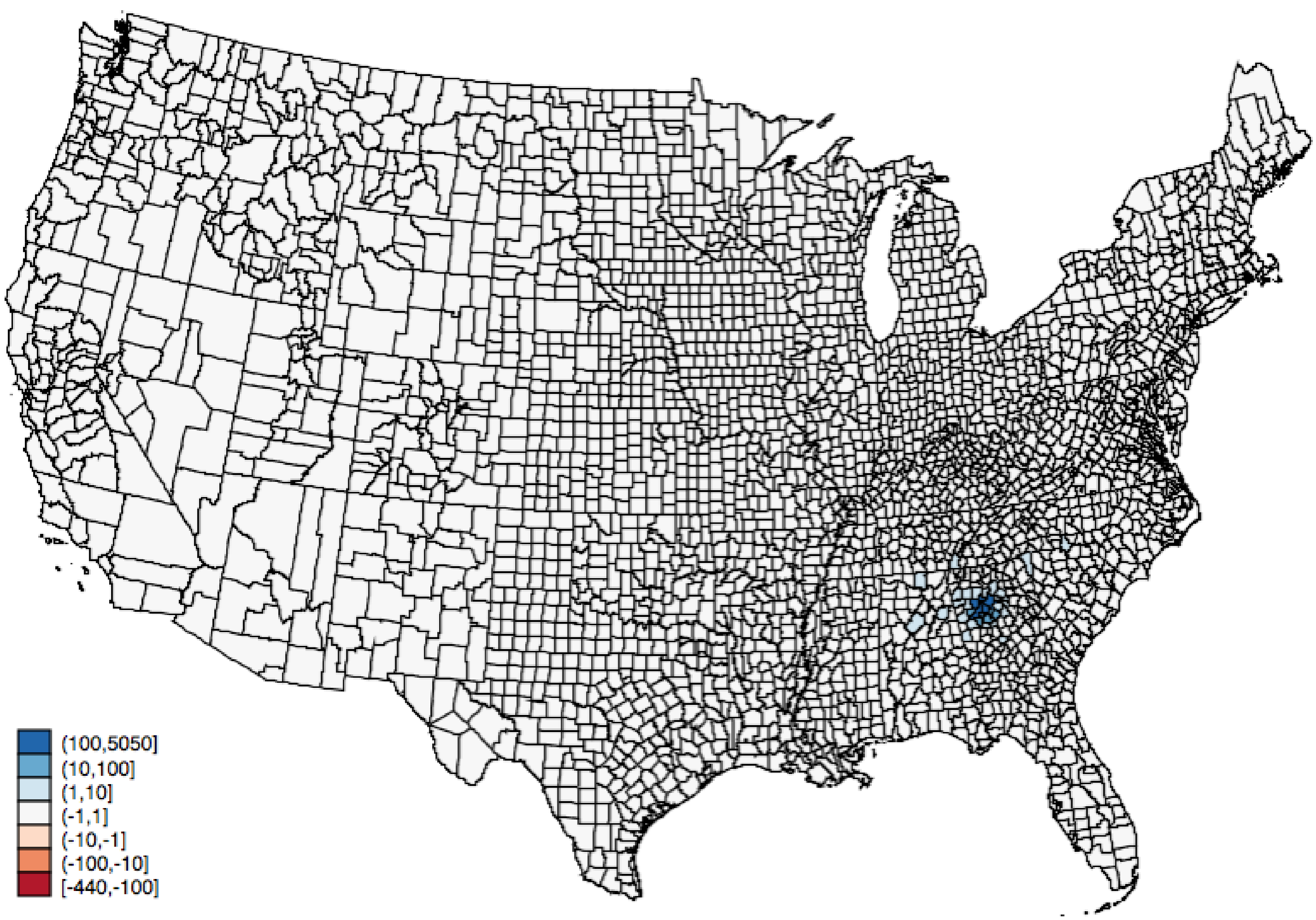

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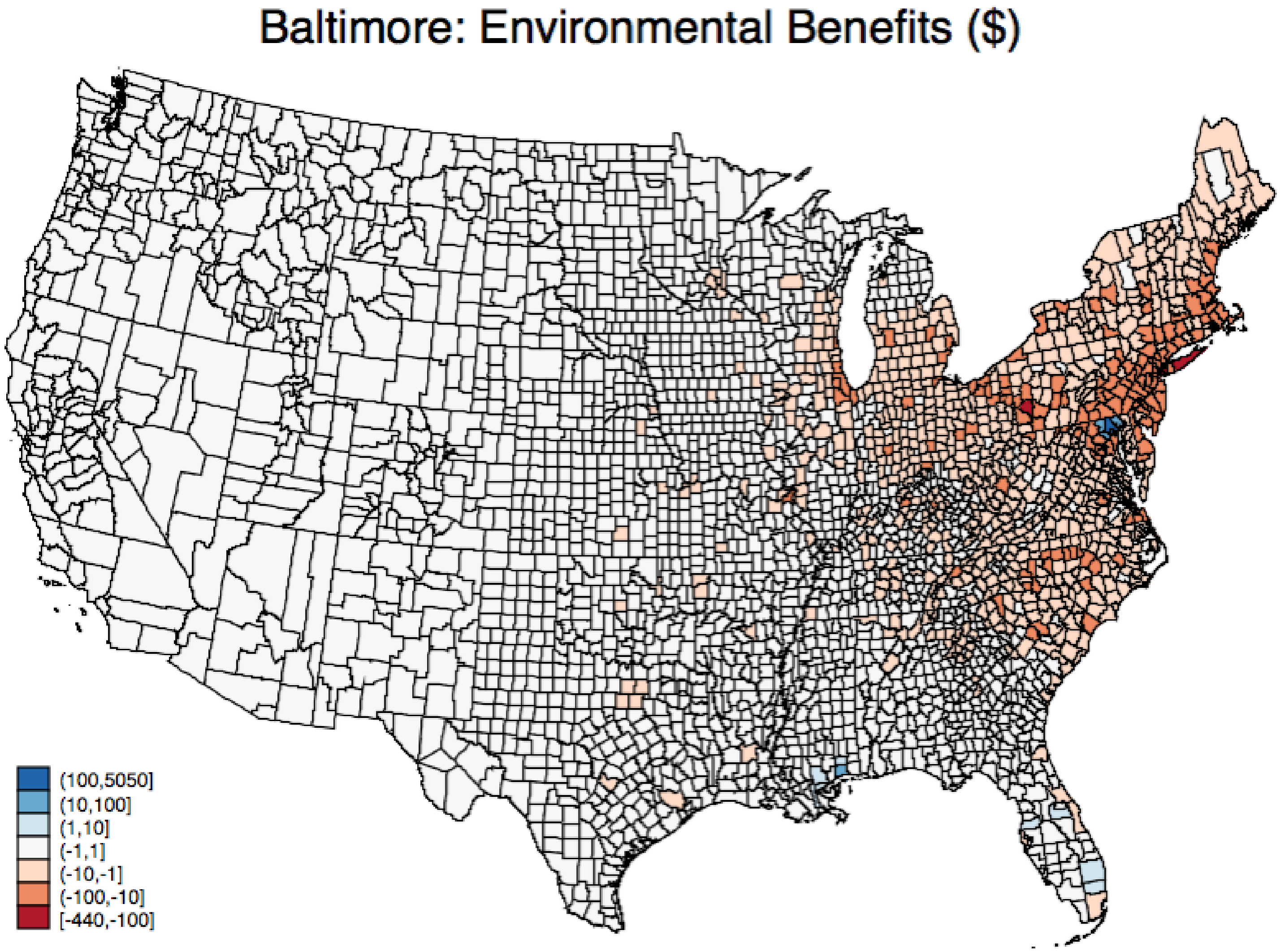

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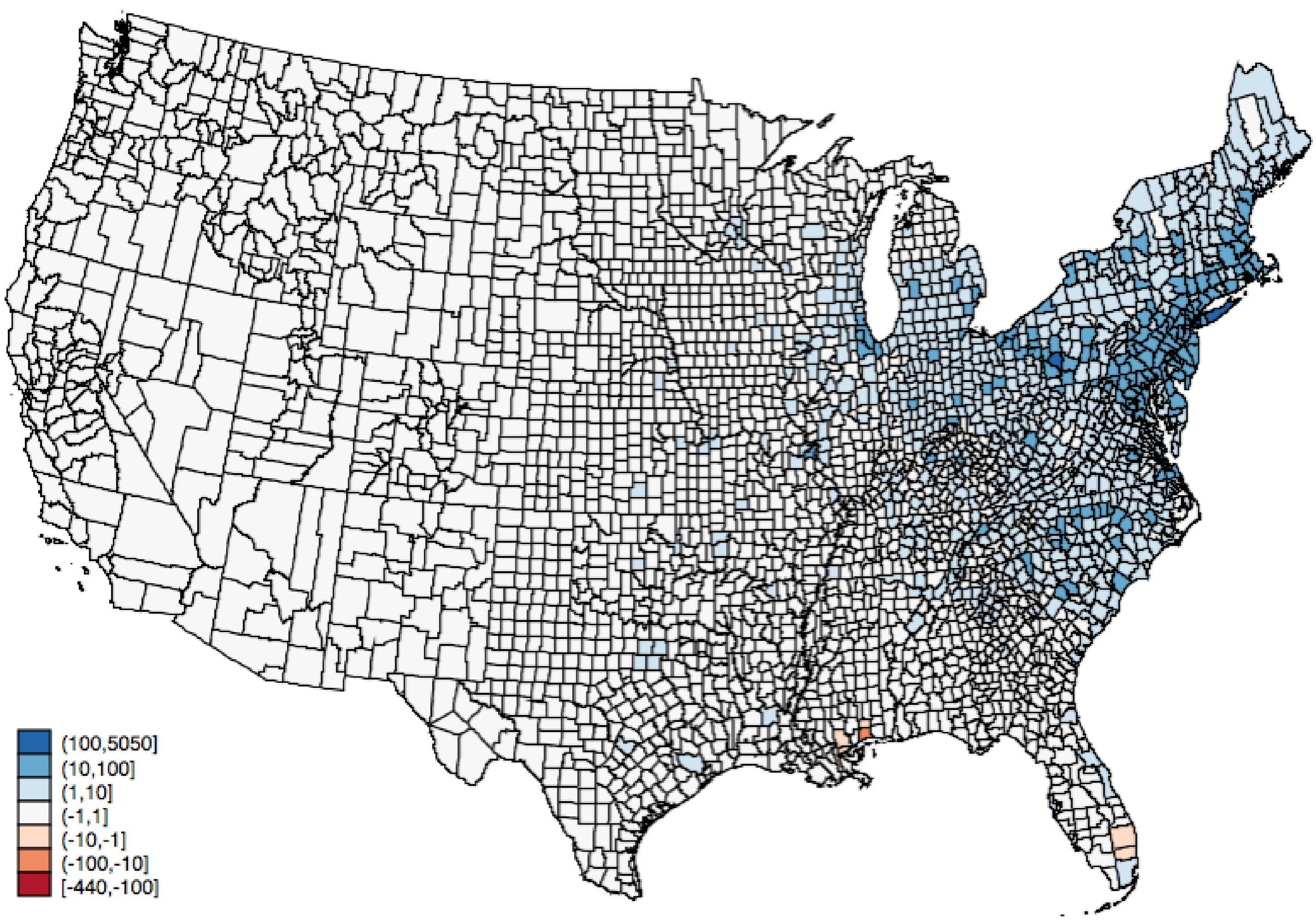

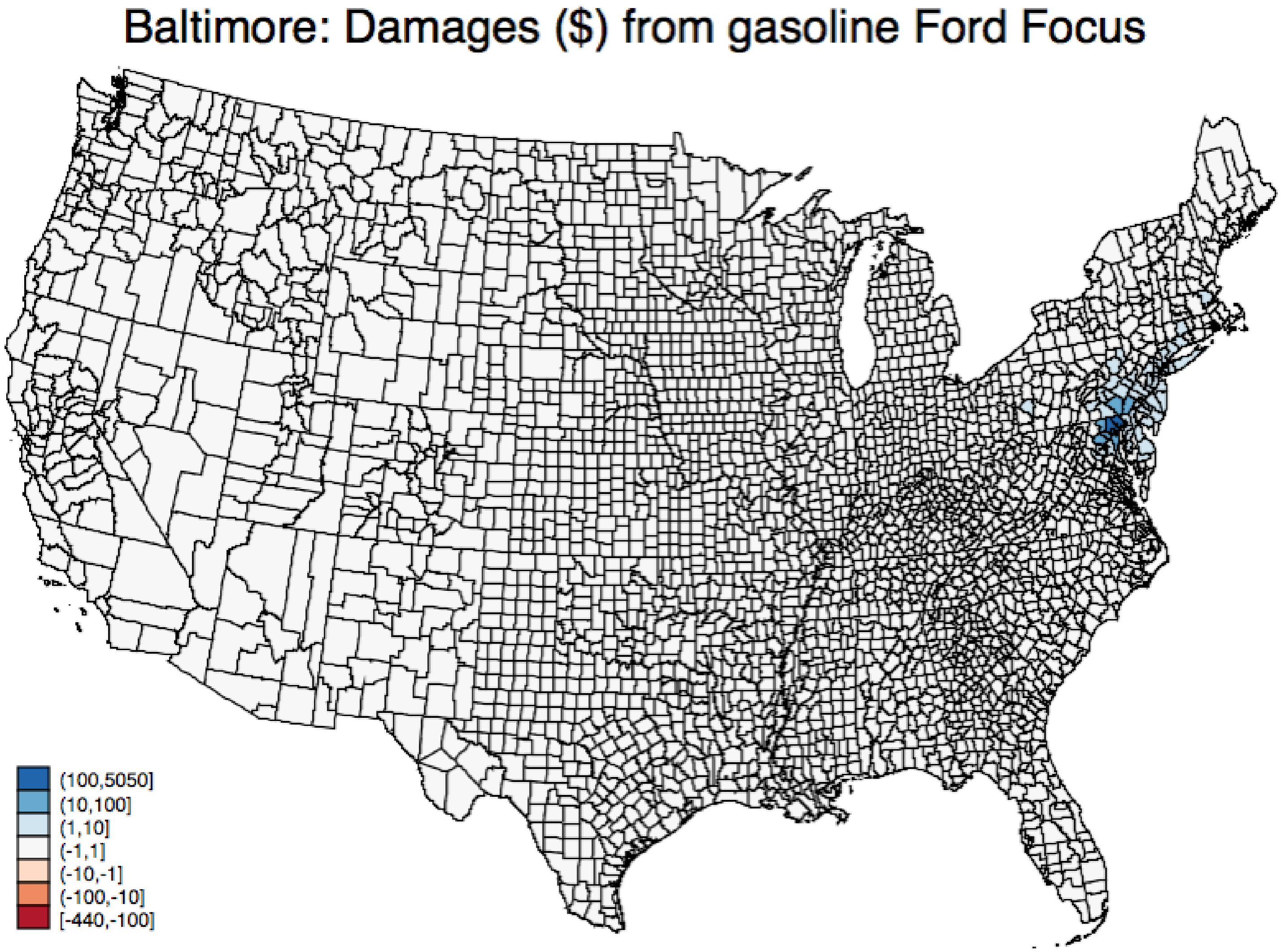
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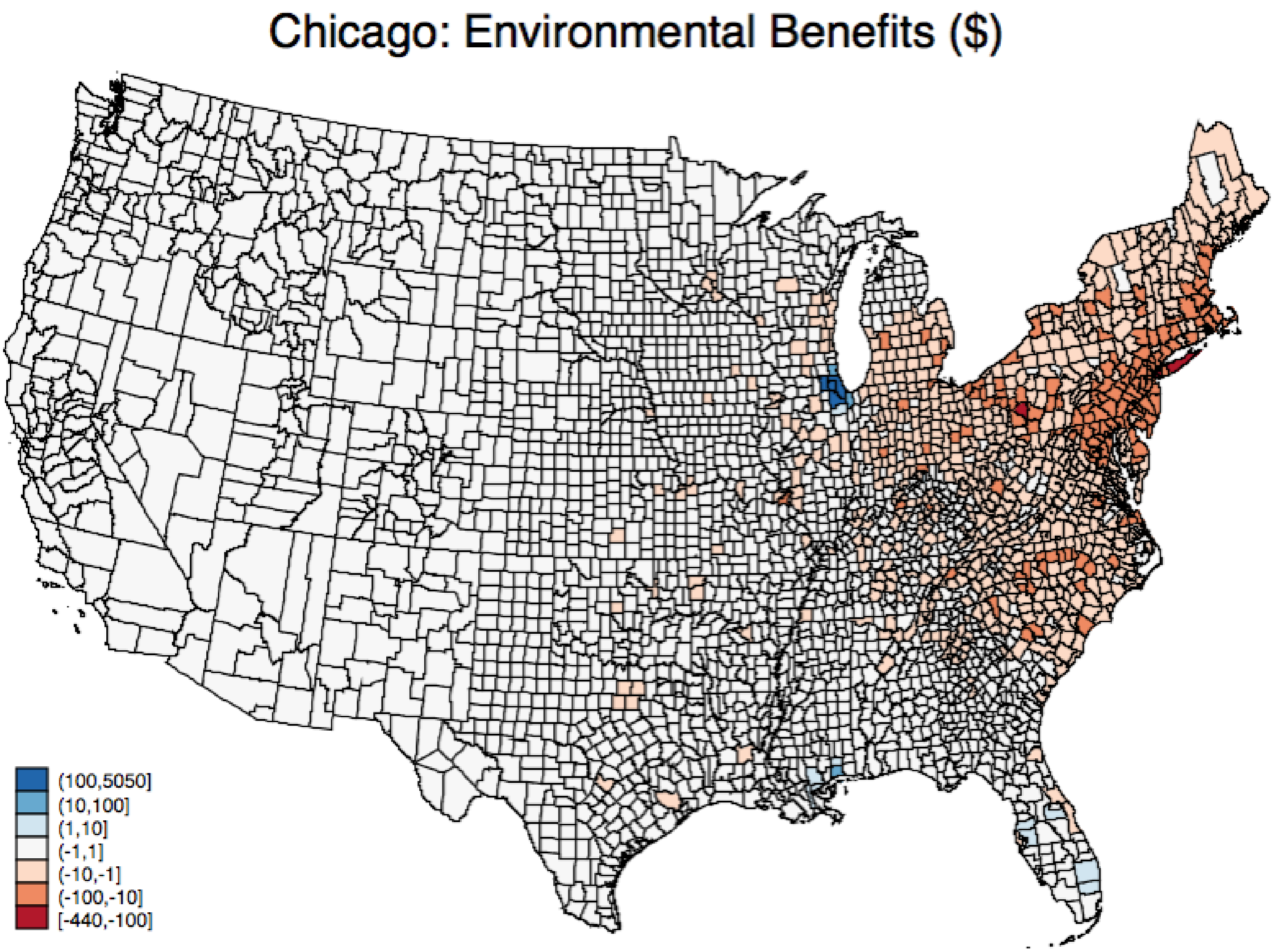
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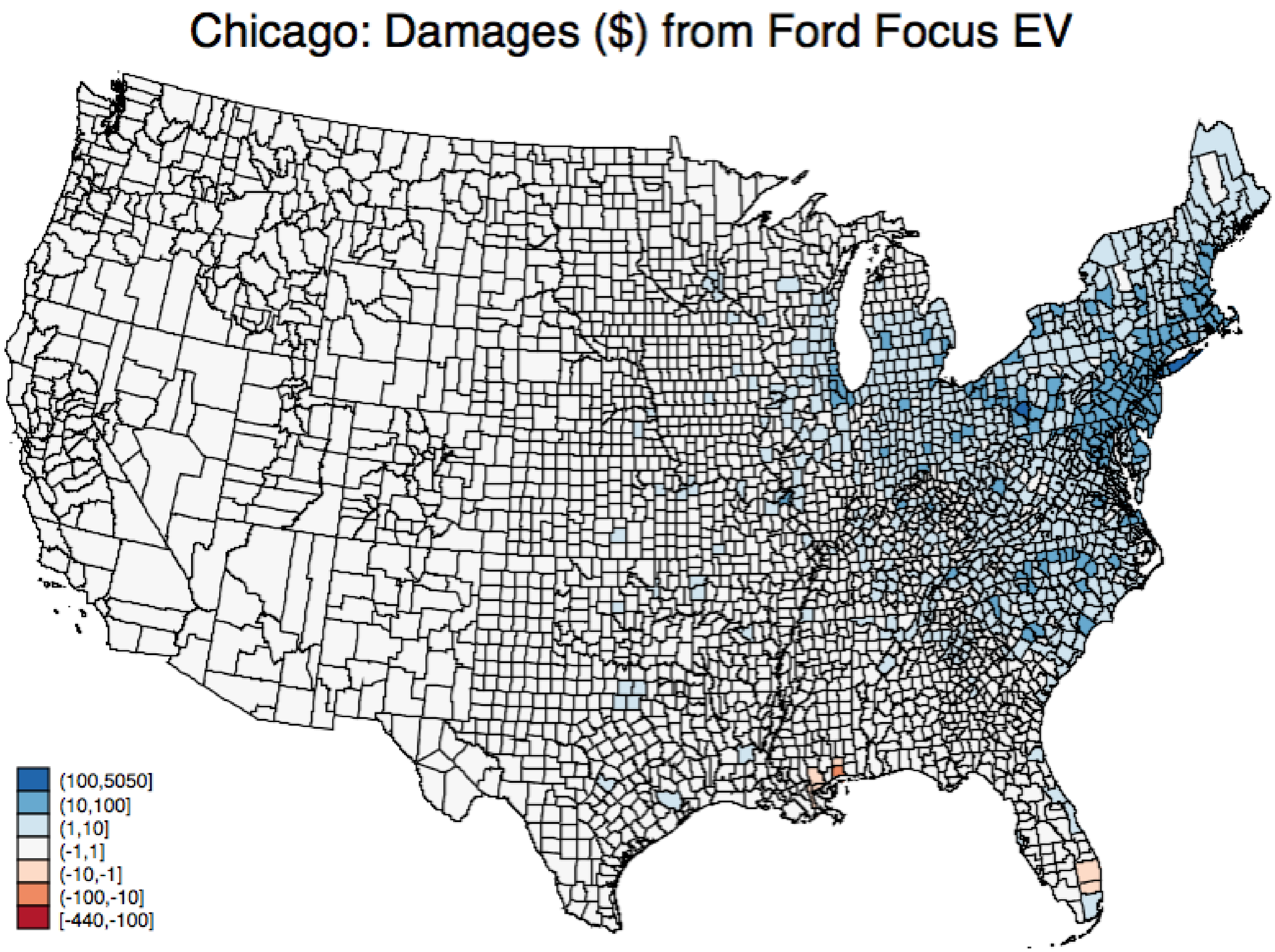

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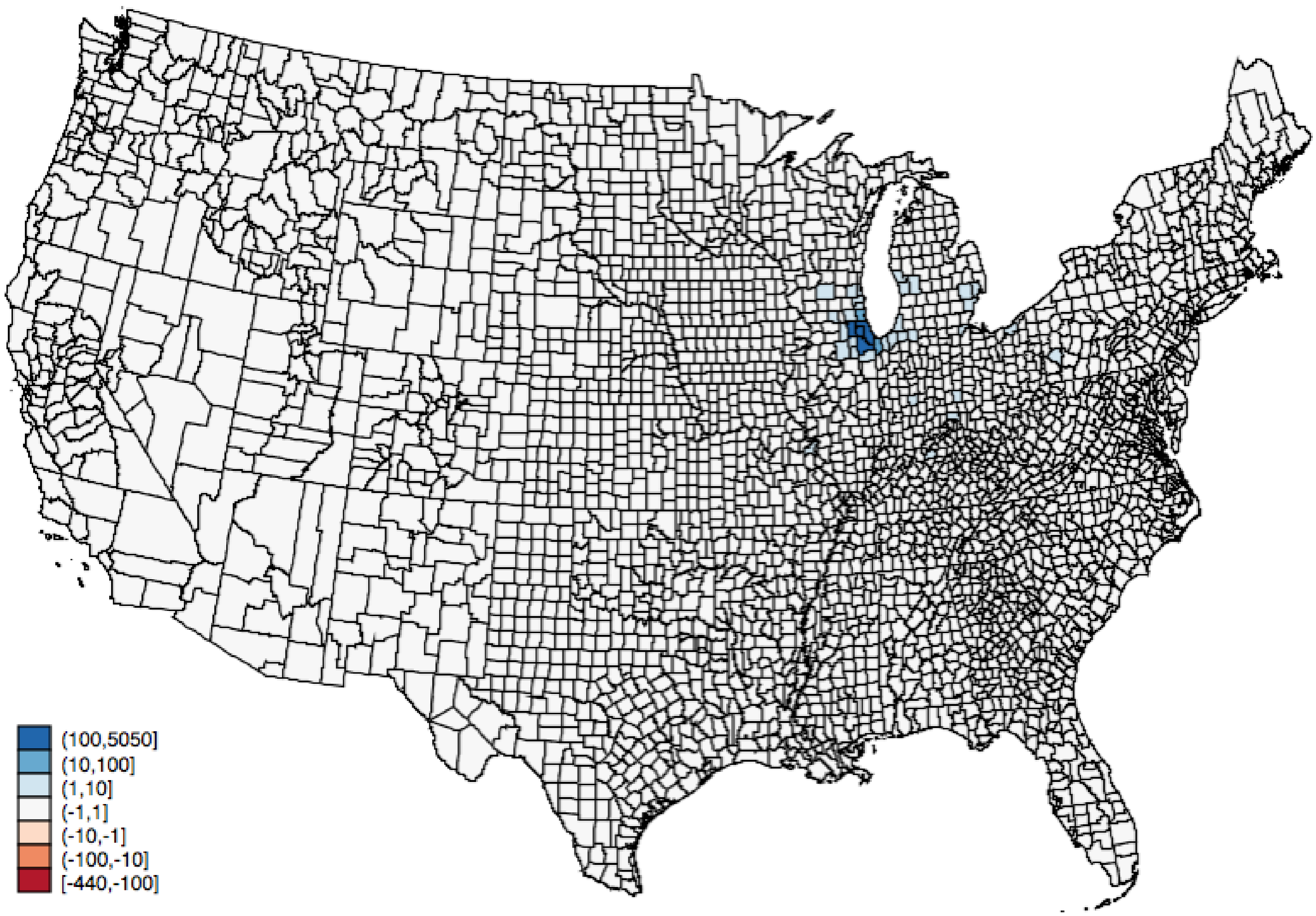

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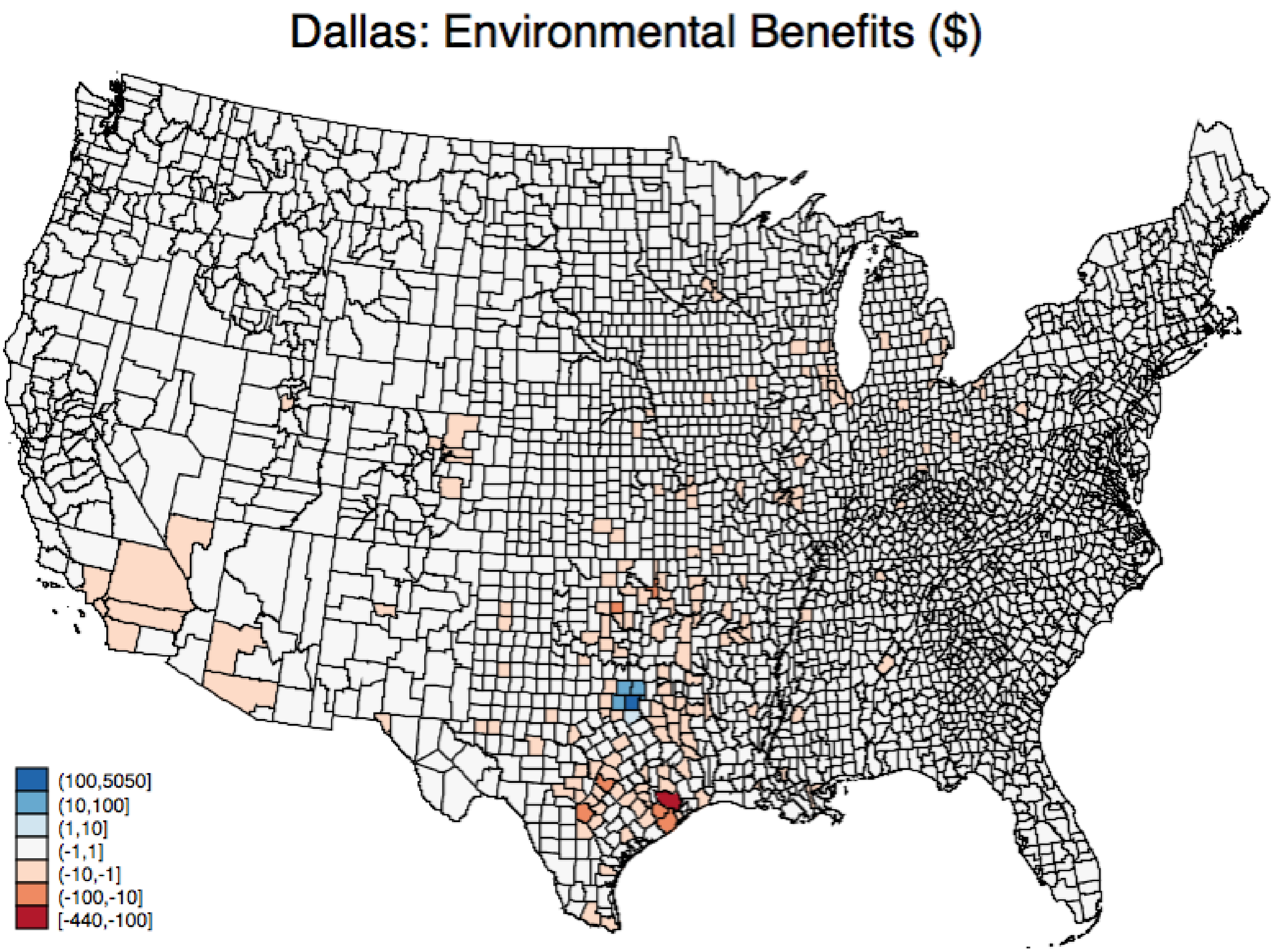

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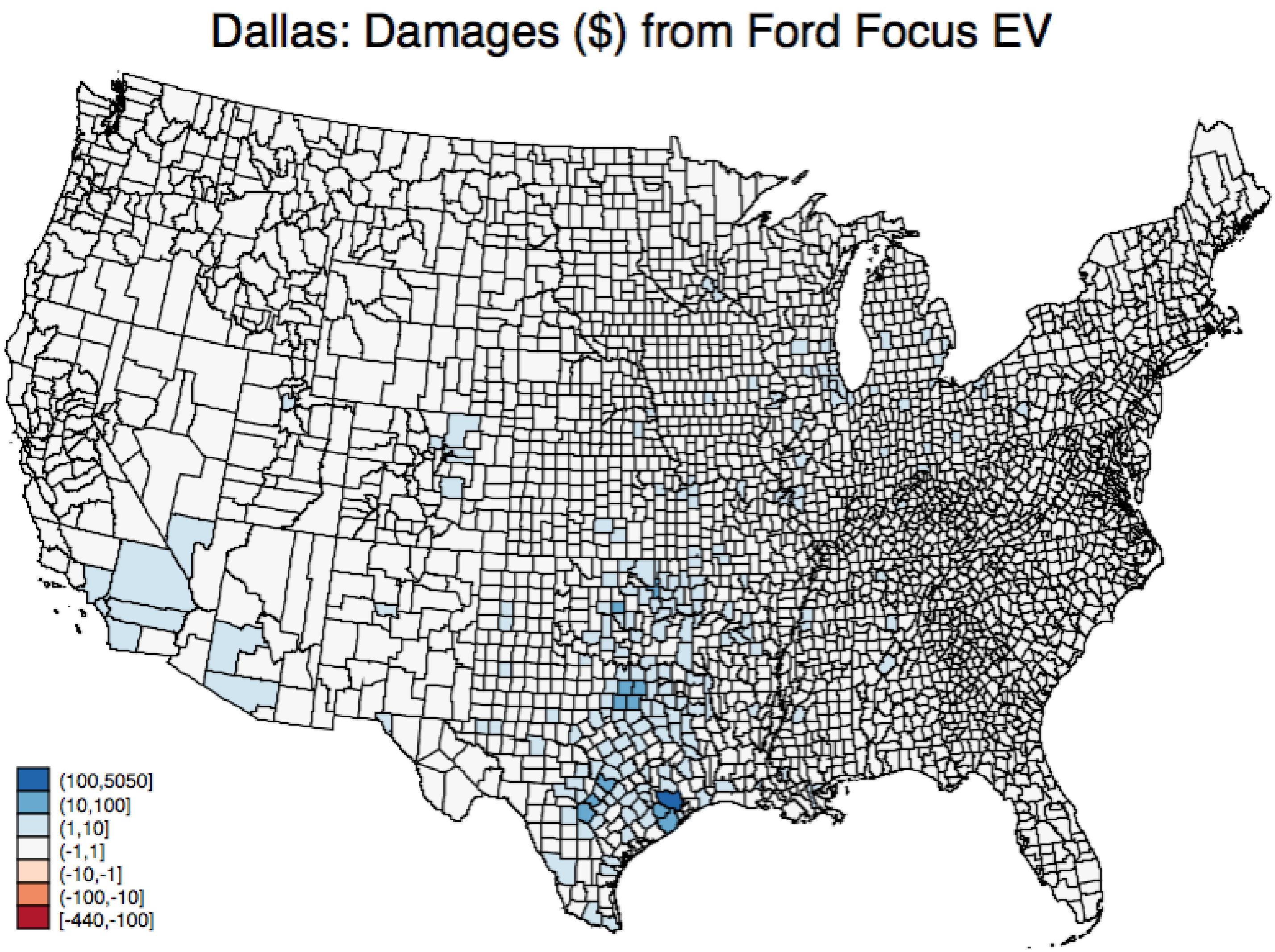
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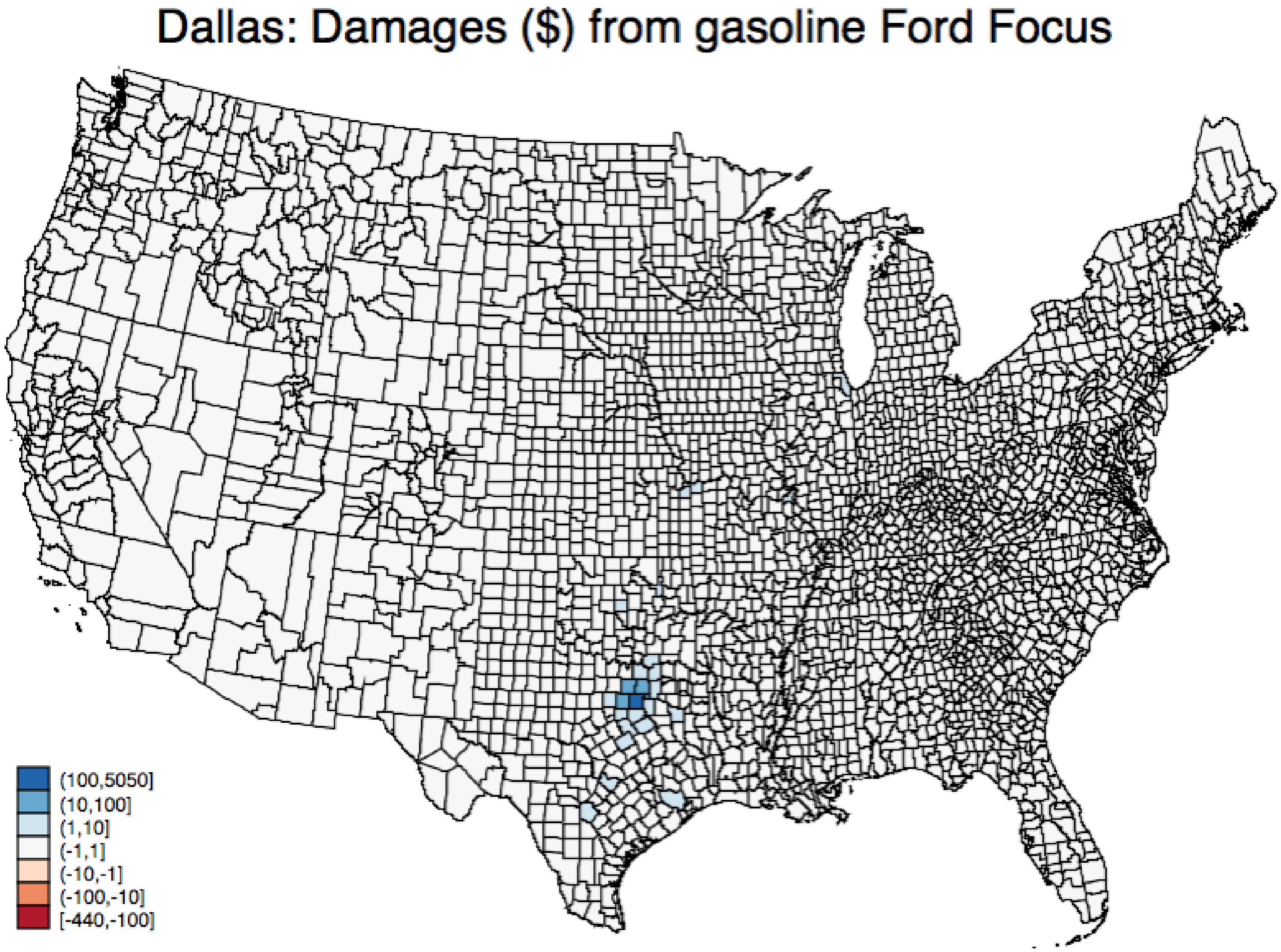
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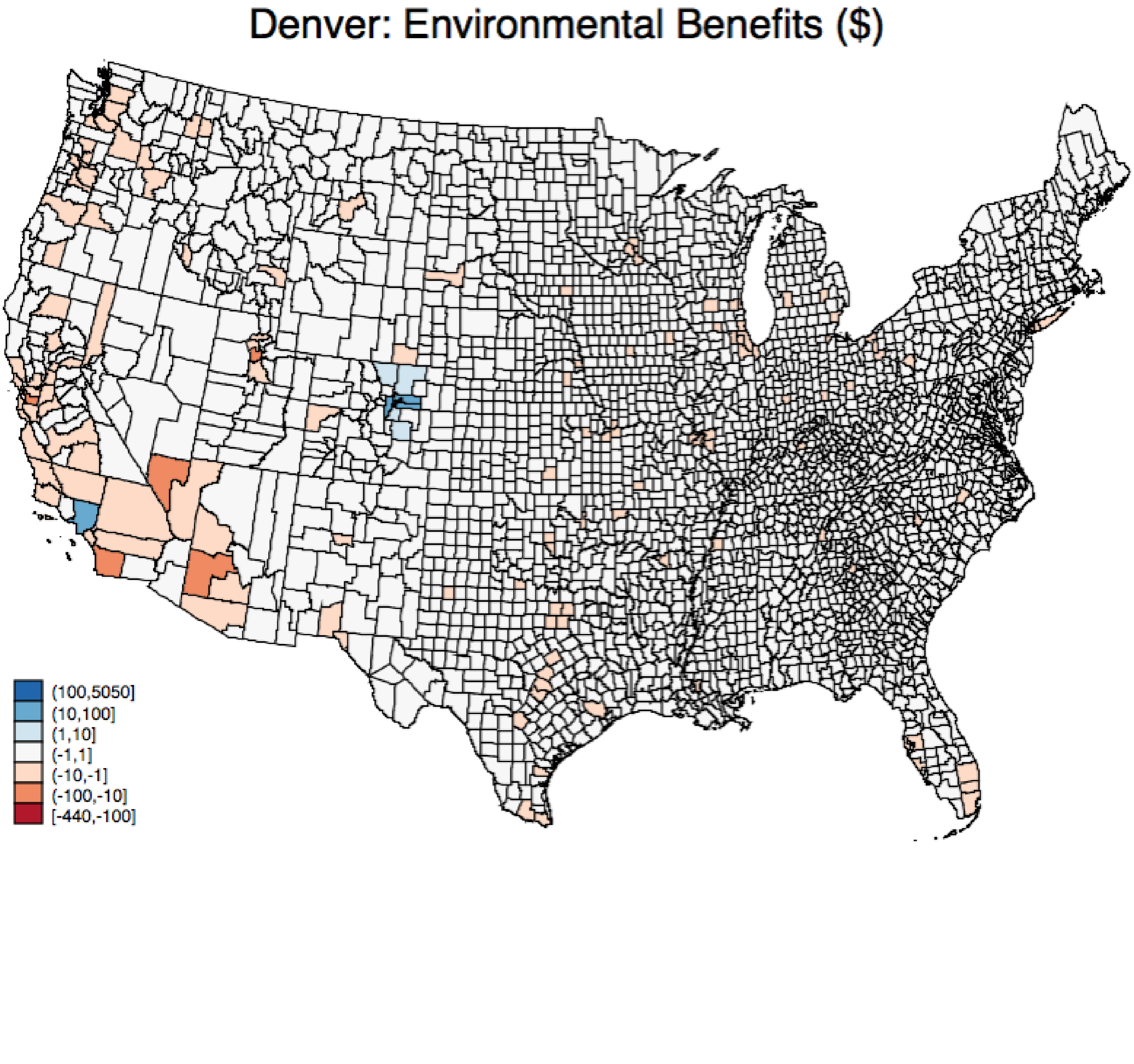

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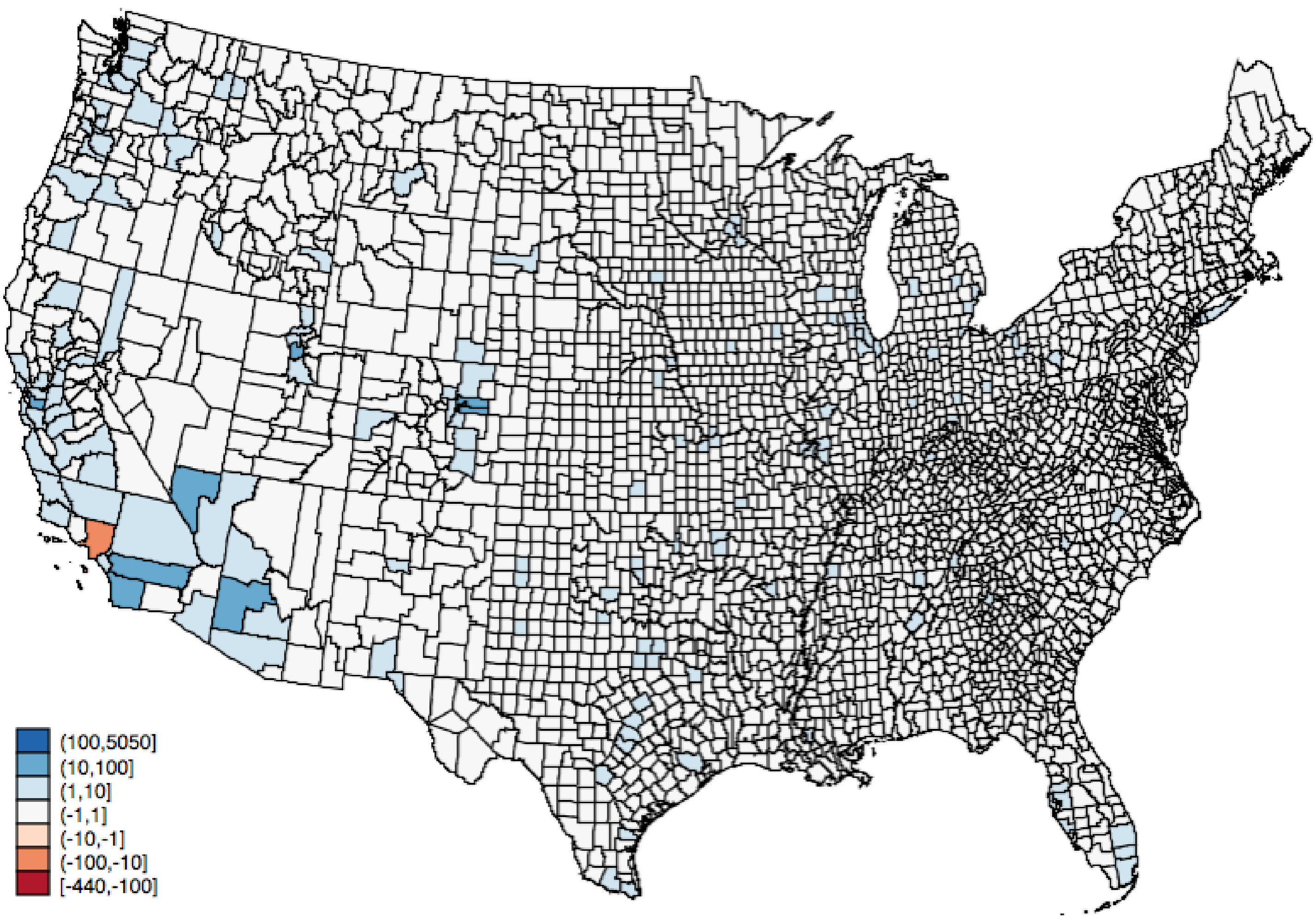

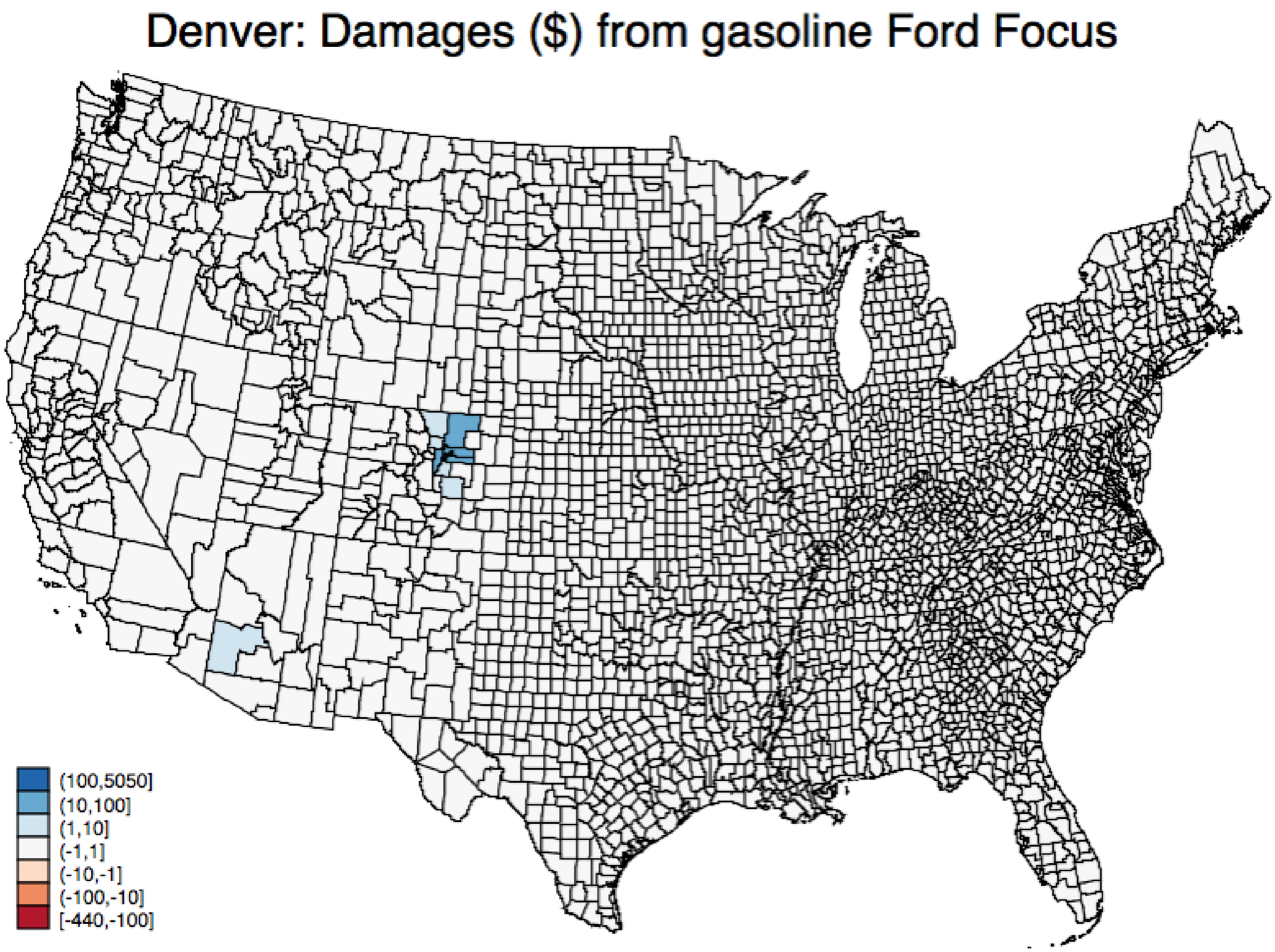
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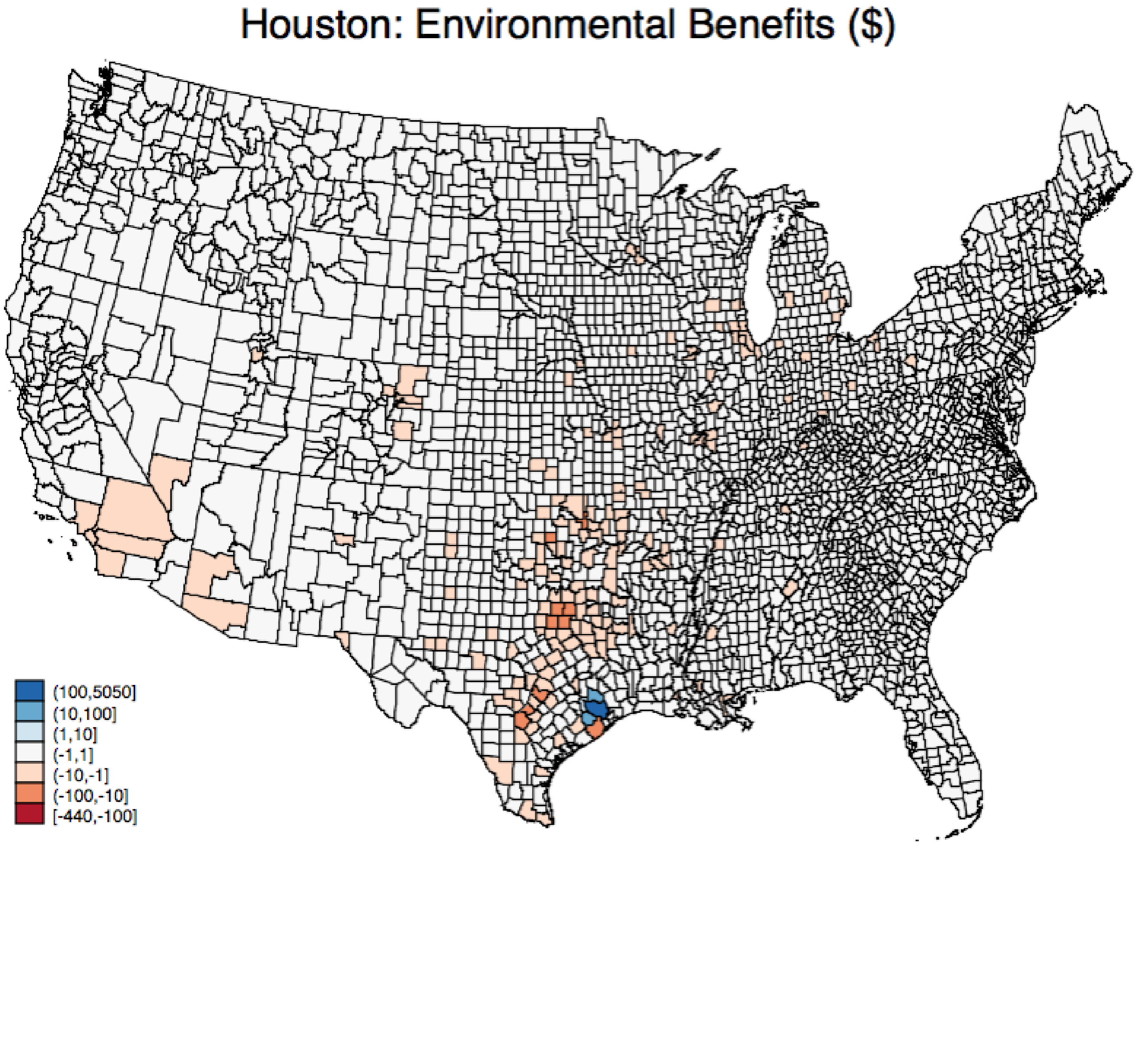
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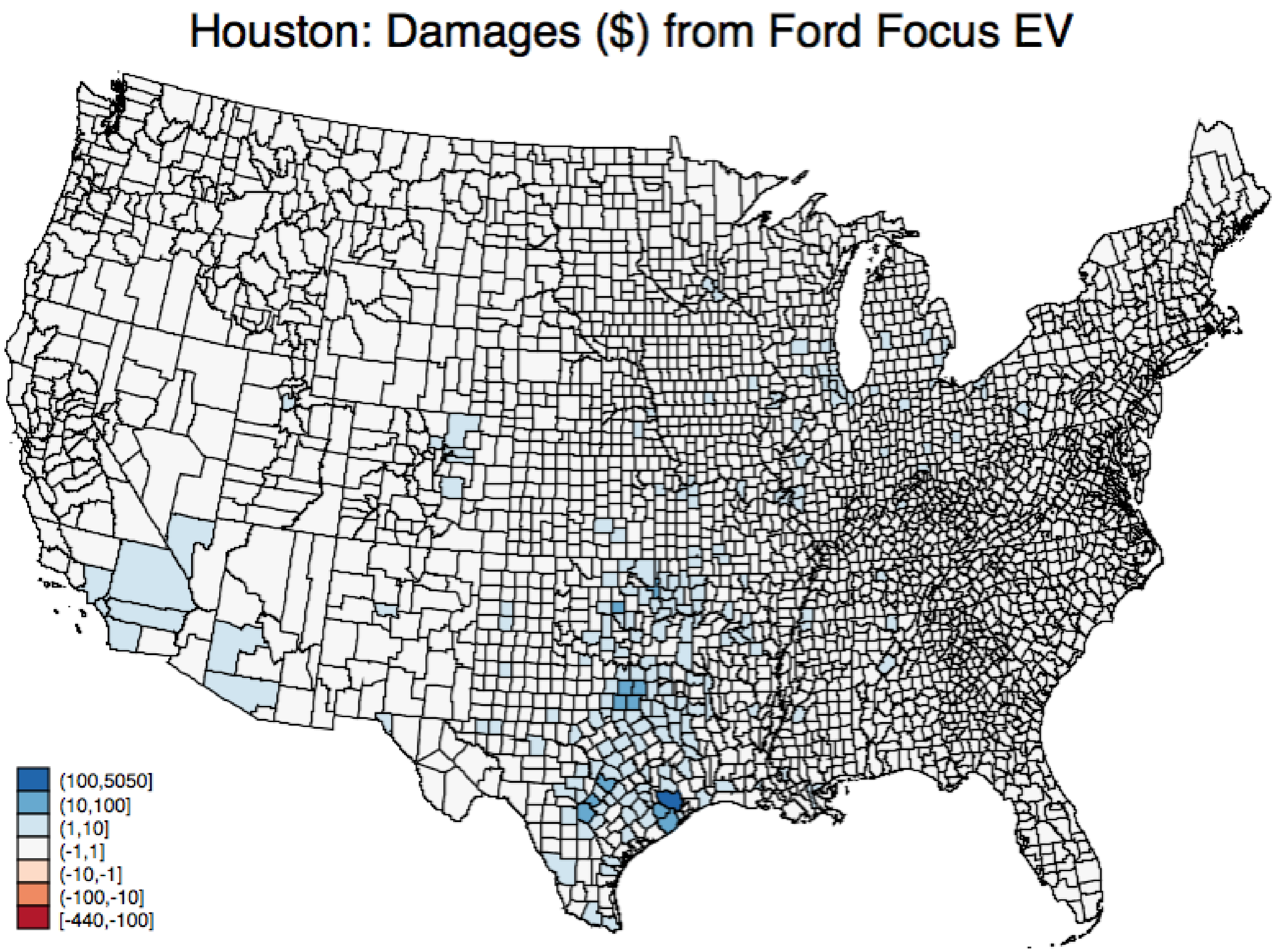
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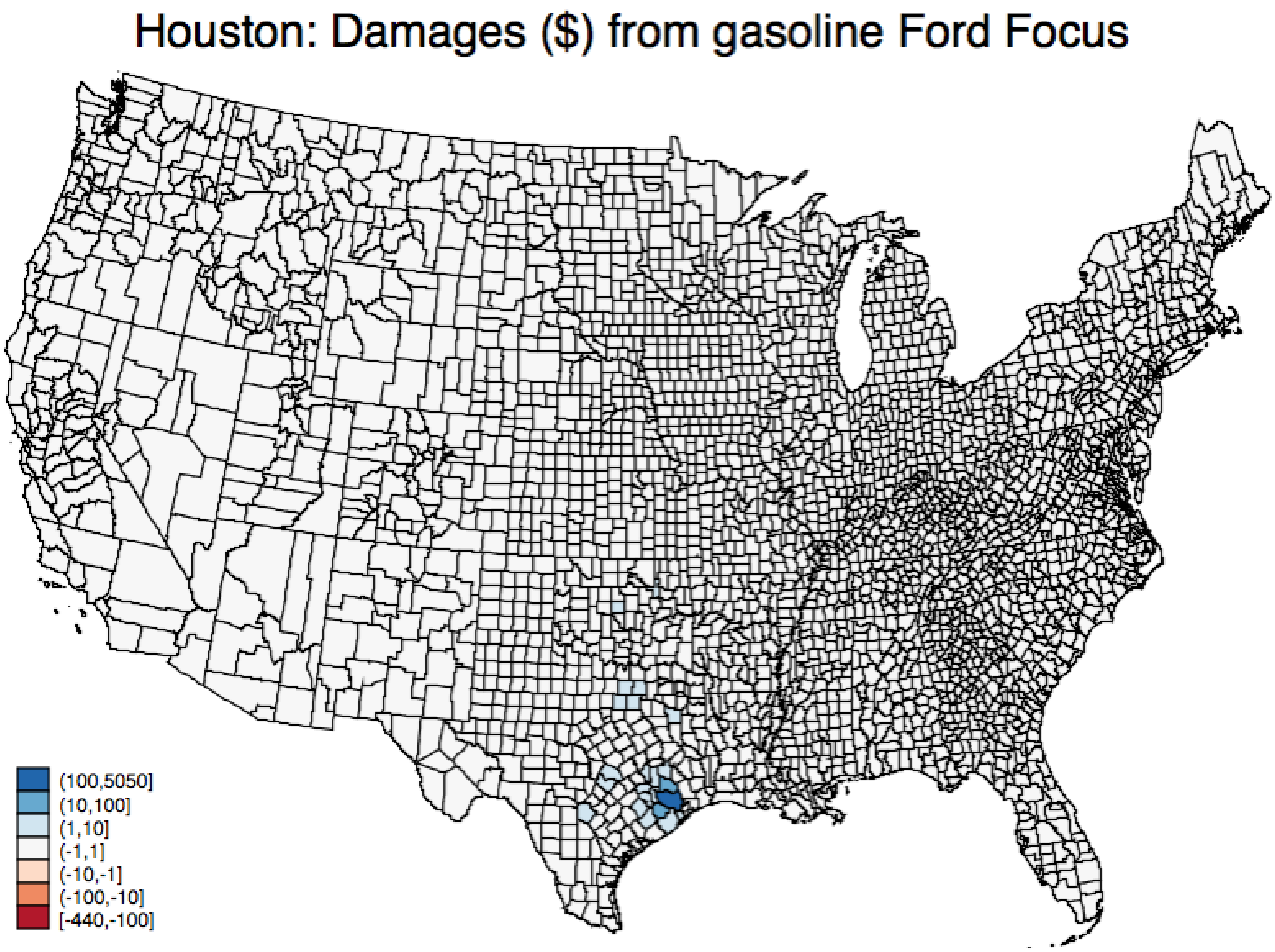
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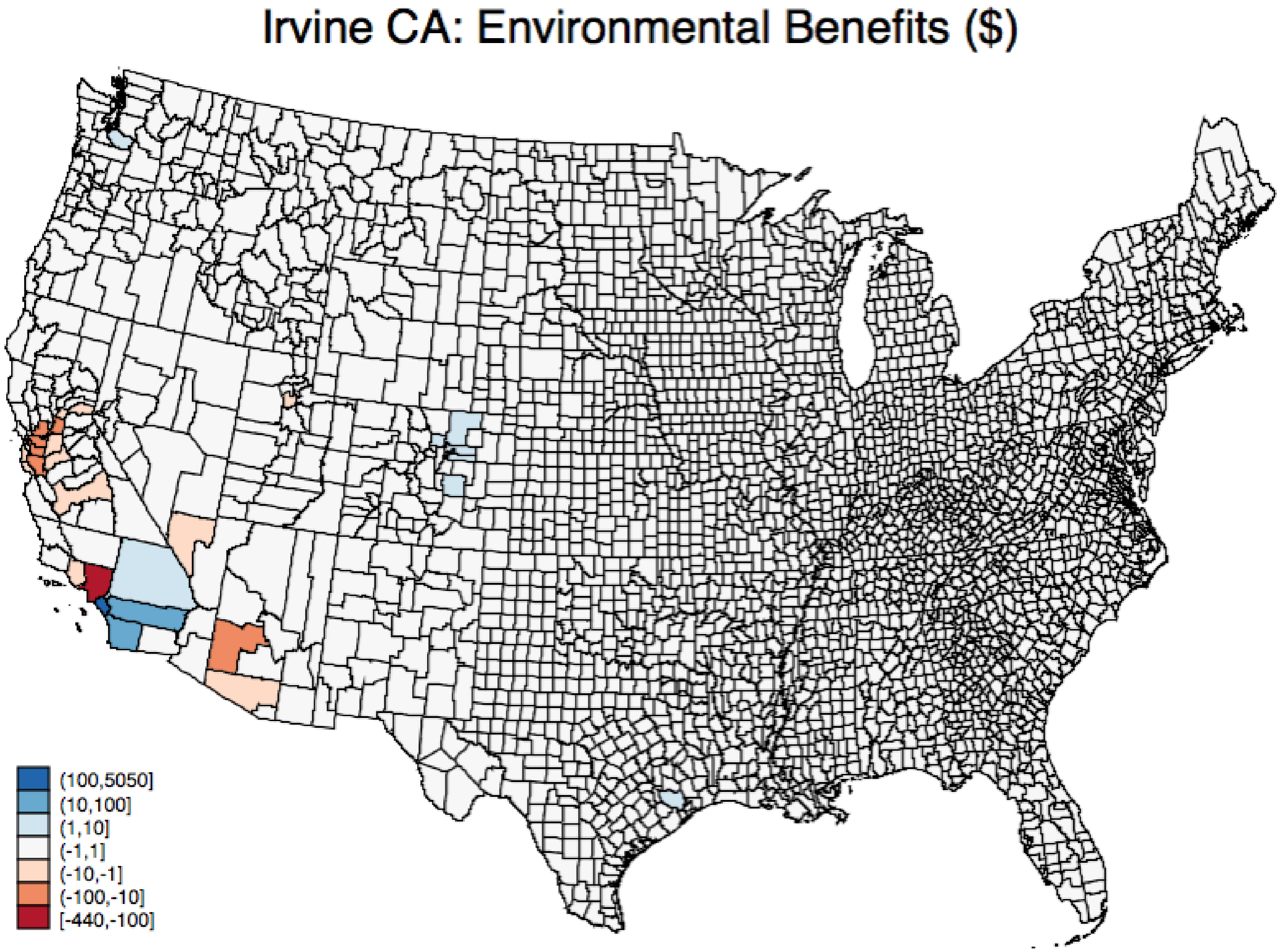
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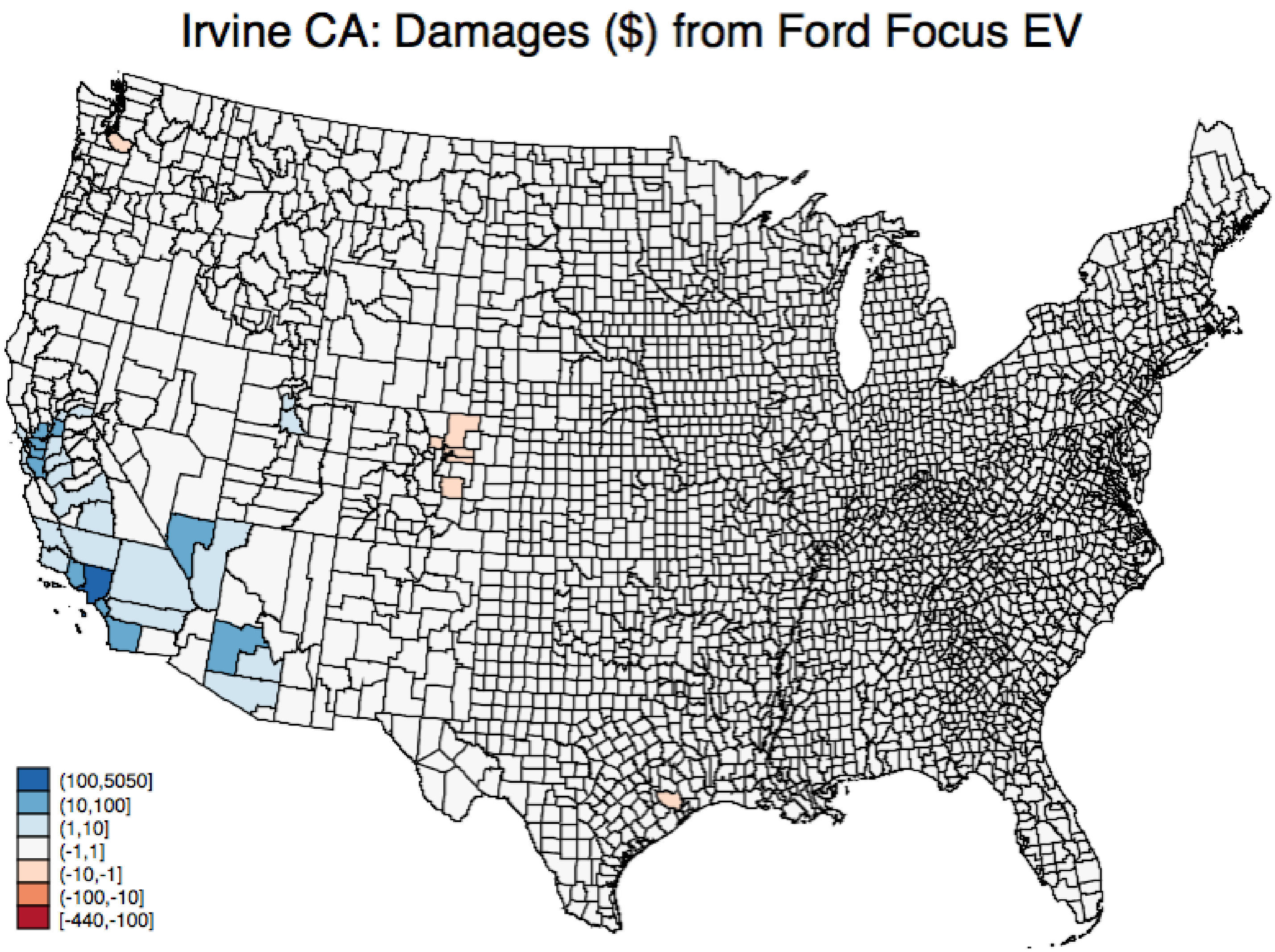
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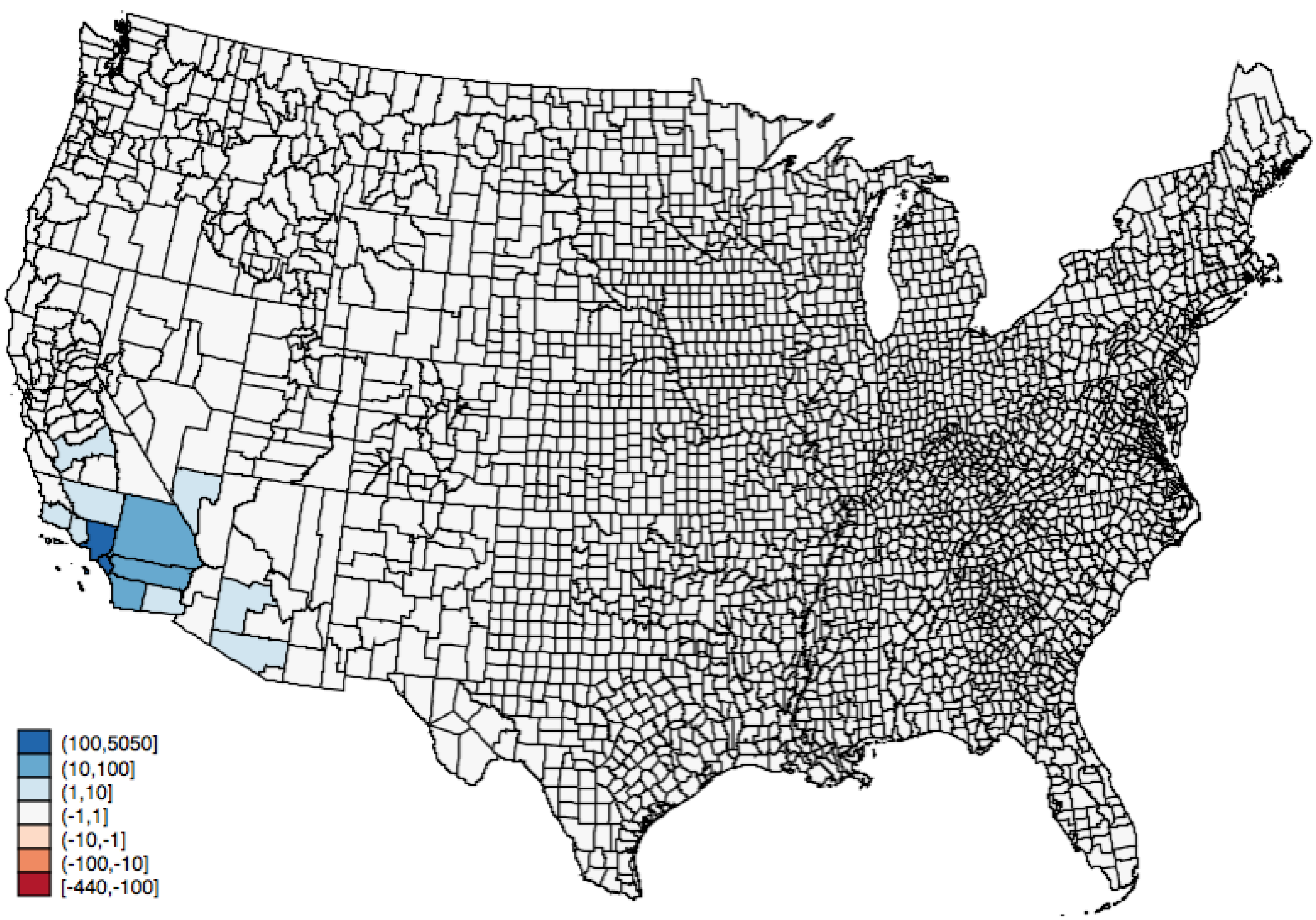

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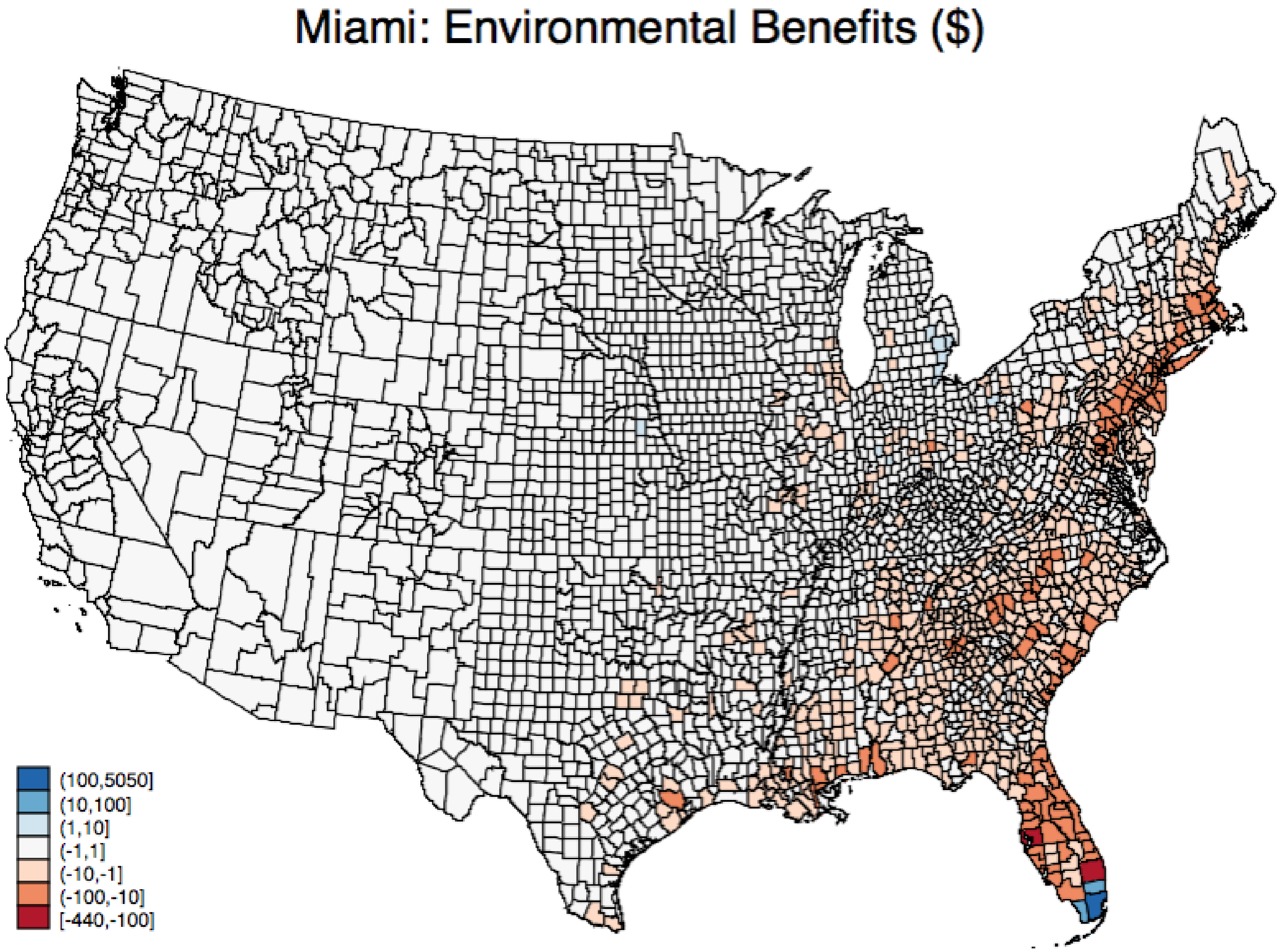
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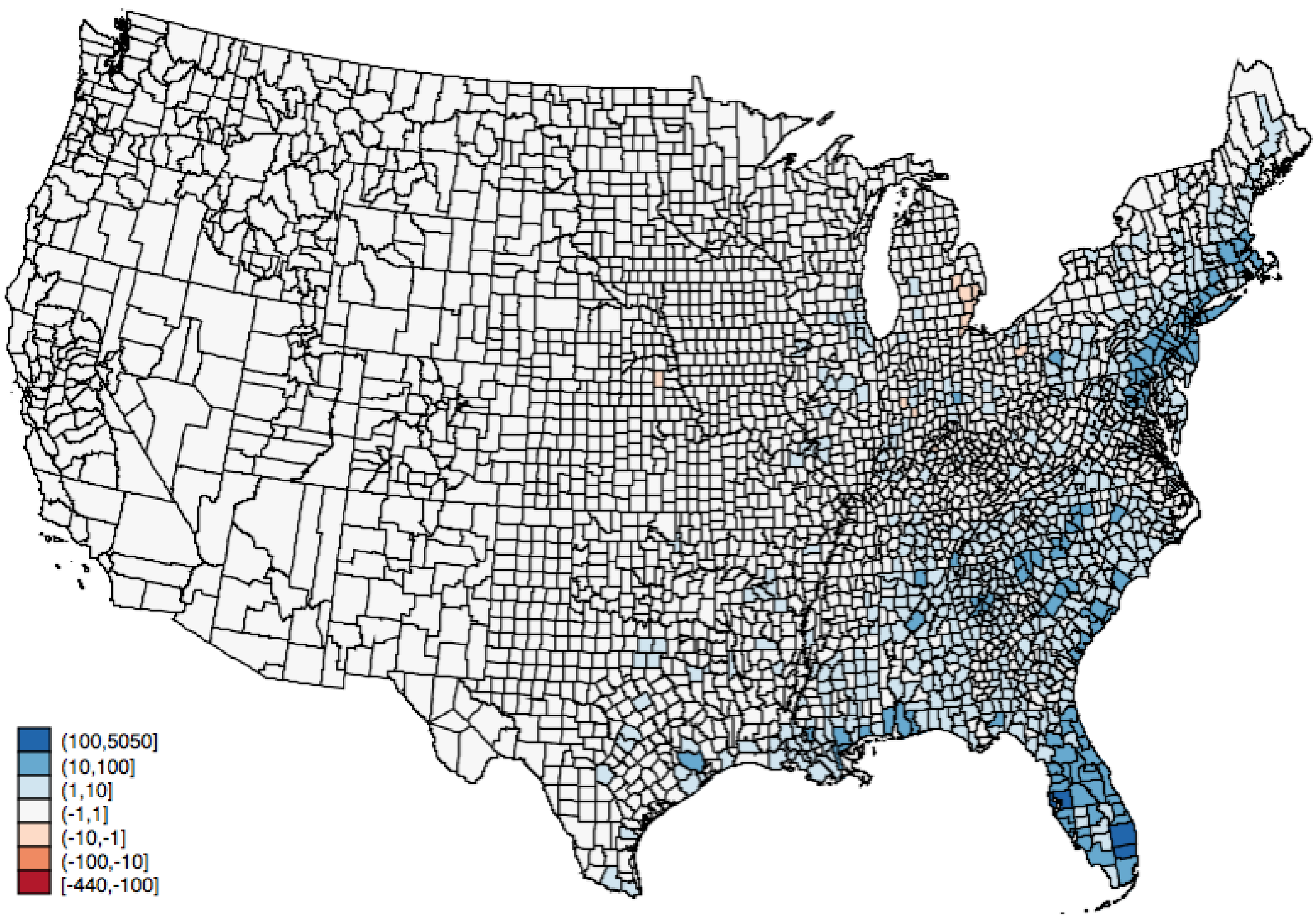

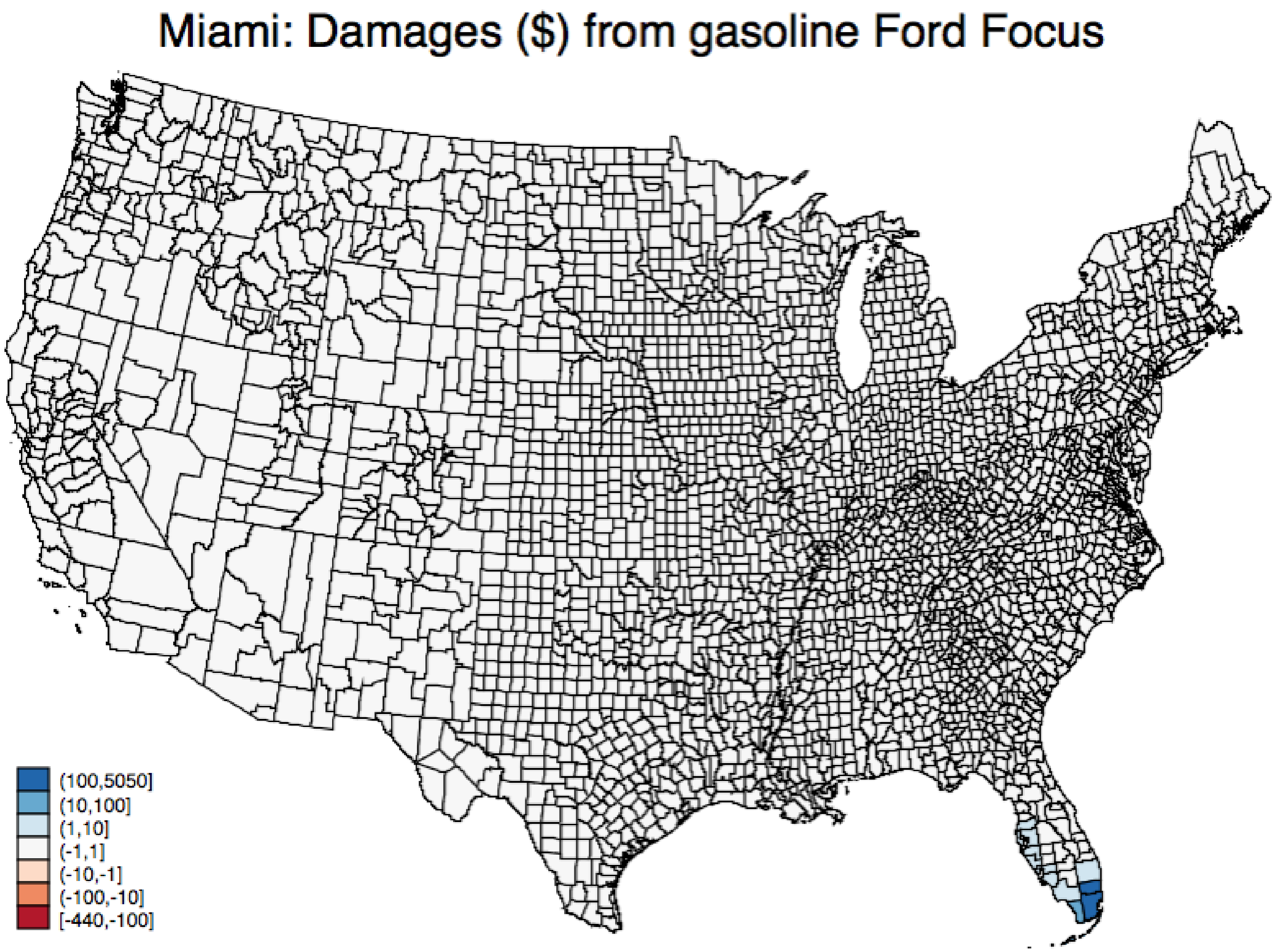
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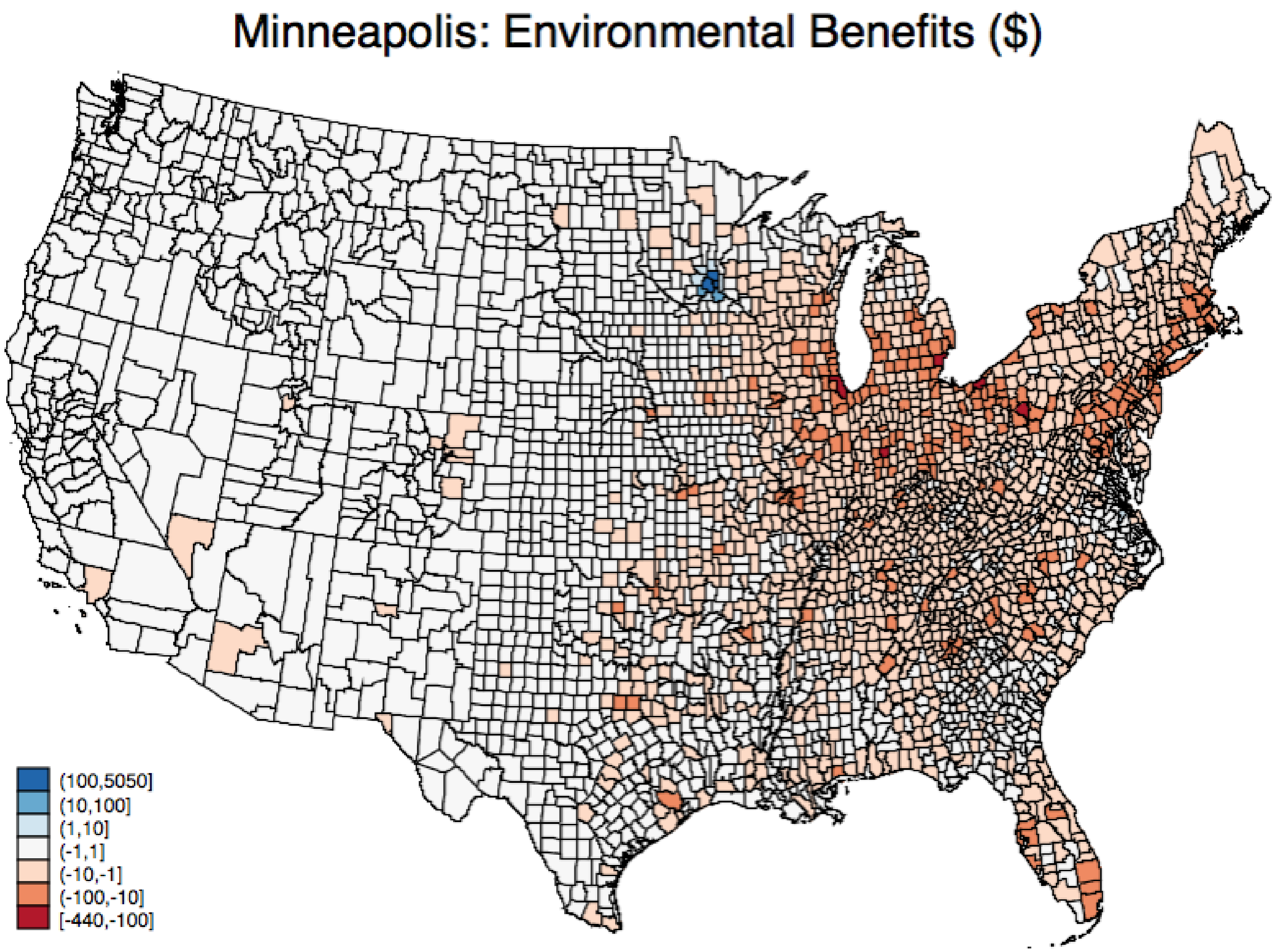

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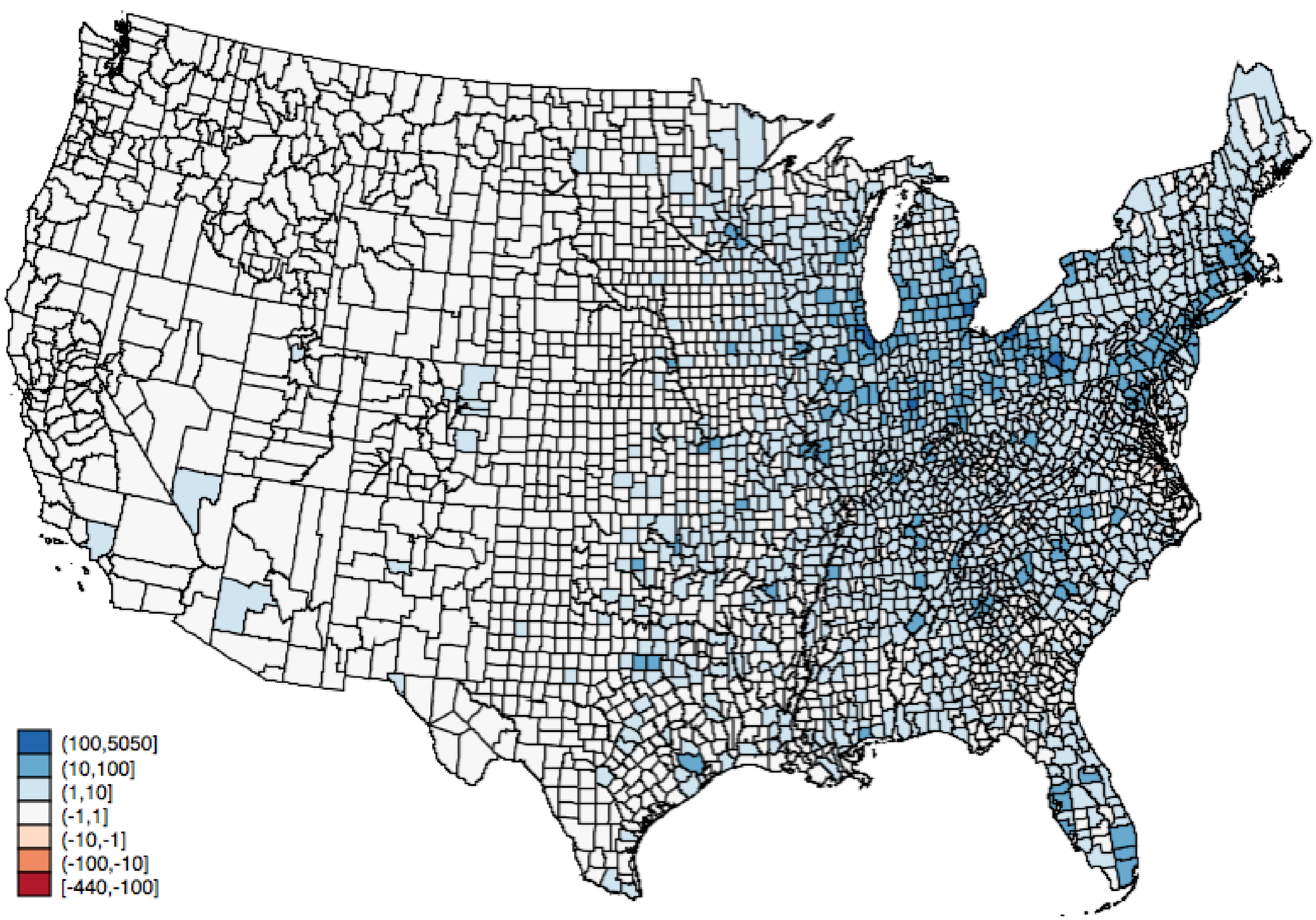

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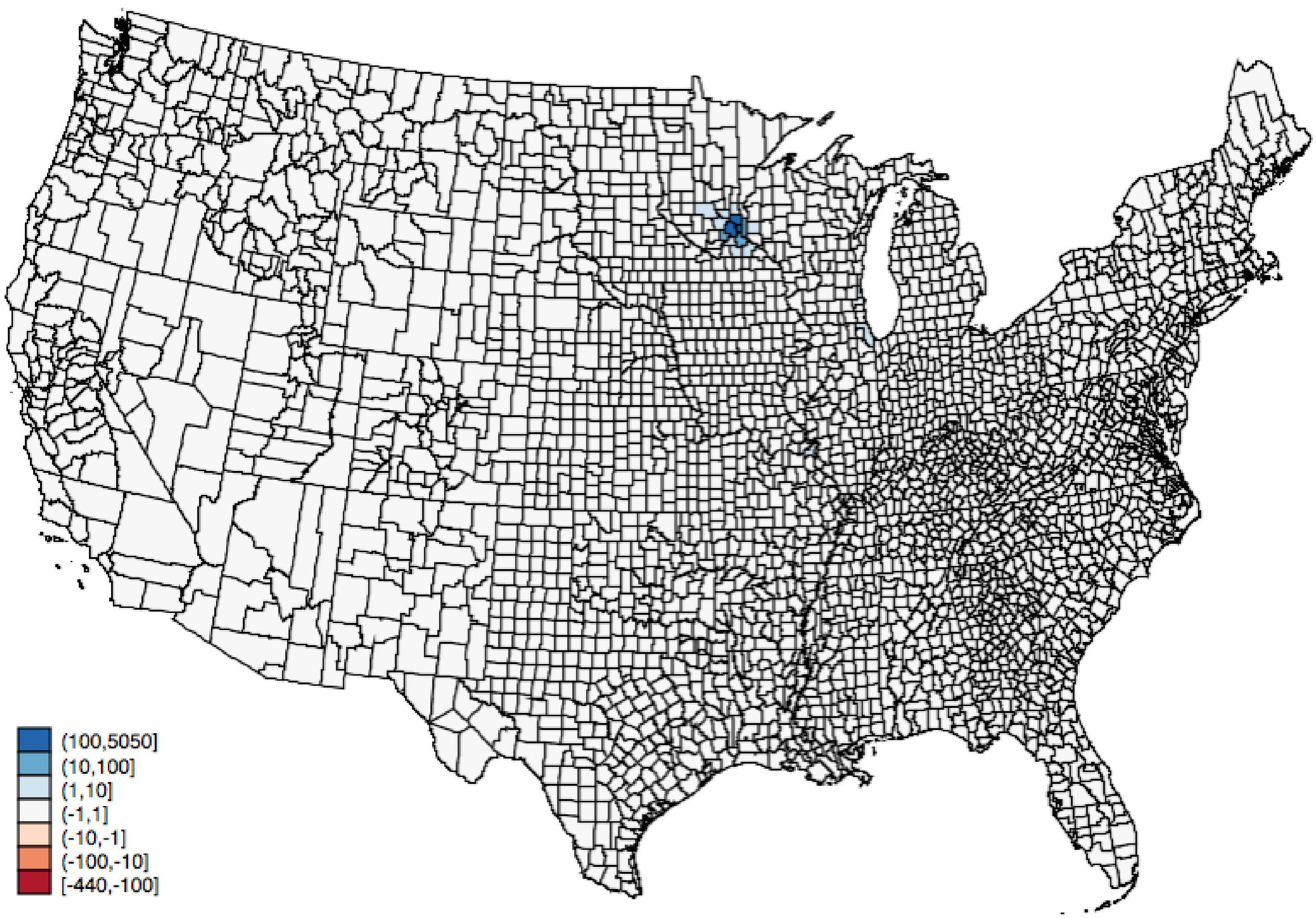

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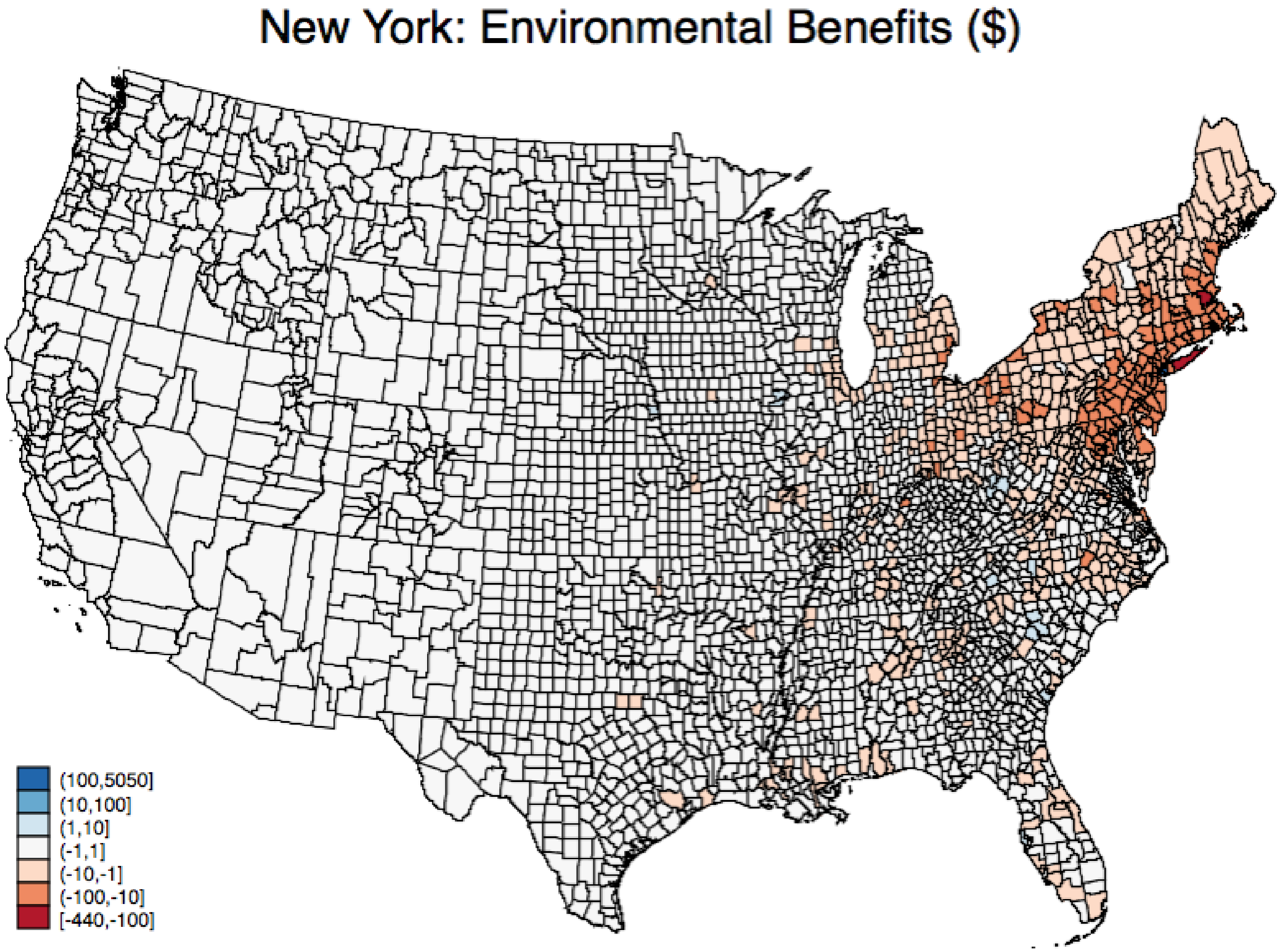
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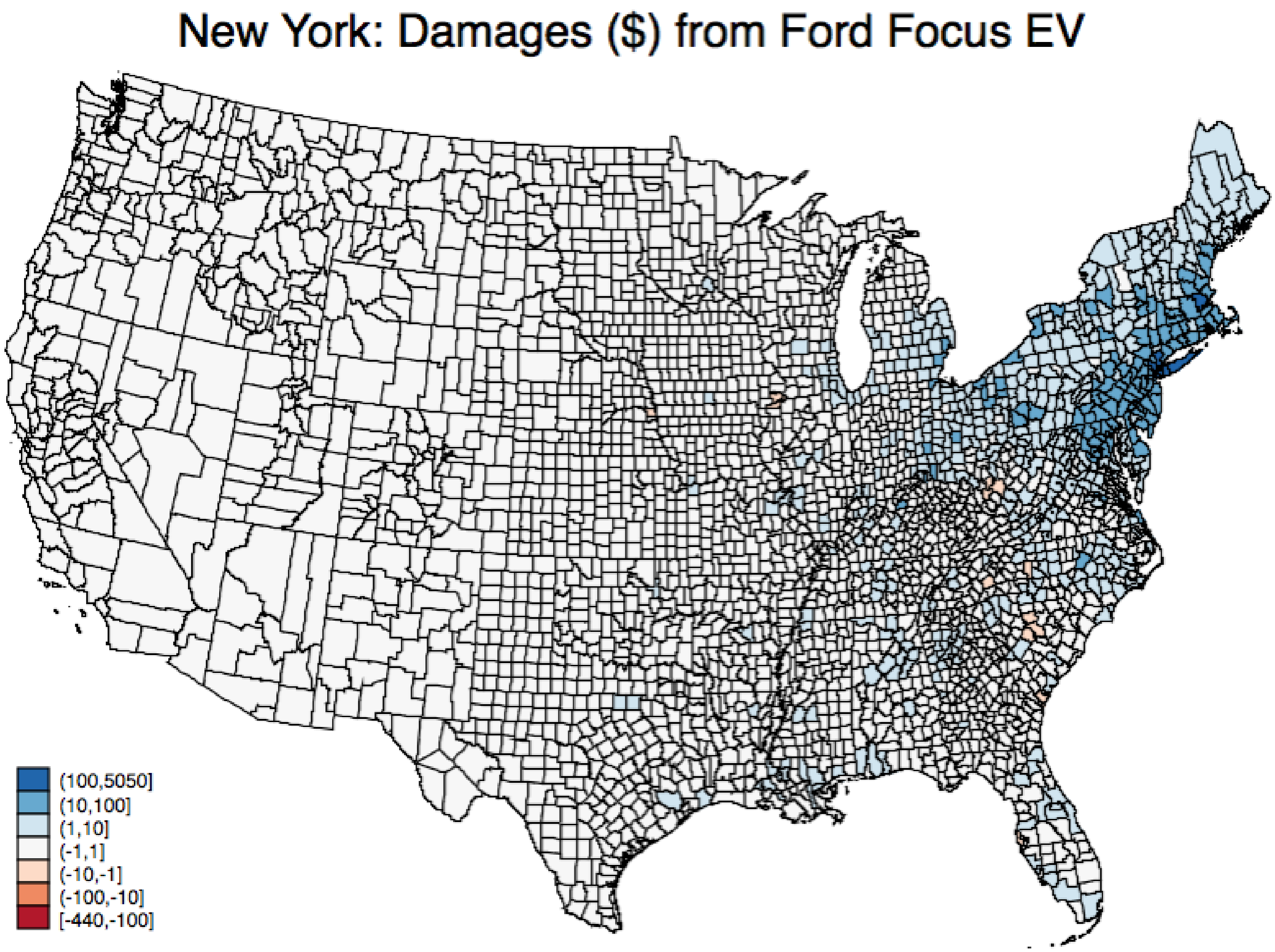
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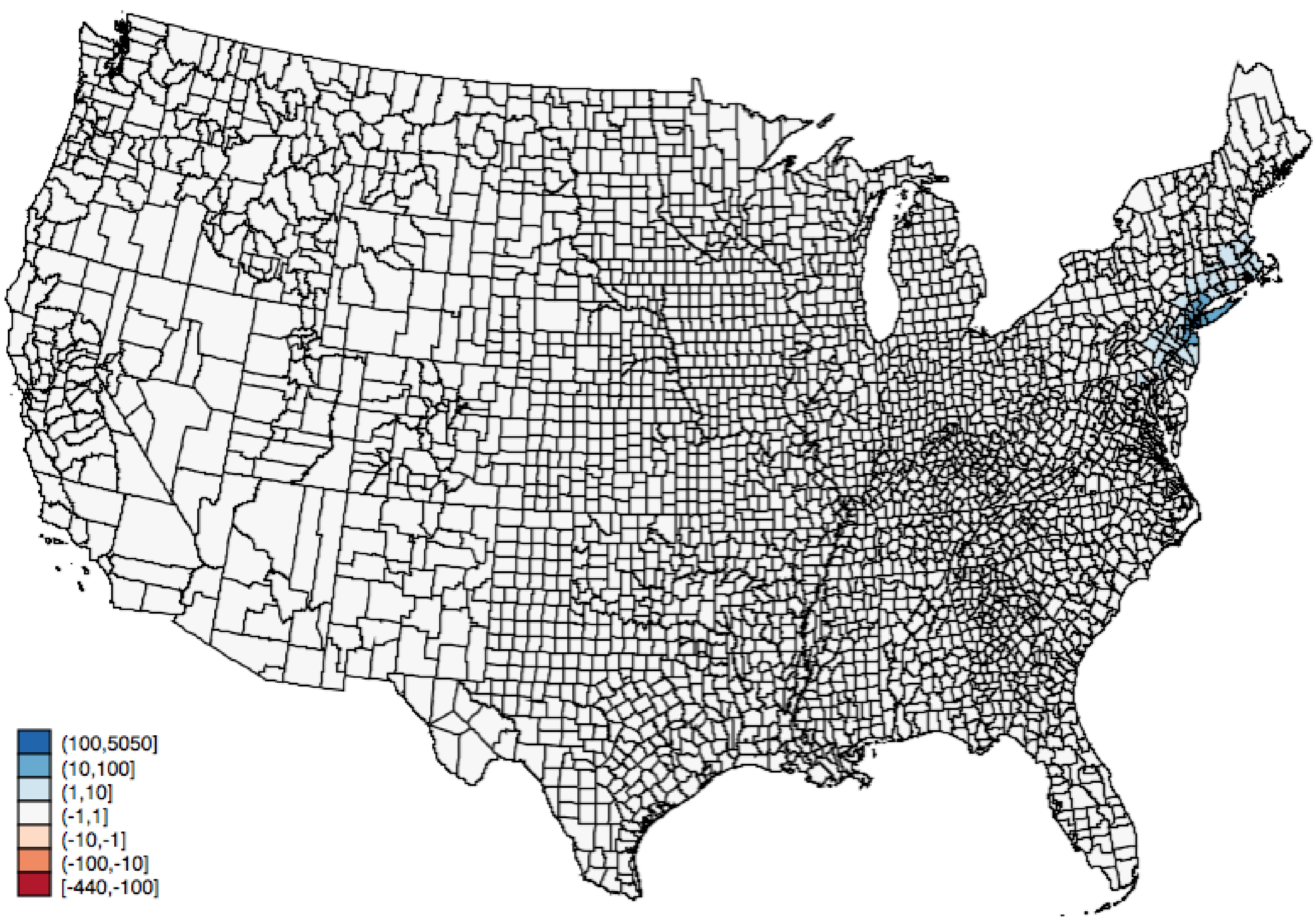

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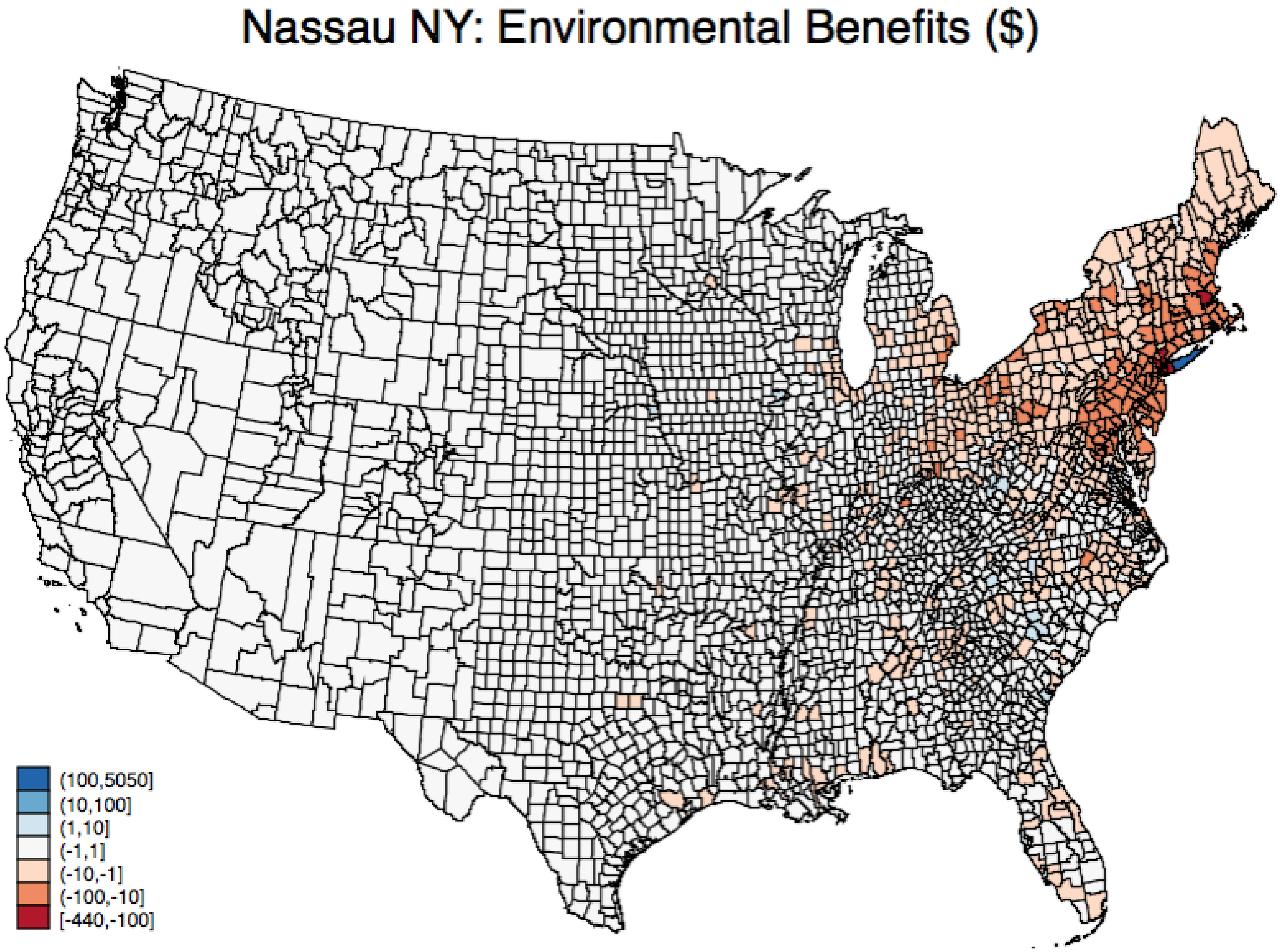
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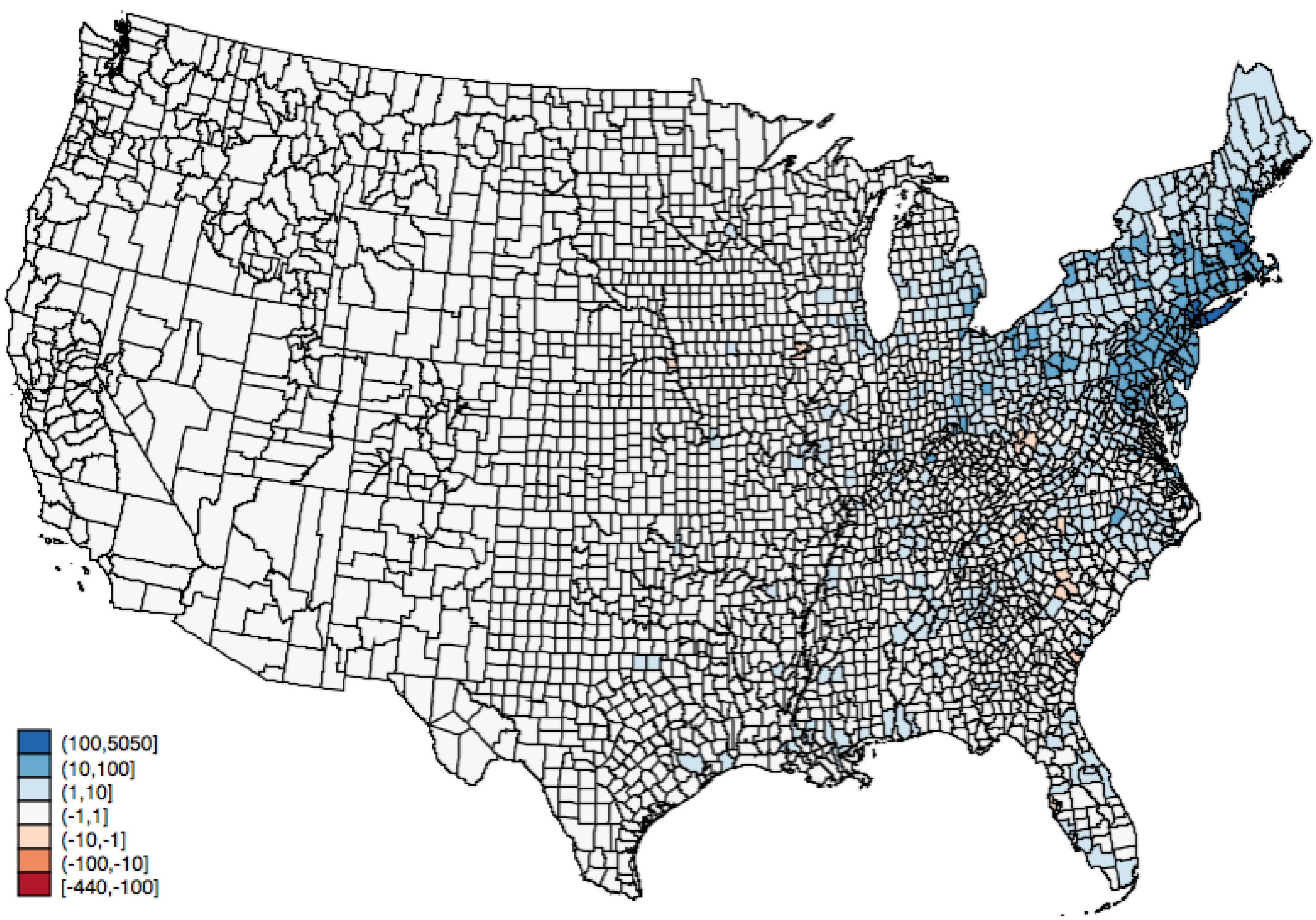

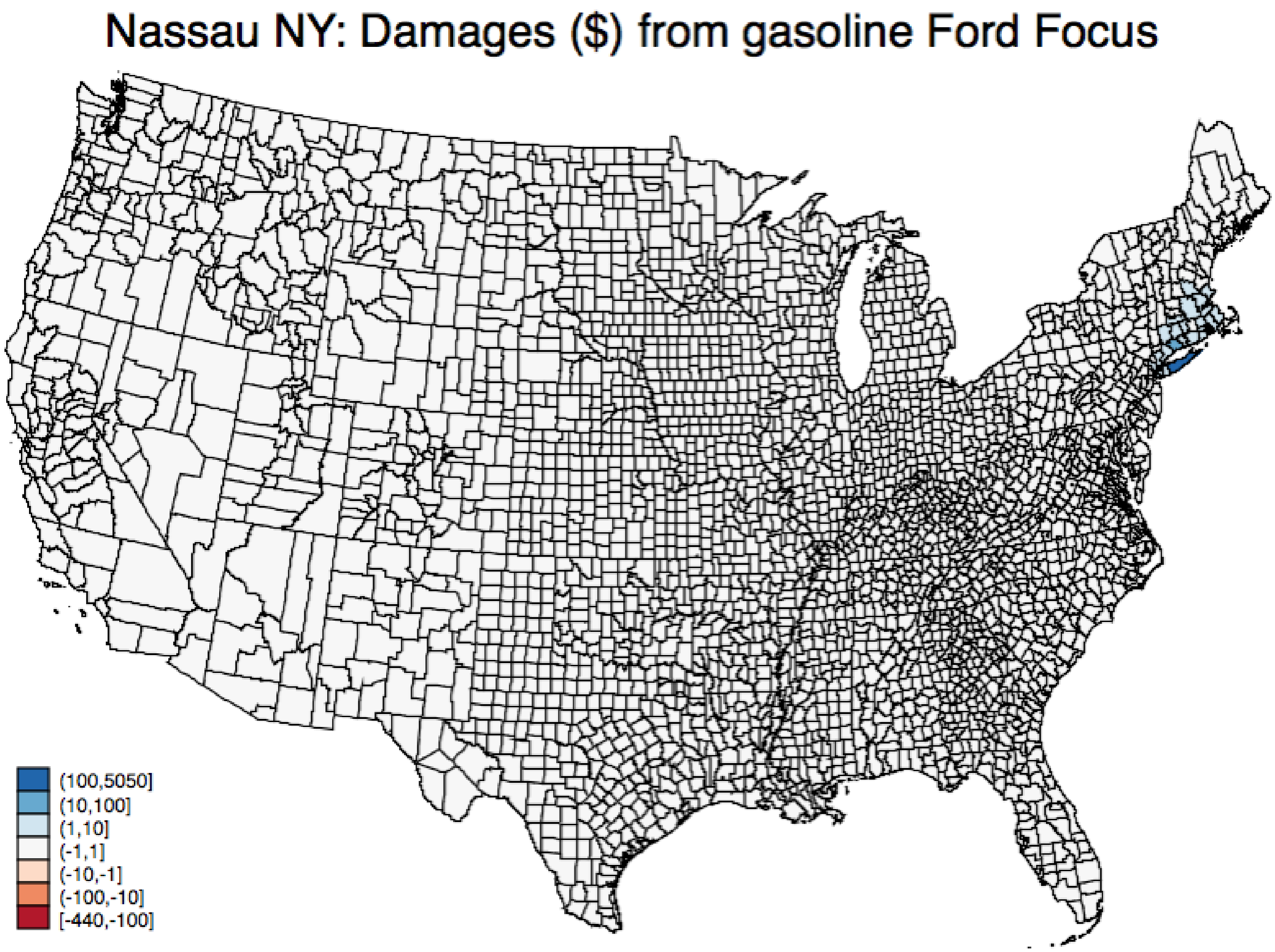
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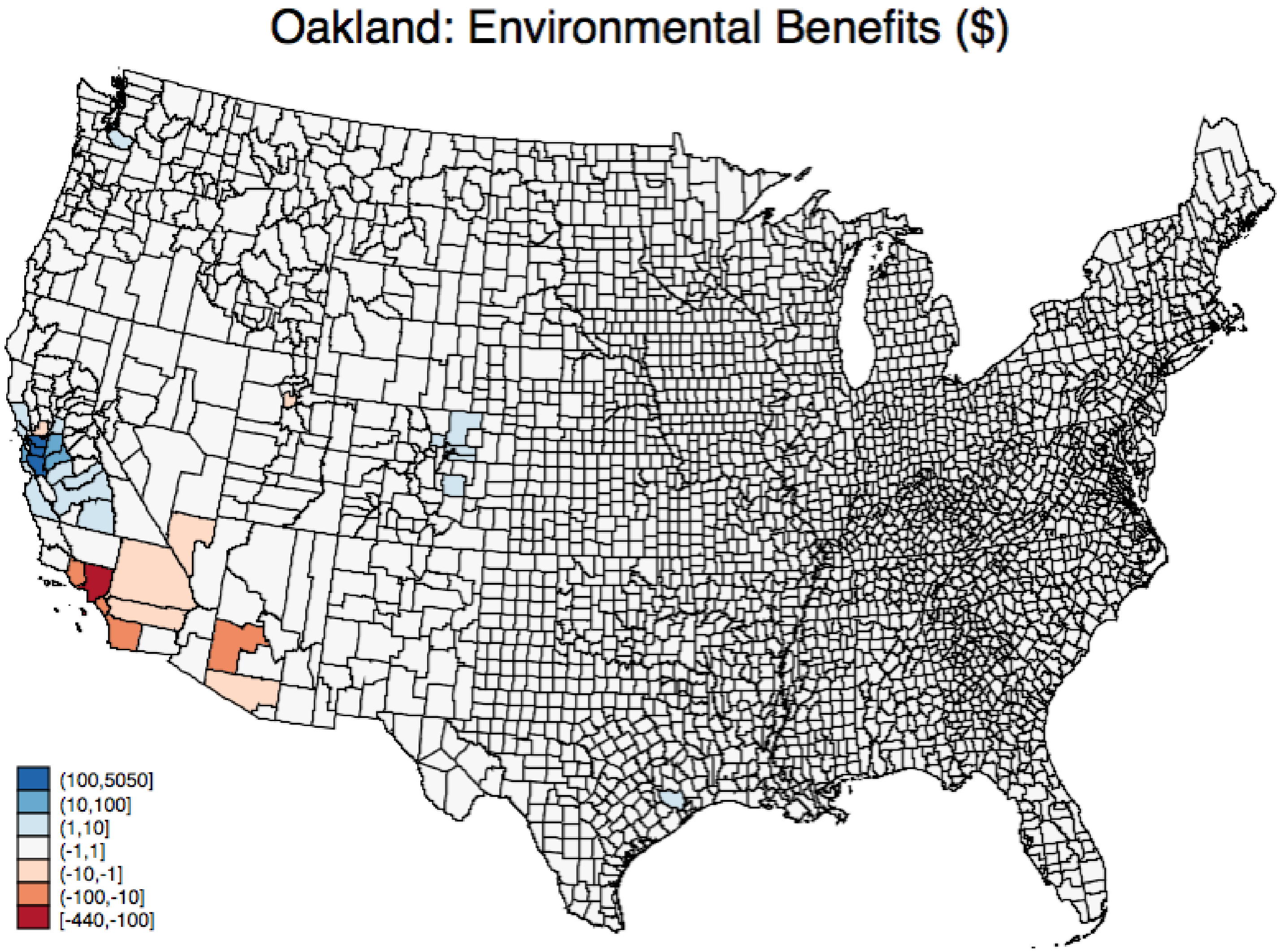
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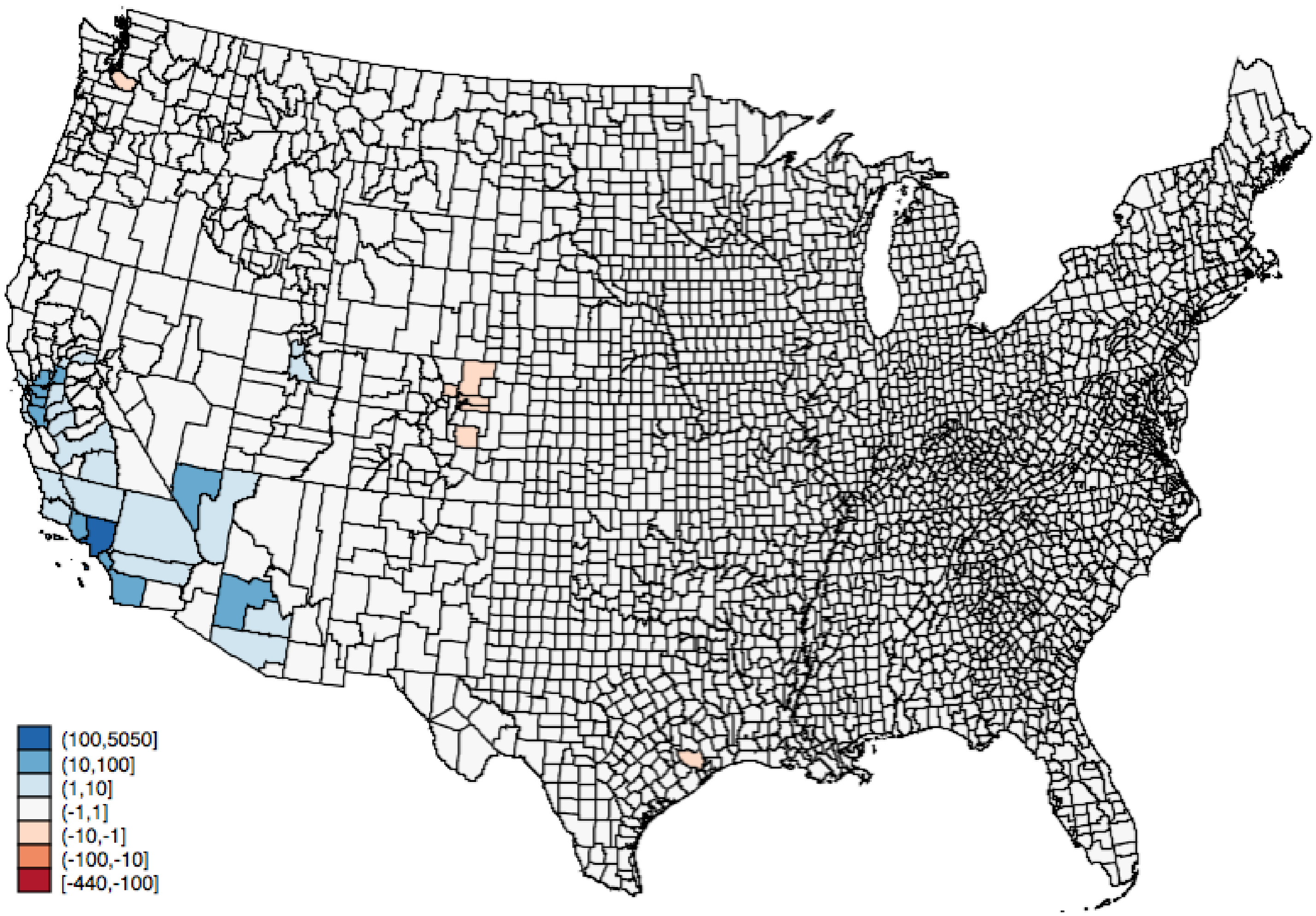

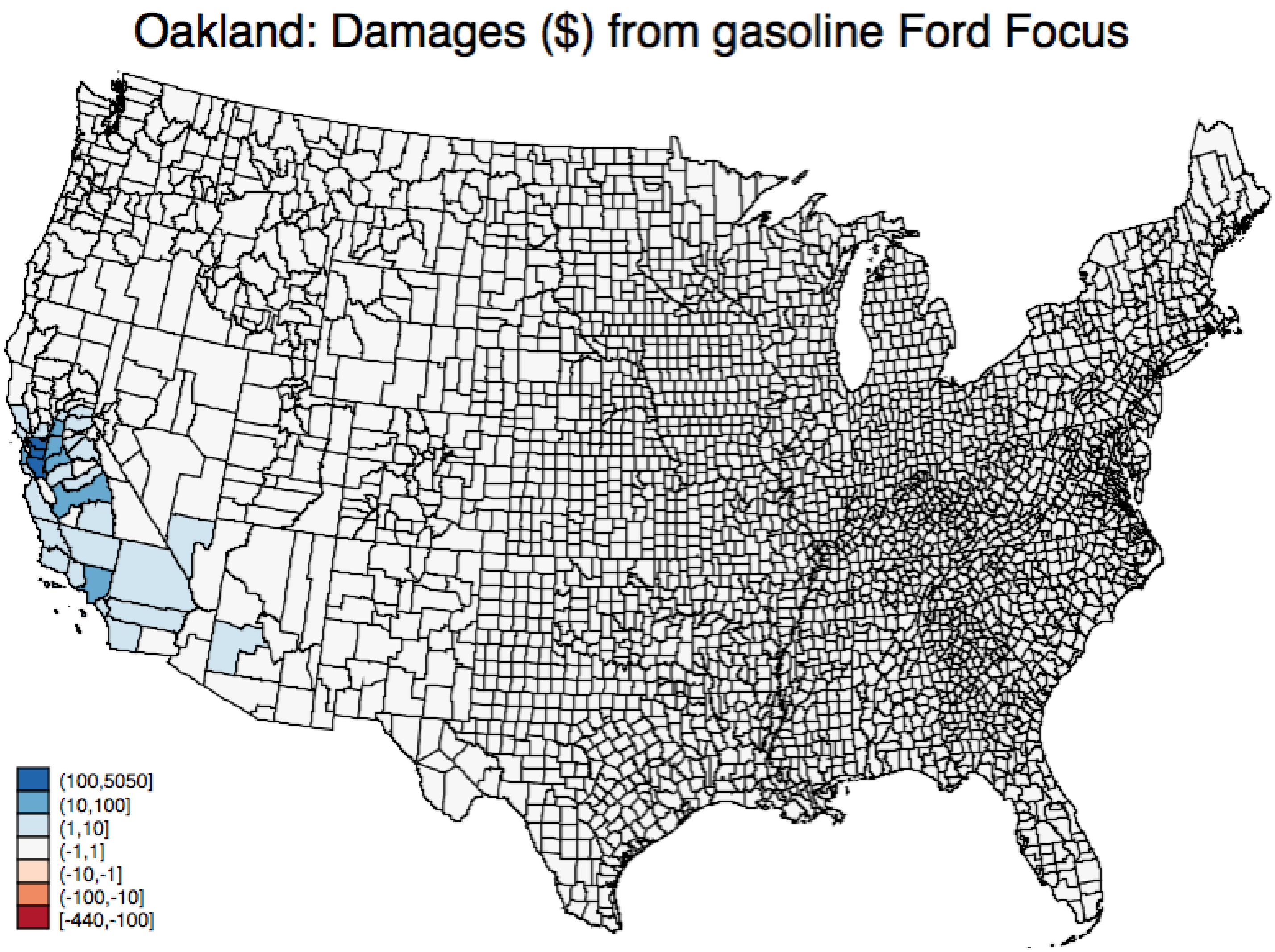
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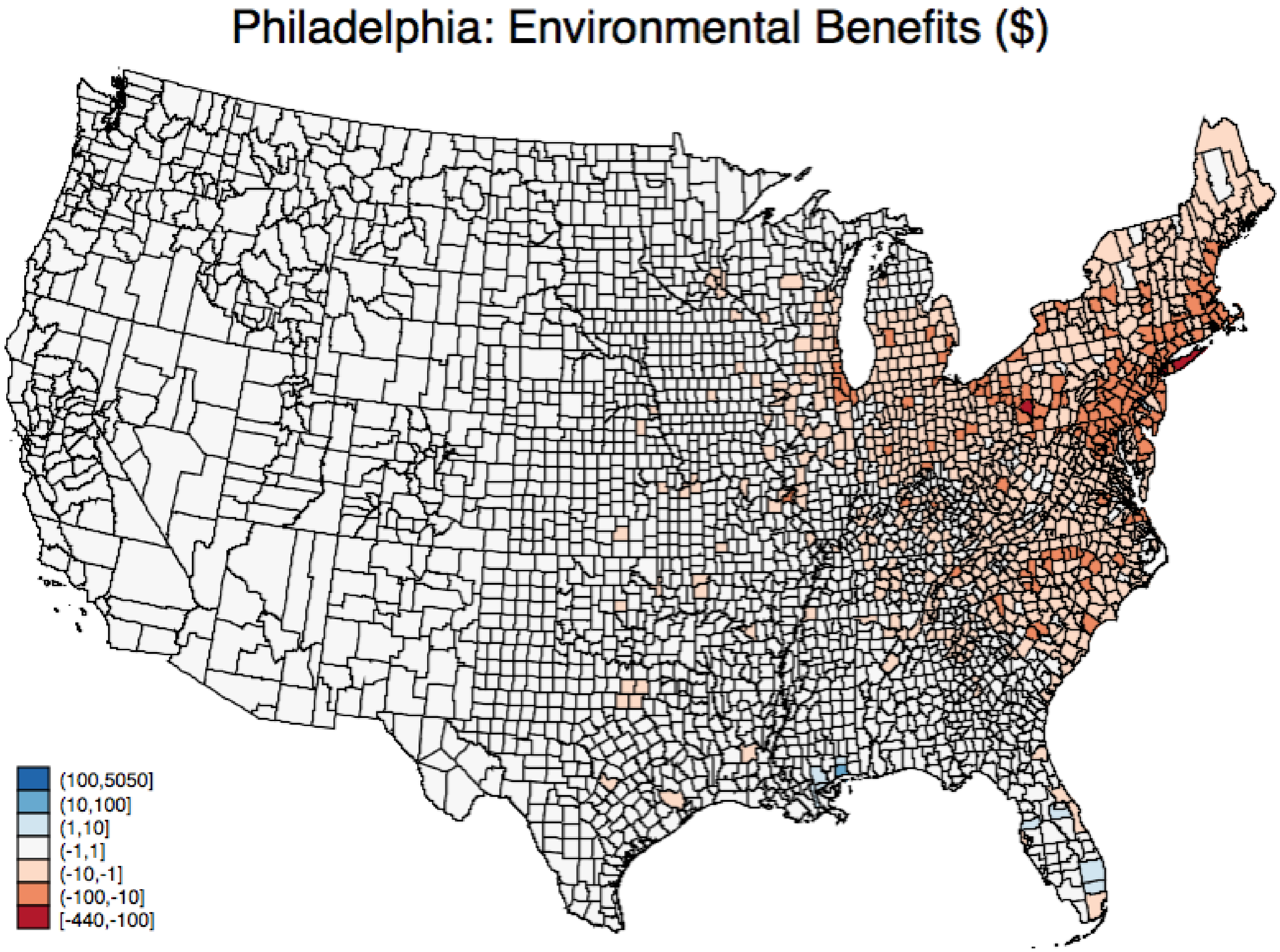

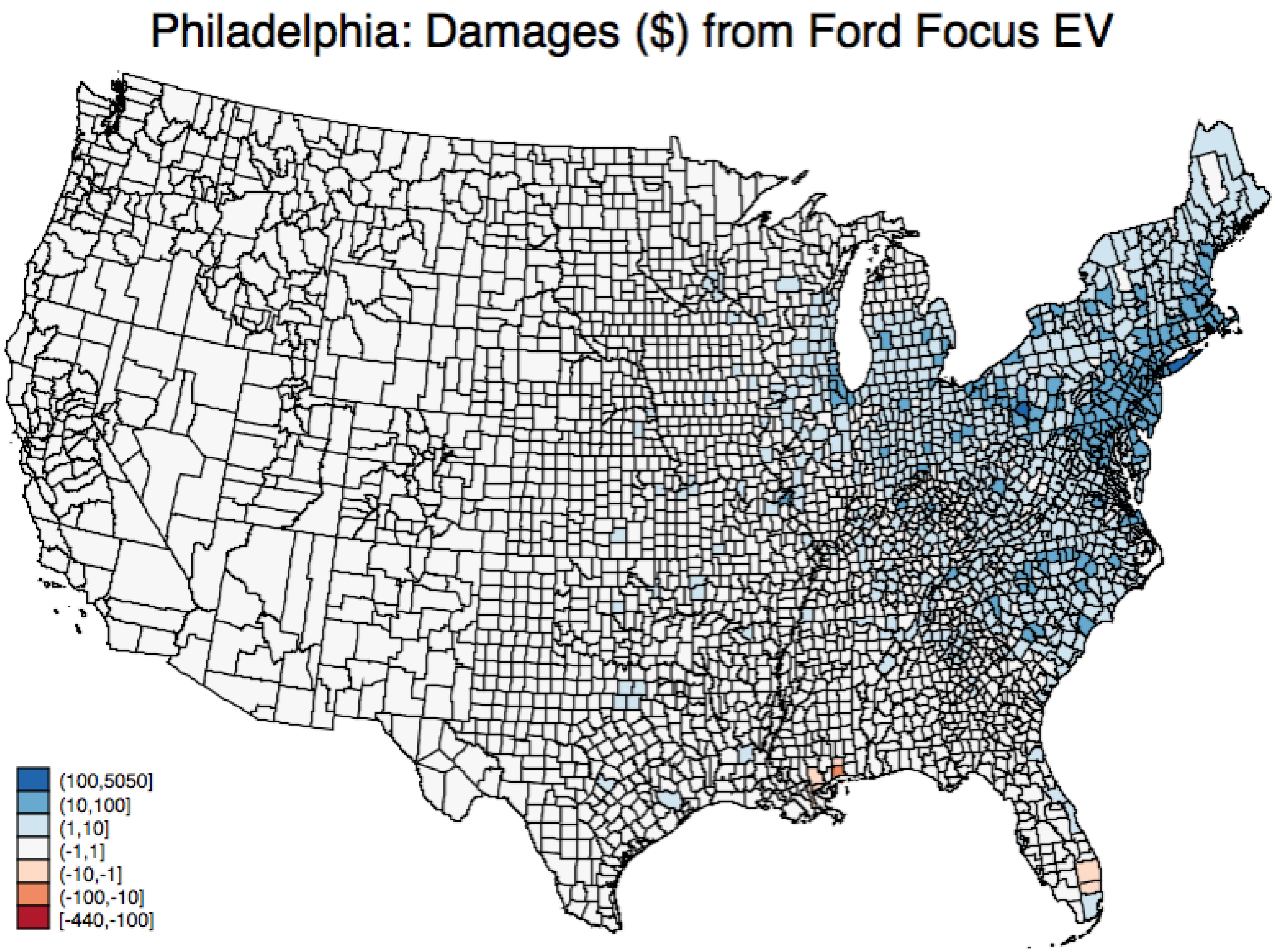
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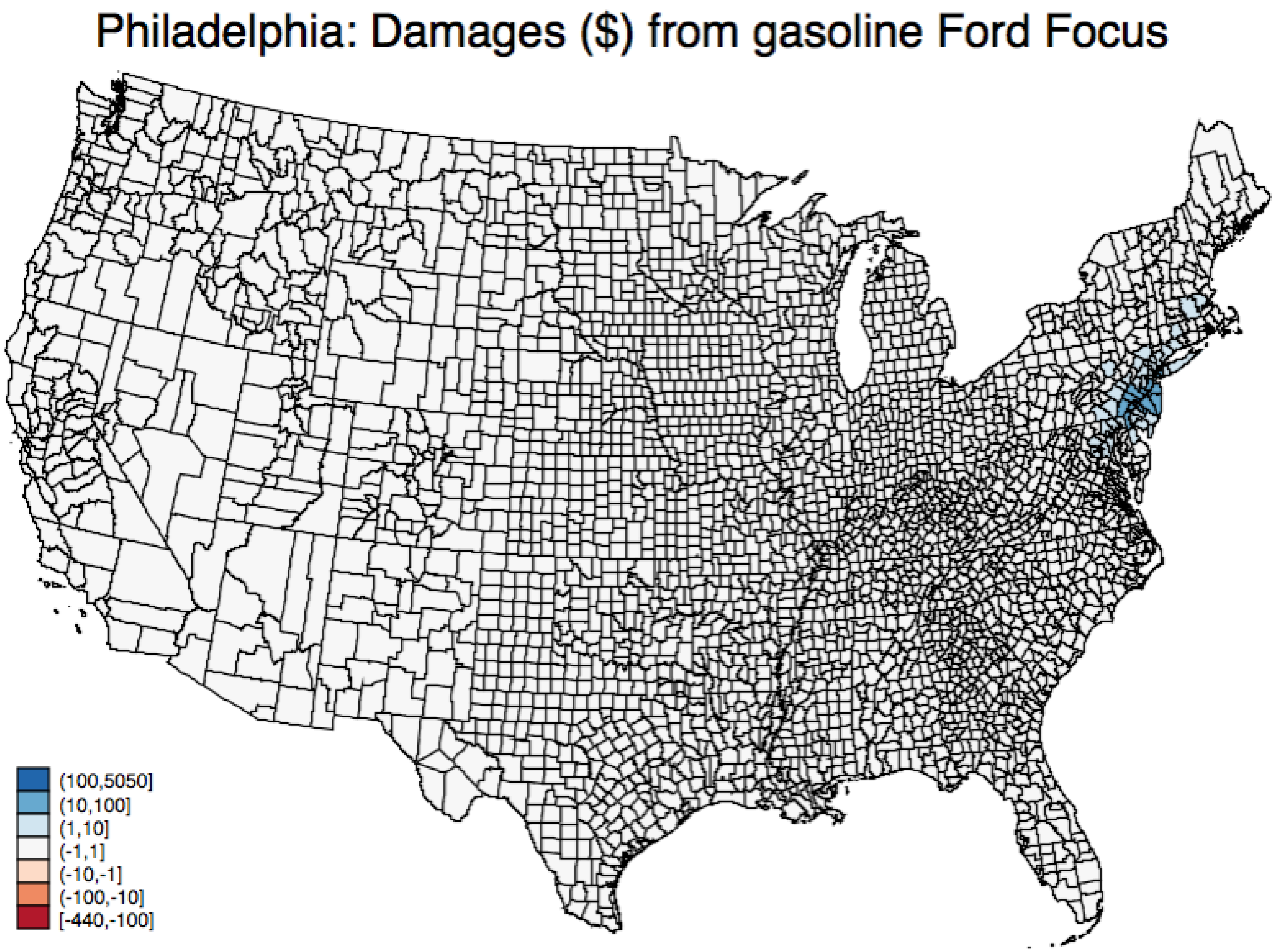
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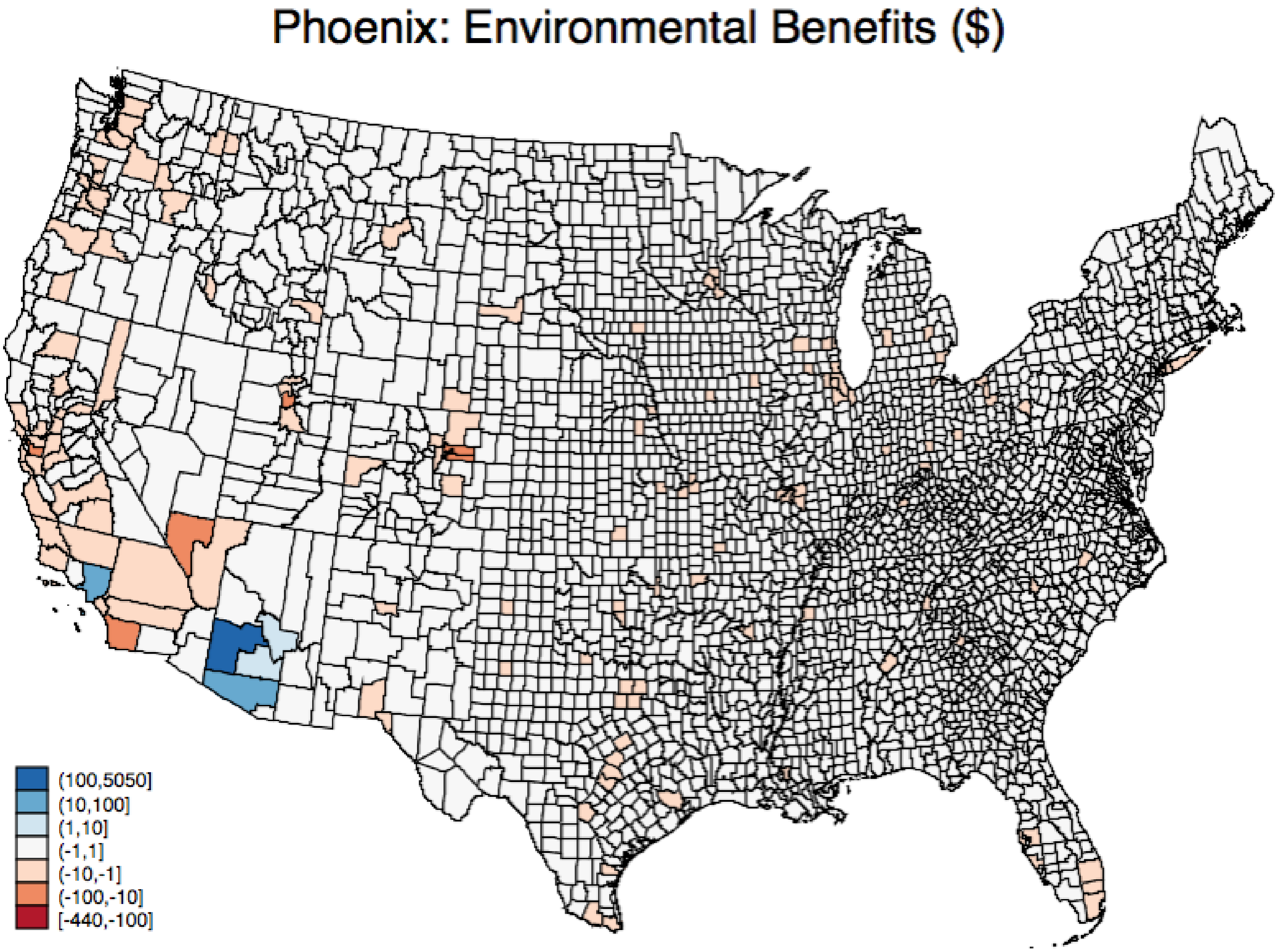
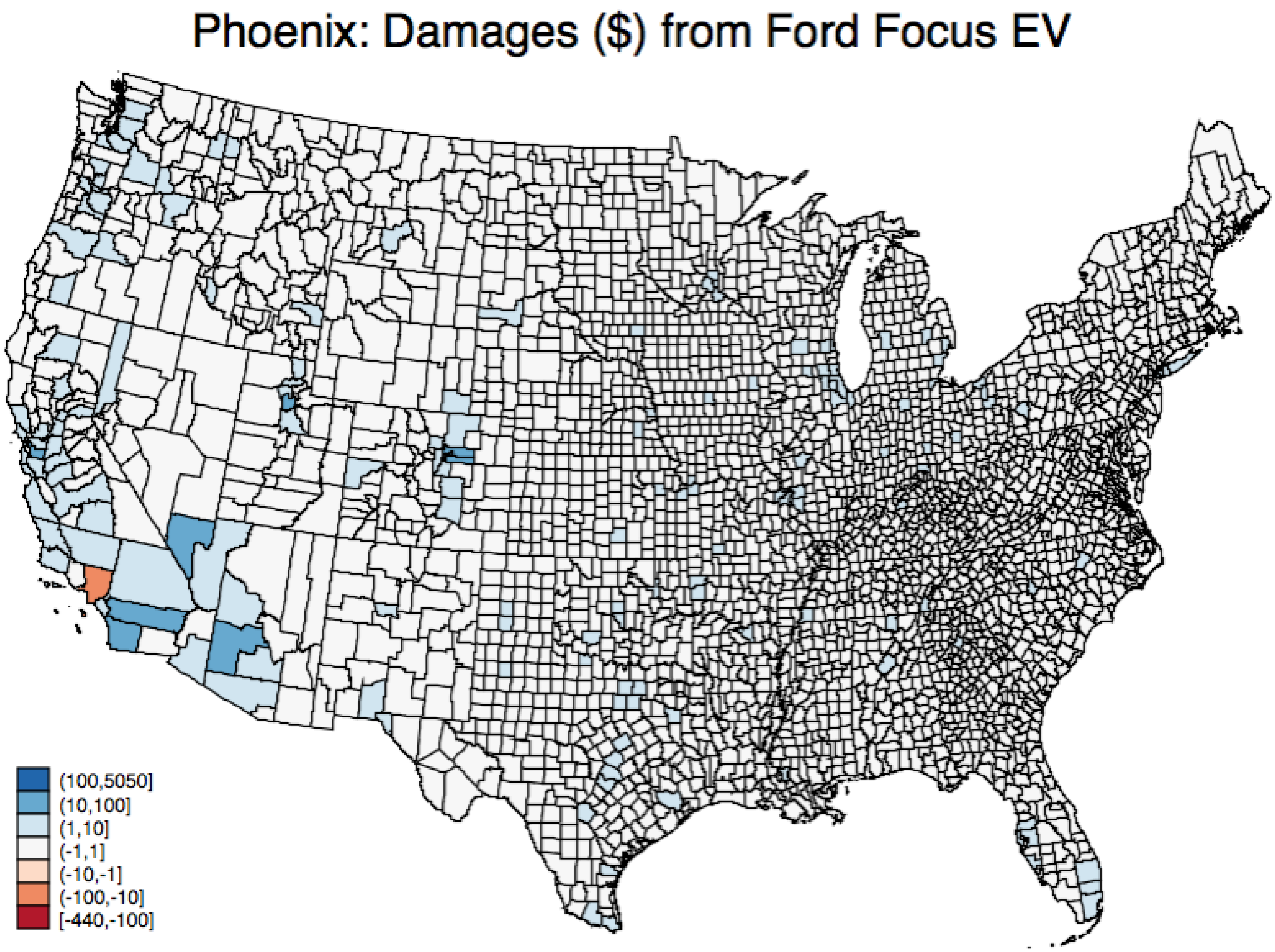
15 Phoenix



Phoenix: Environmental Benefits ($)
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
[-440,-100]


Phoenix: Damages ($) from Ford Focus EV
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
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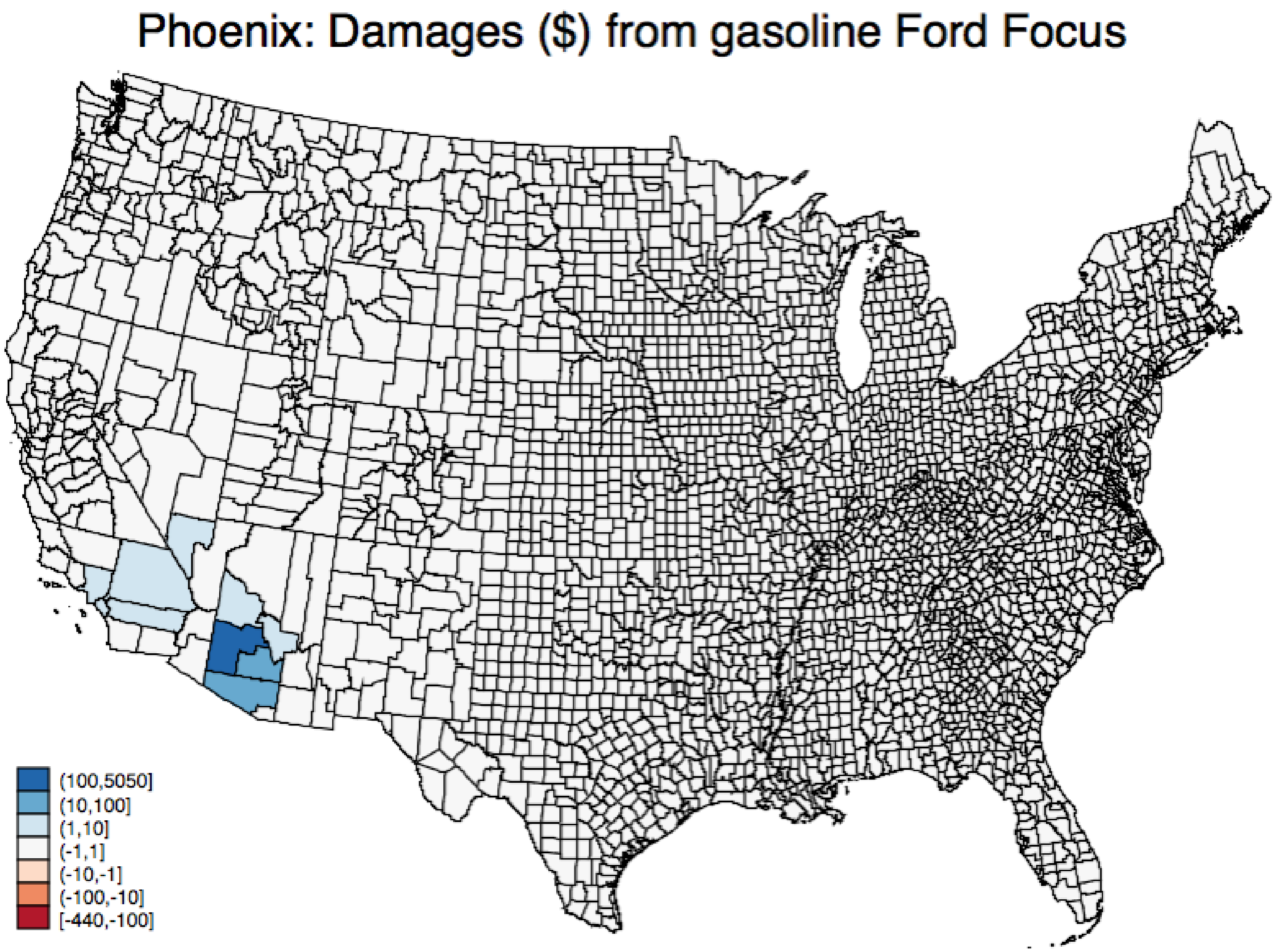
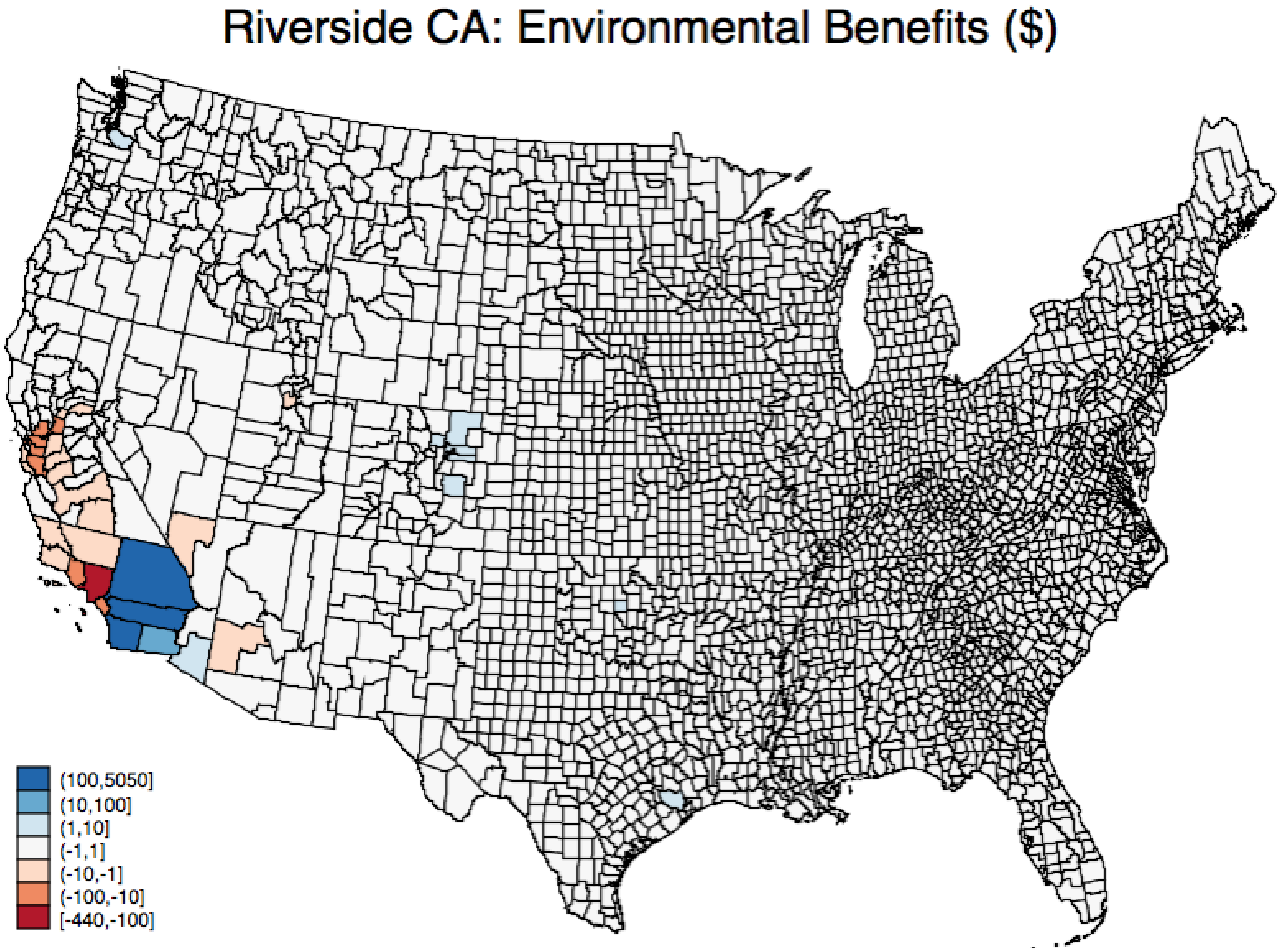
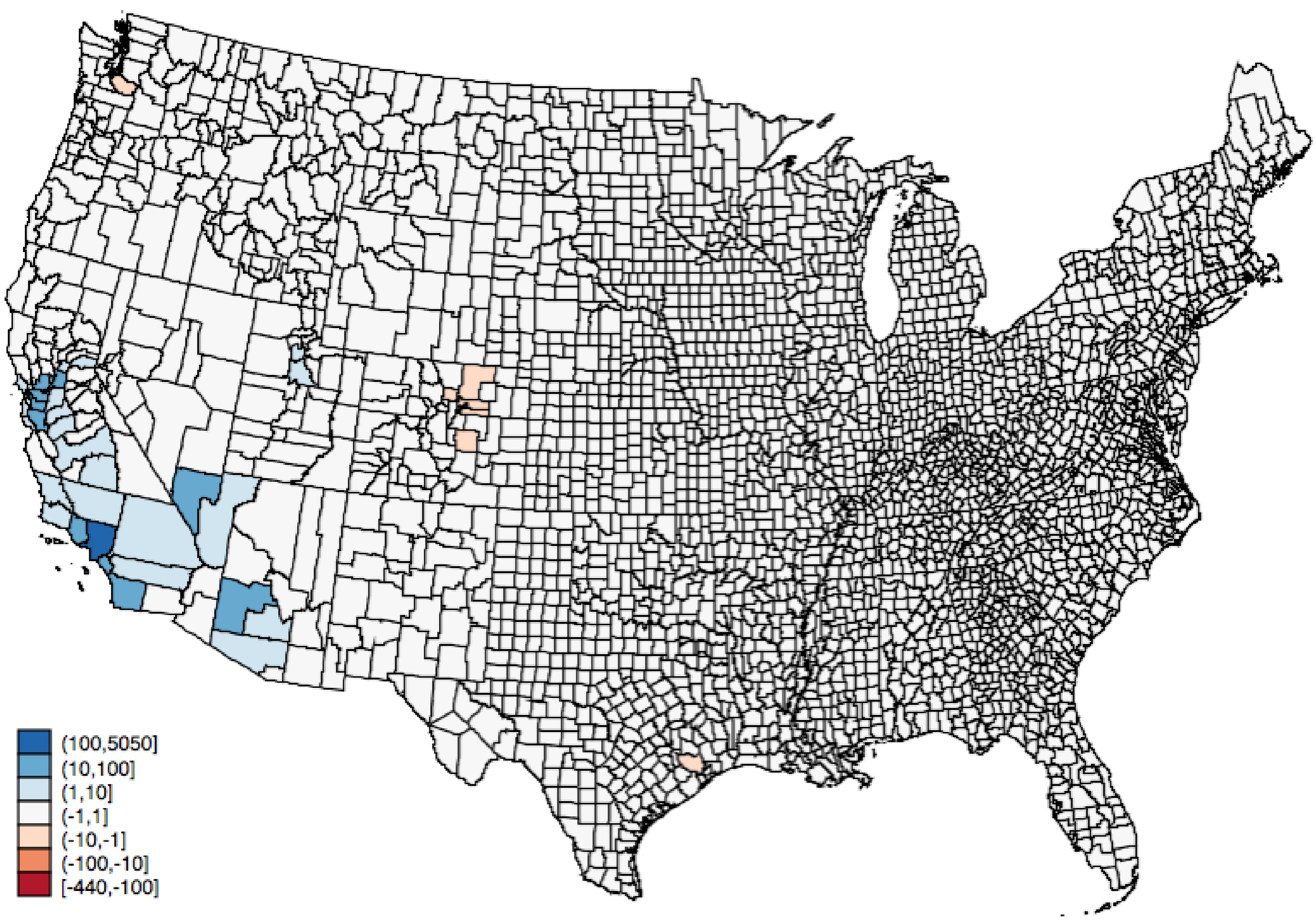
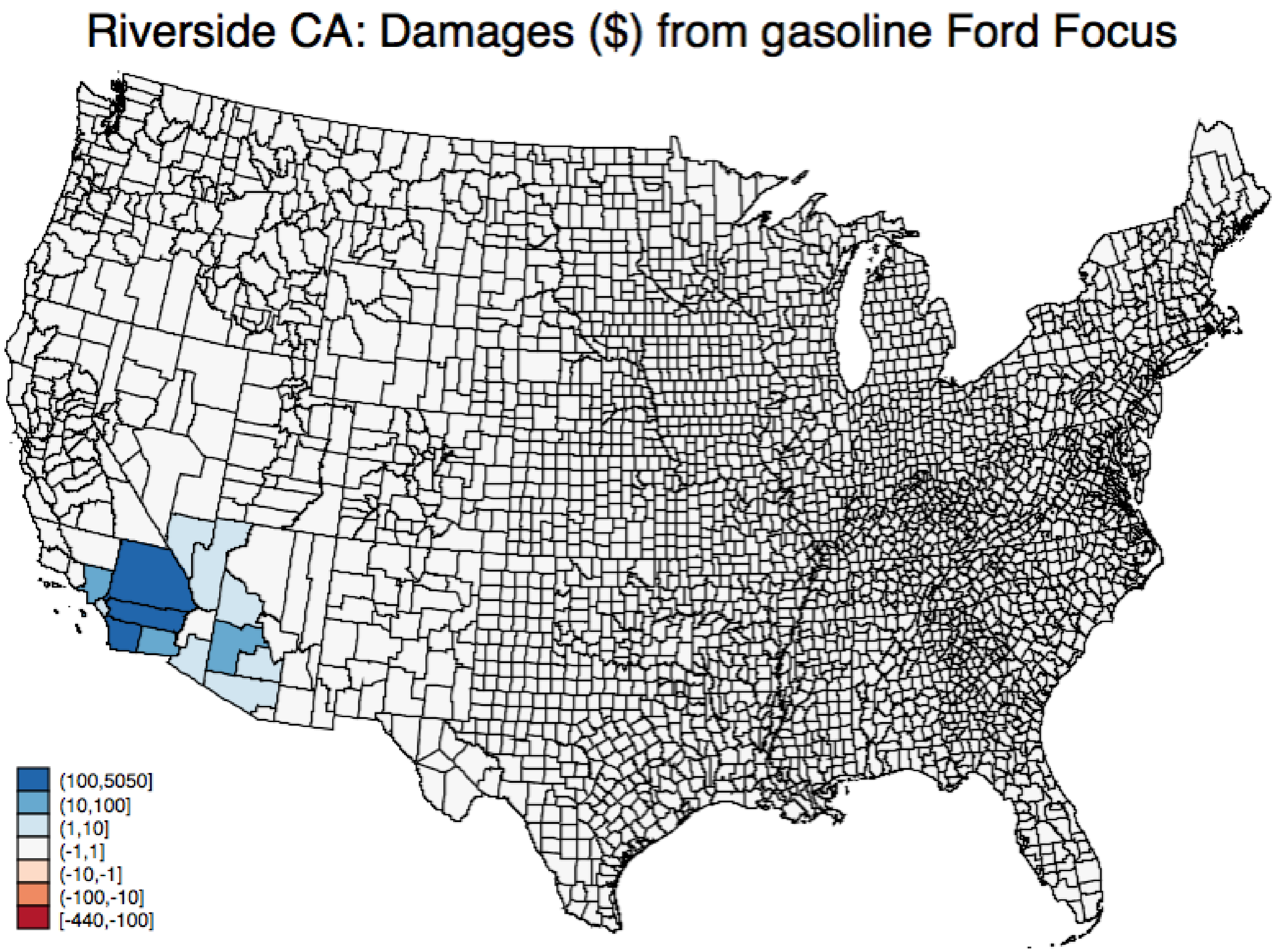

Phoenix: Damages ($) from gasoline Ford Focus
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
[-440,-100]

16 Riverside CA

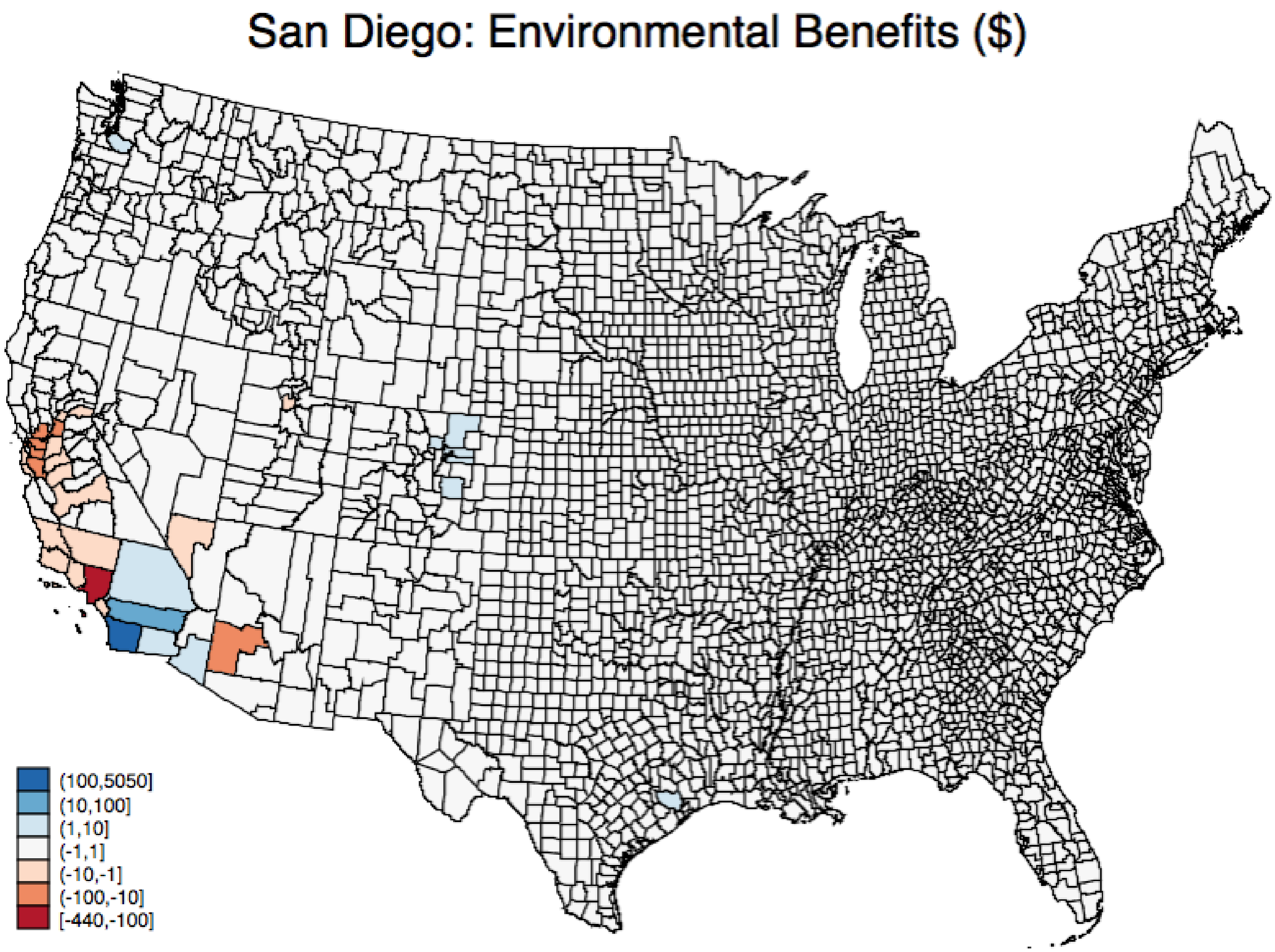


Riverside CA: Damages ($) from Ford Focus EV




Riverside CA: Damages ($) from gasoline Ford Focus
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
[-440,-100]

17 San Diego


San Diego: Environmental Benefits ($)
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(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
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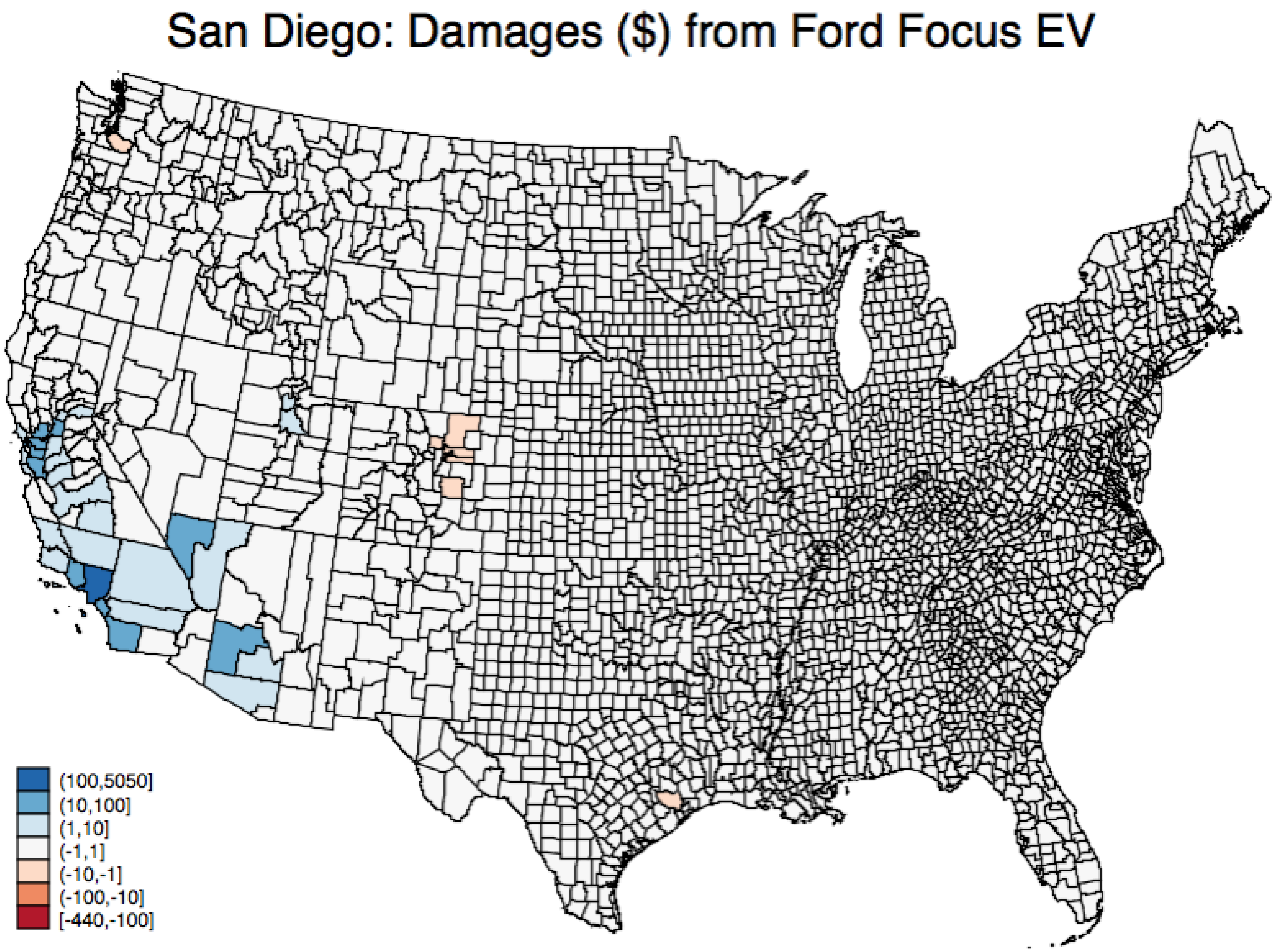
San Diego: Damages ($) from Ford Focus EV
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(10,100]
(1,10]
(-1,1]
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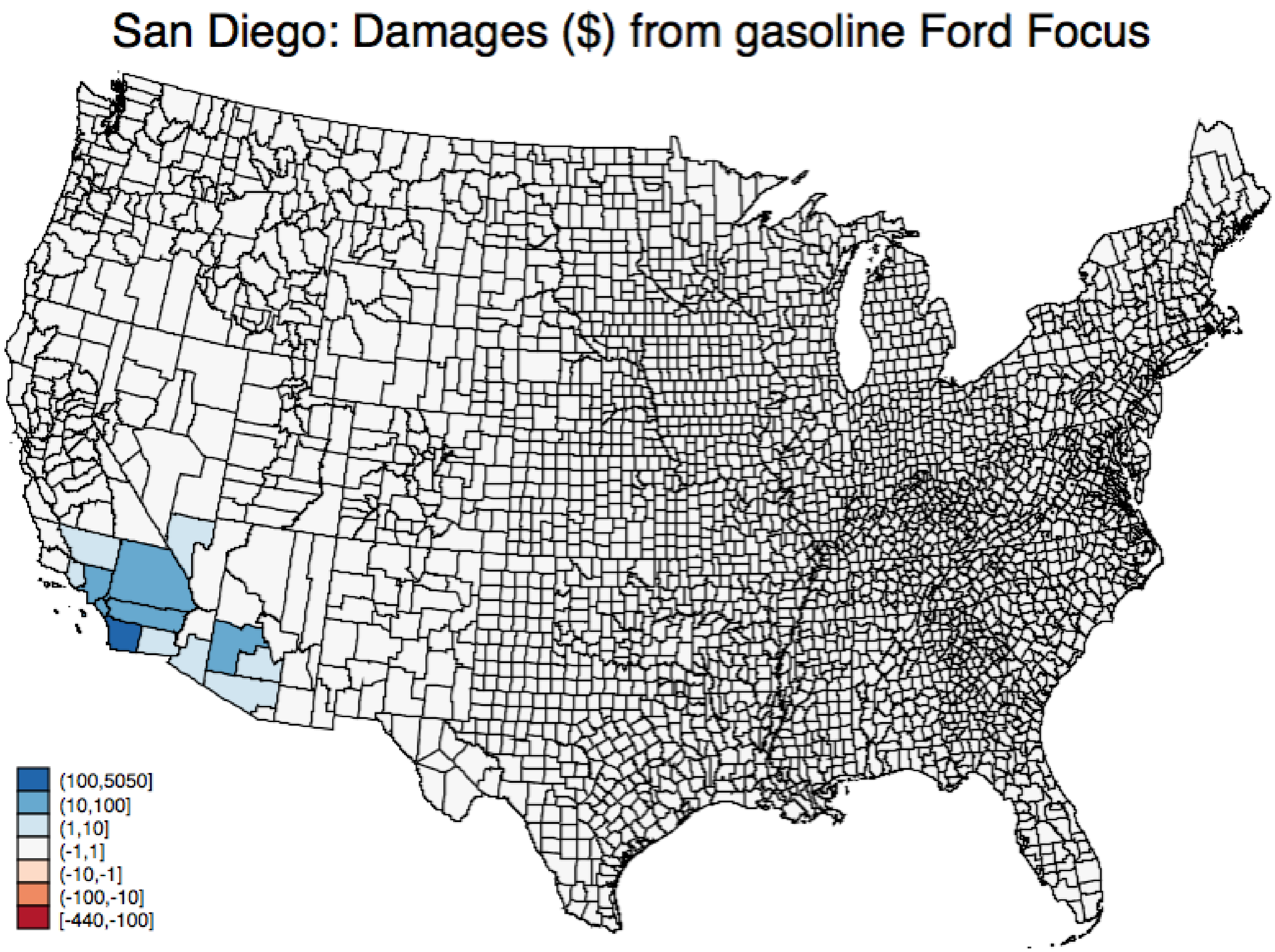
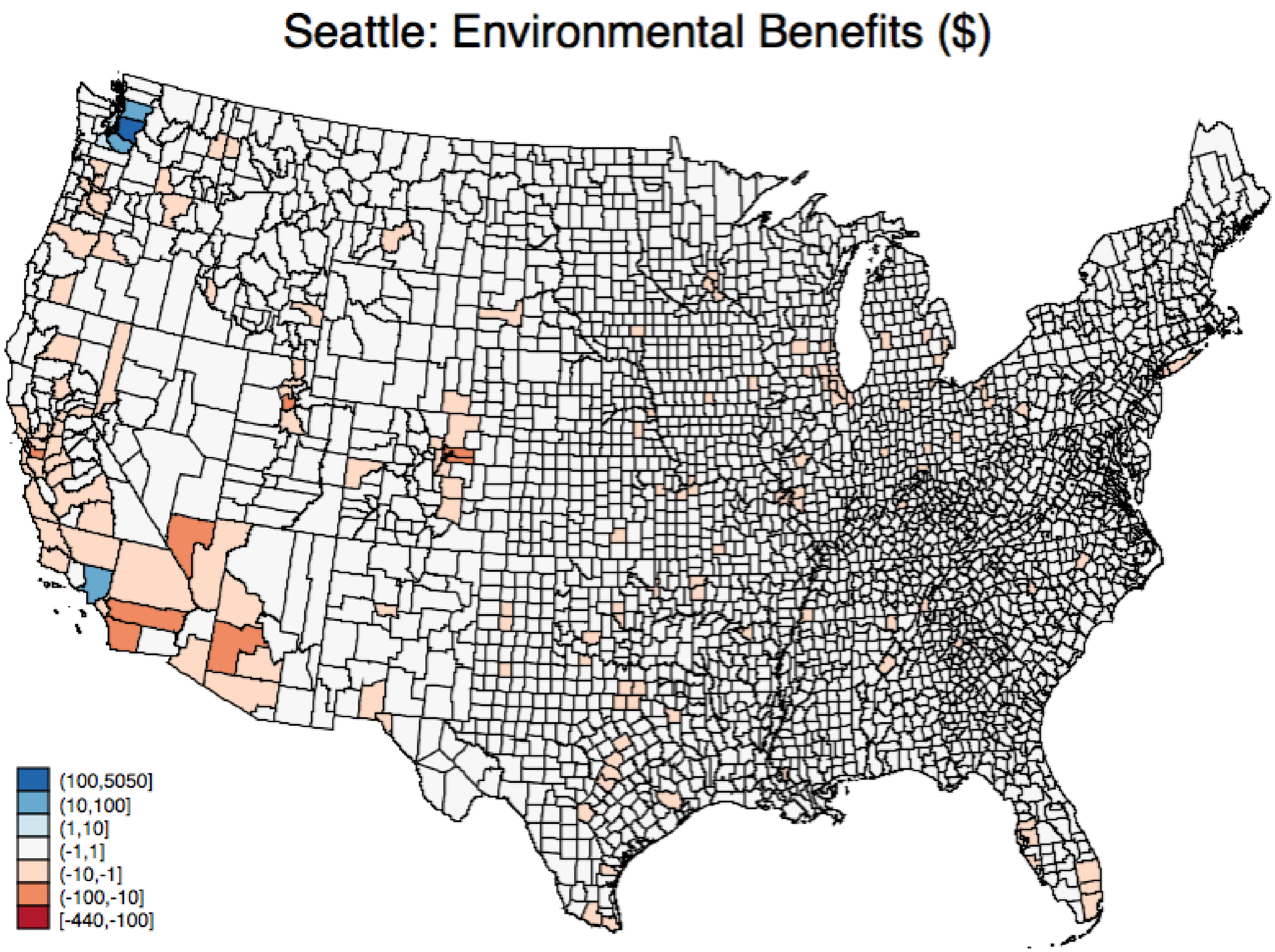

San Diego: Damages ($) from gasoline Ford Focus
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
[-440,-100]

18 Seattle


Seattle: Environmental Benefits ($)
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
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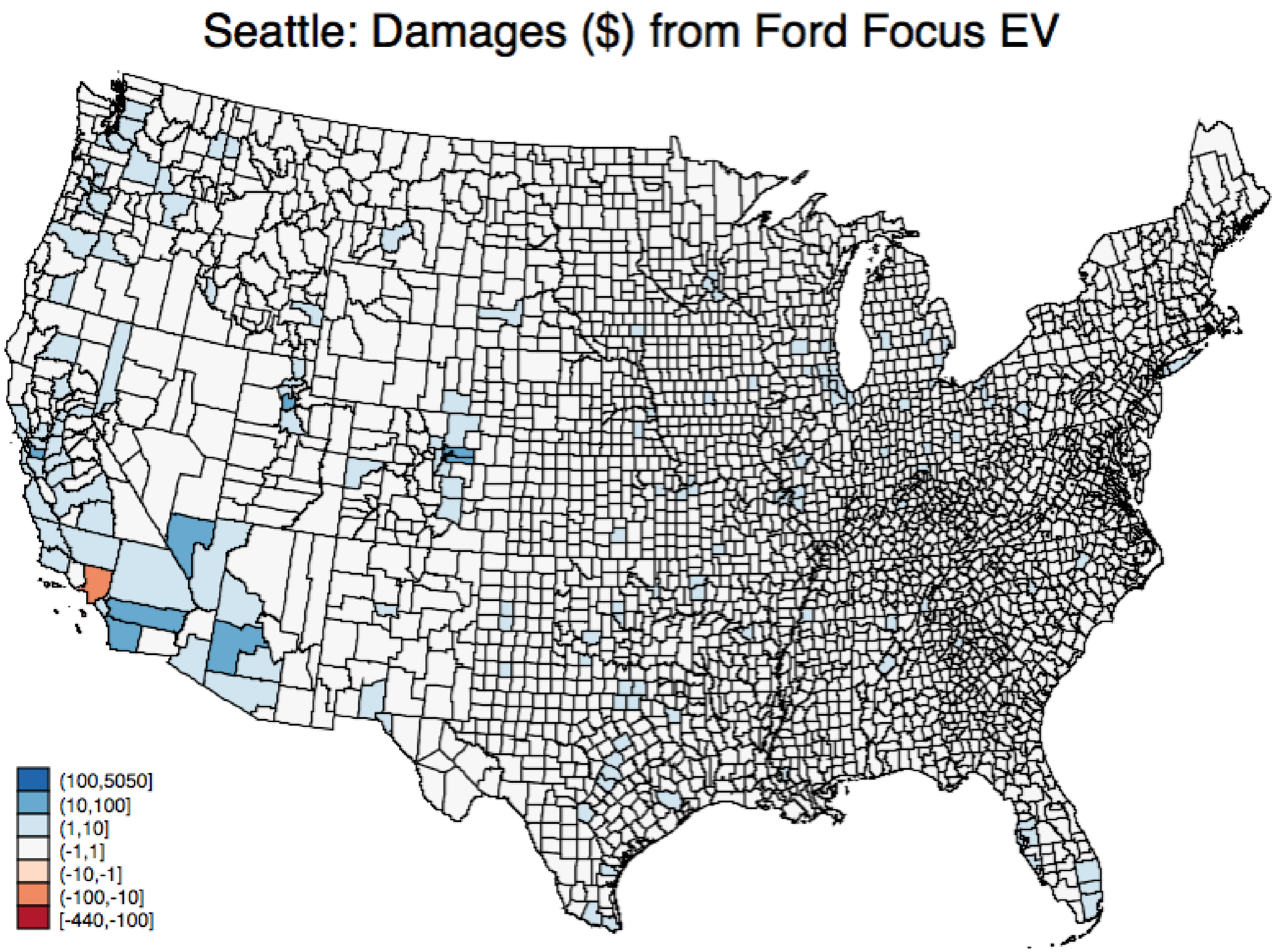
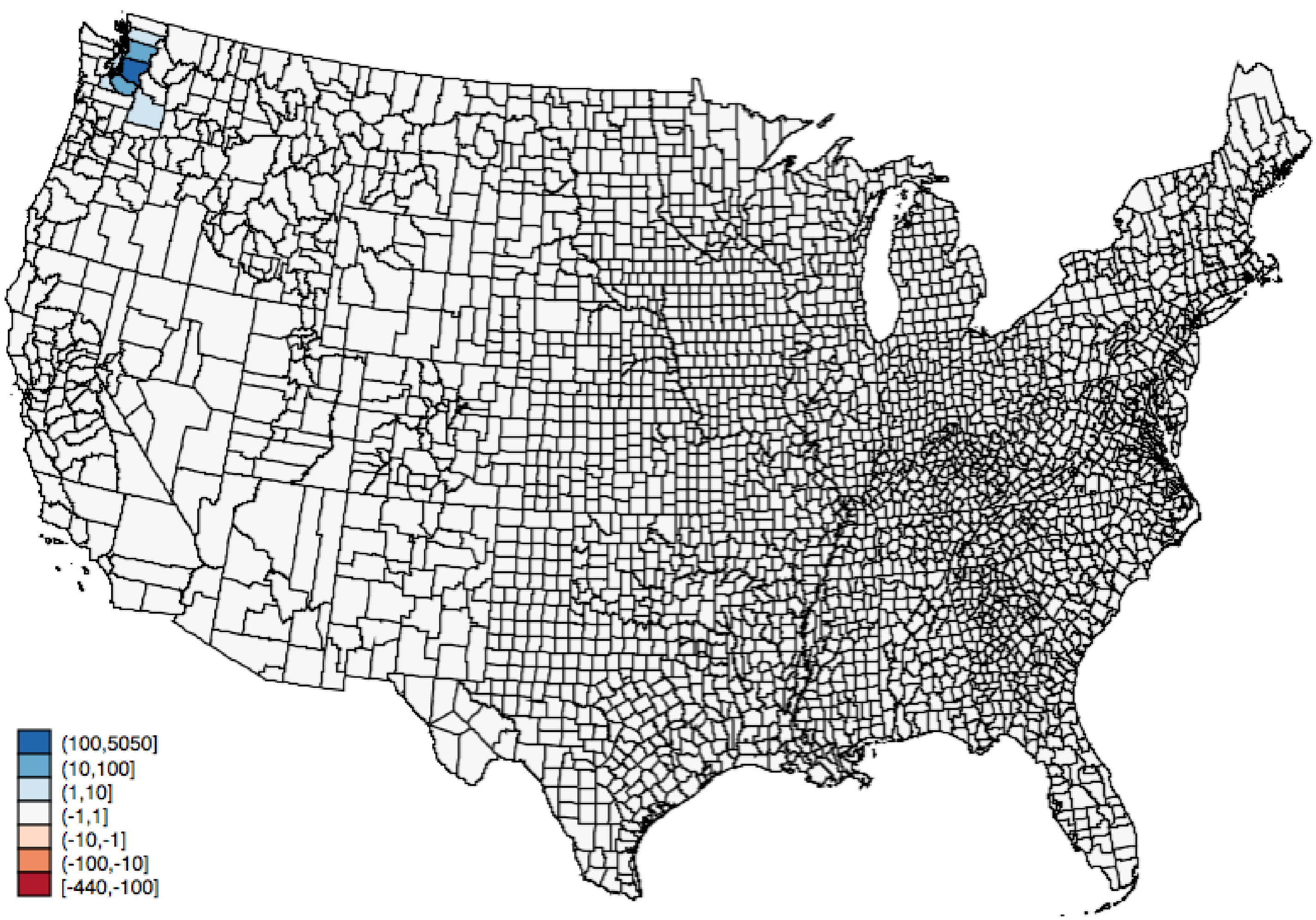
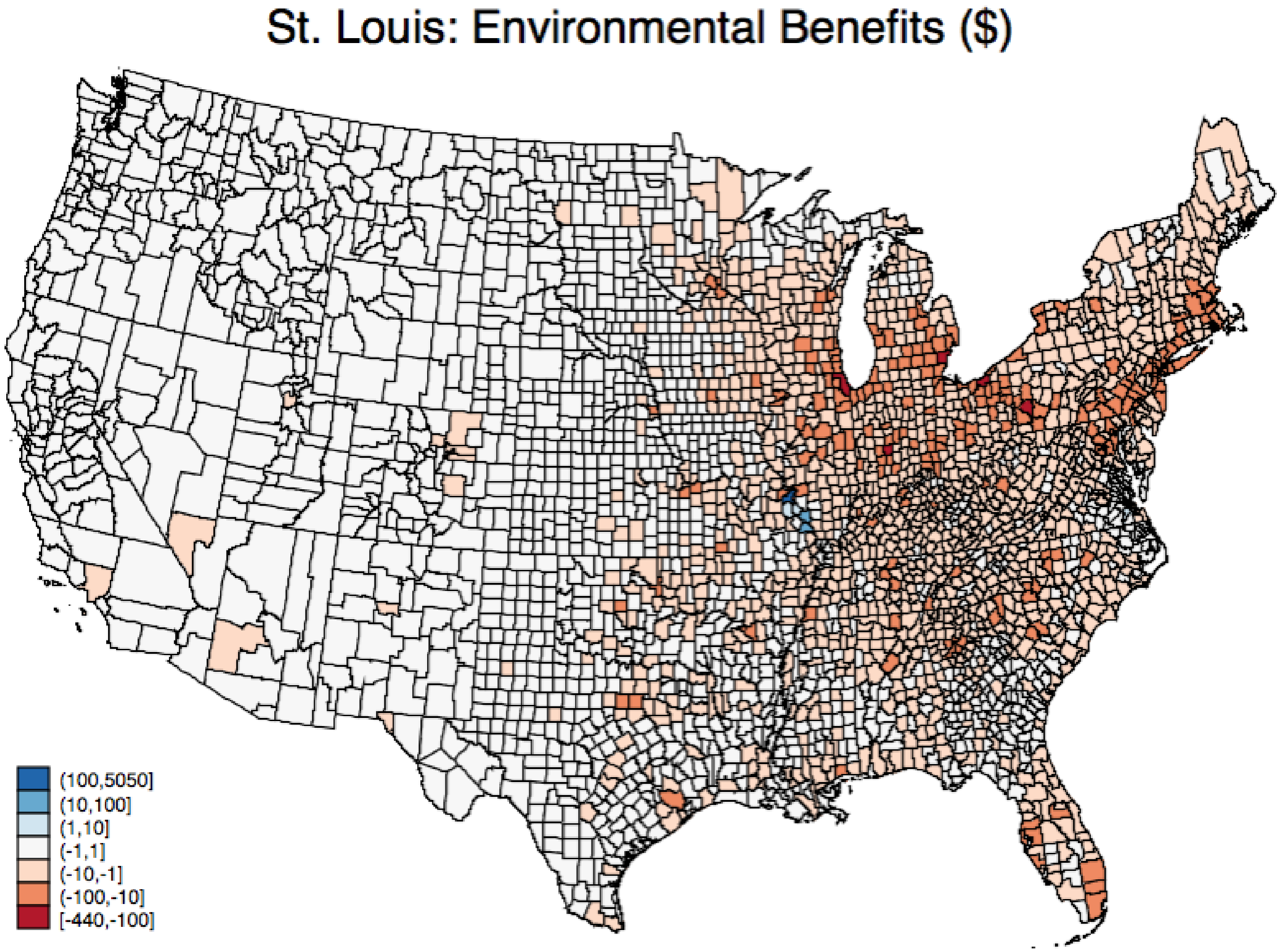
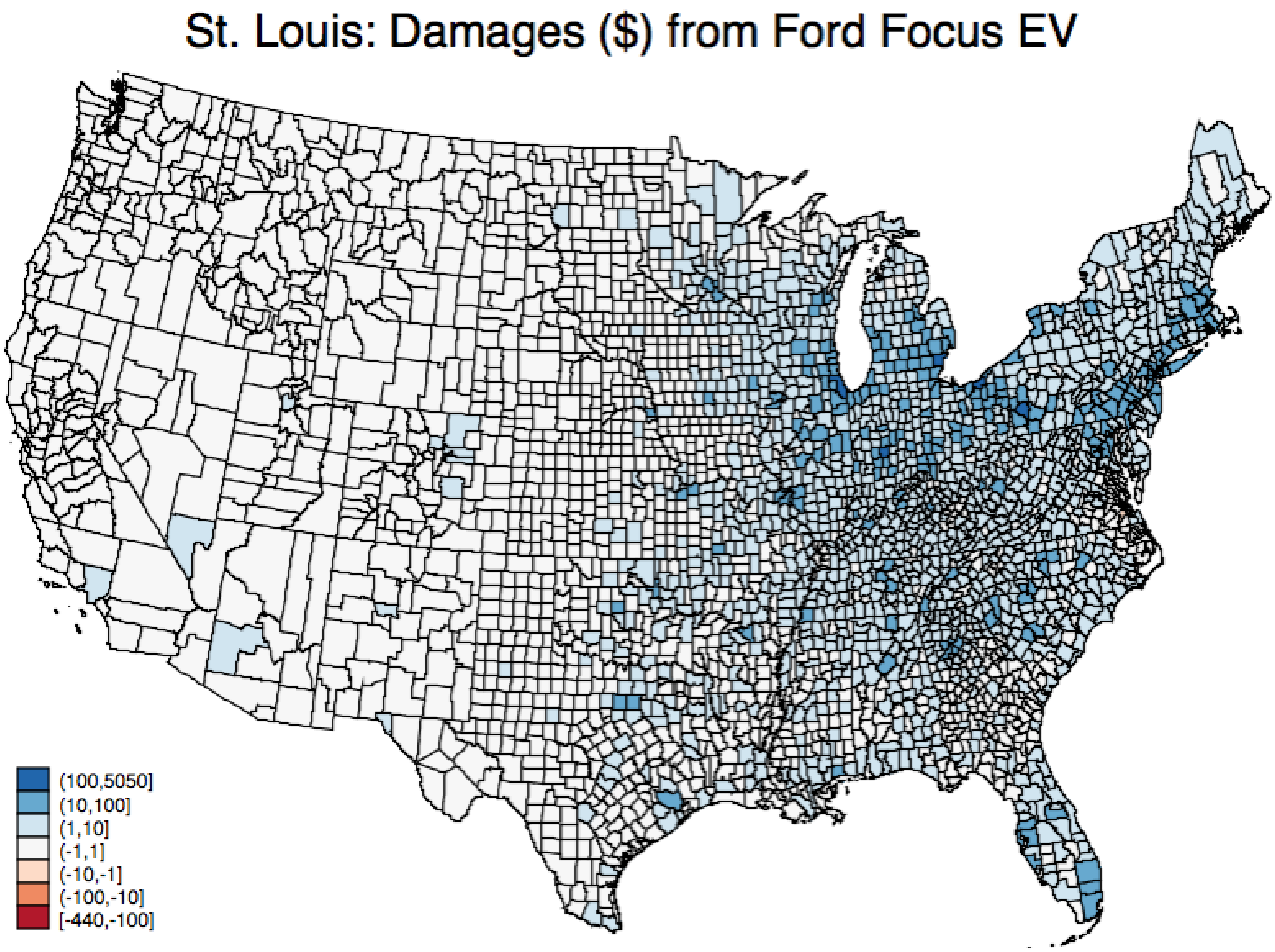

Seattle: Damages ($) from Ford Focus EV
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
[-440,-100]

Seattle: Damages ($) from gasoline Ford Focus

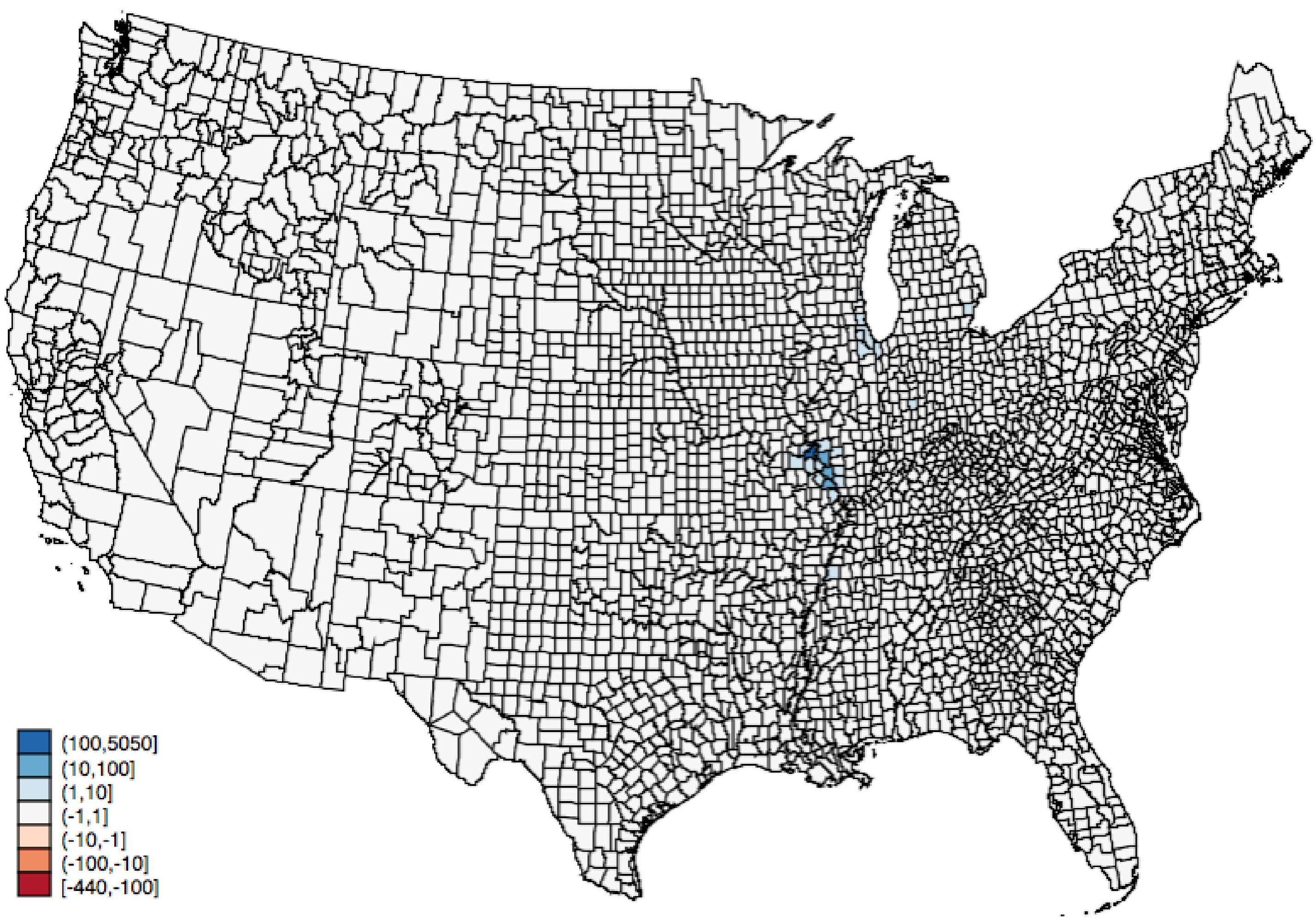


19 St. Louis

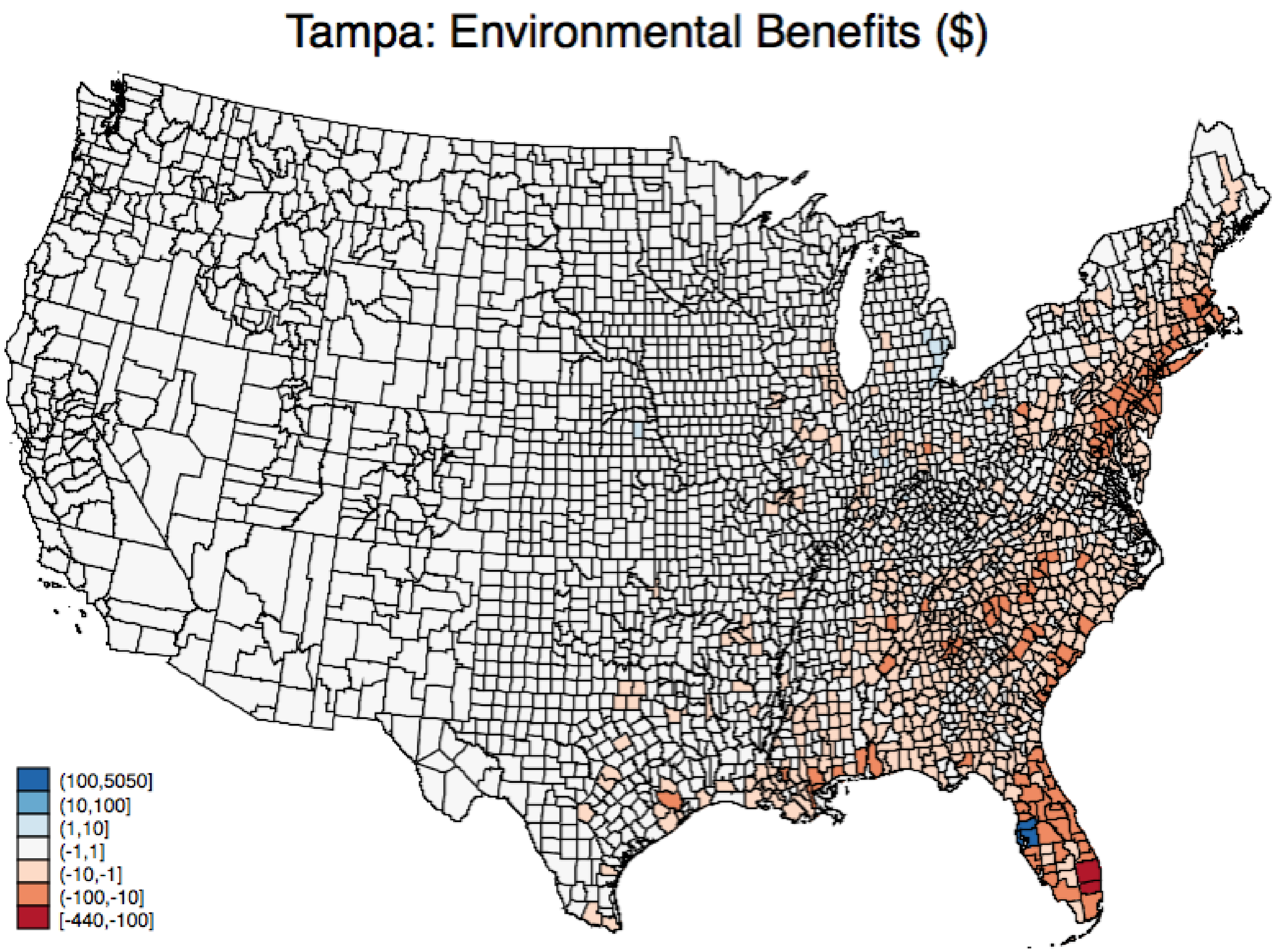

St. Louis: Environmental Benefits ($)
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
[-440,-100]

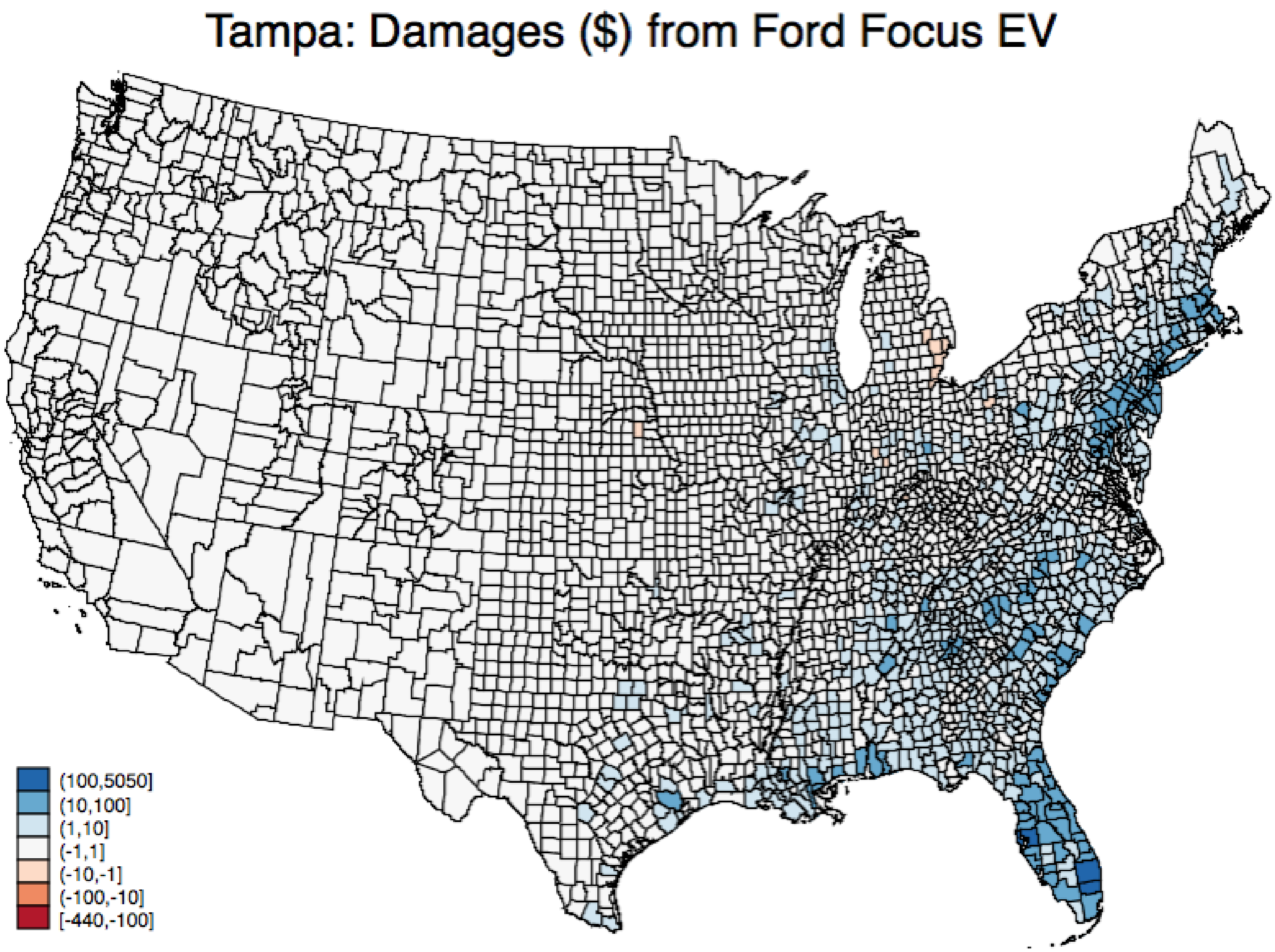

St. Louis: Damages ($) from Ford Focus EV
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
[-440,-100]

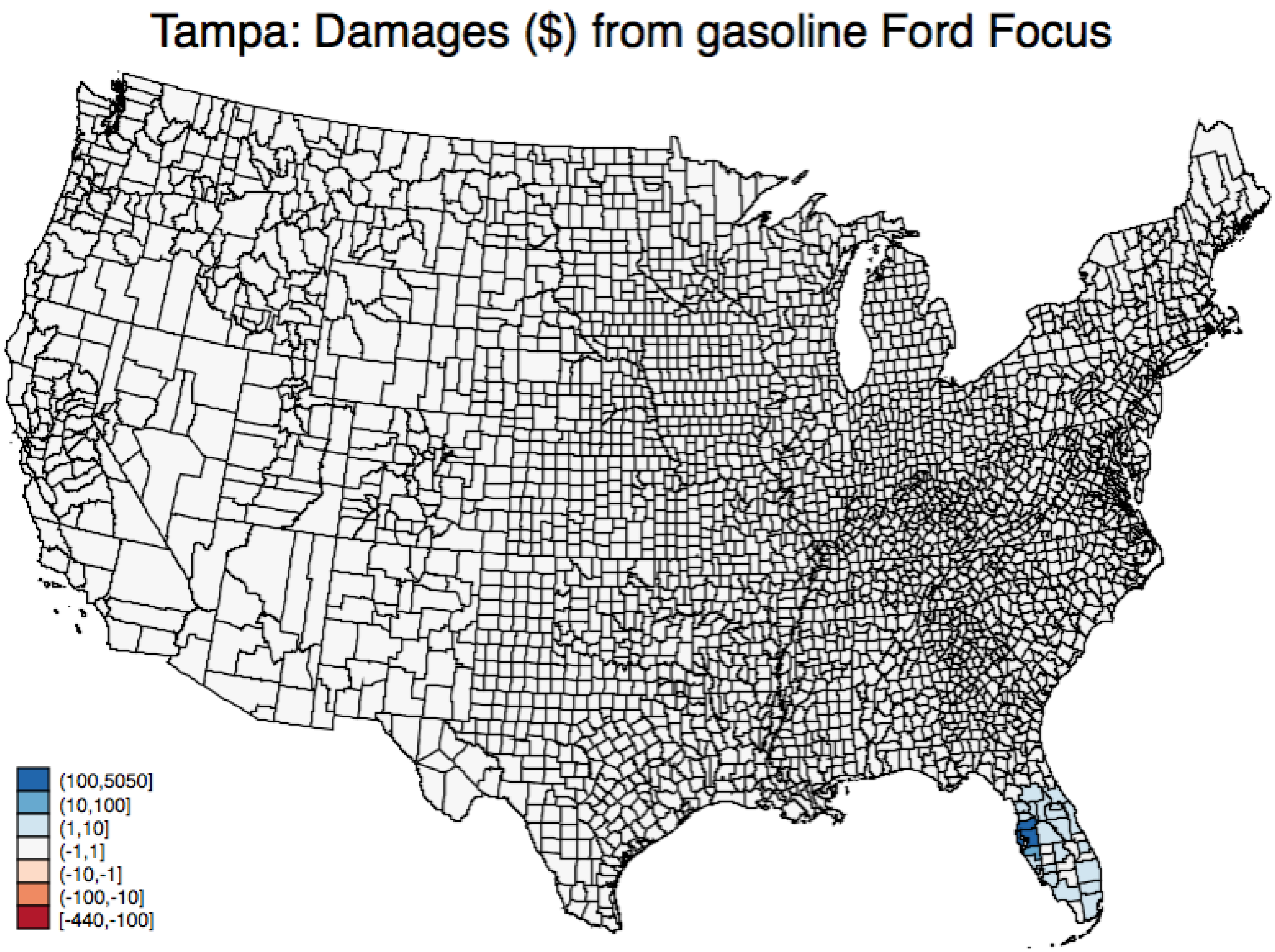
St. Louis: Damages ($) from gasoline Ford Focus



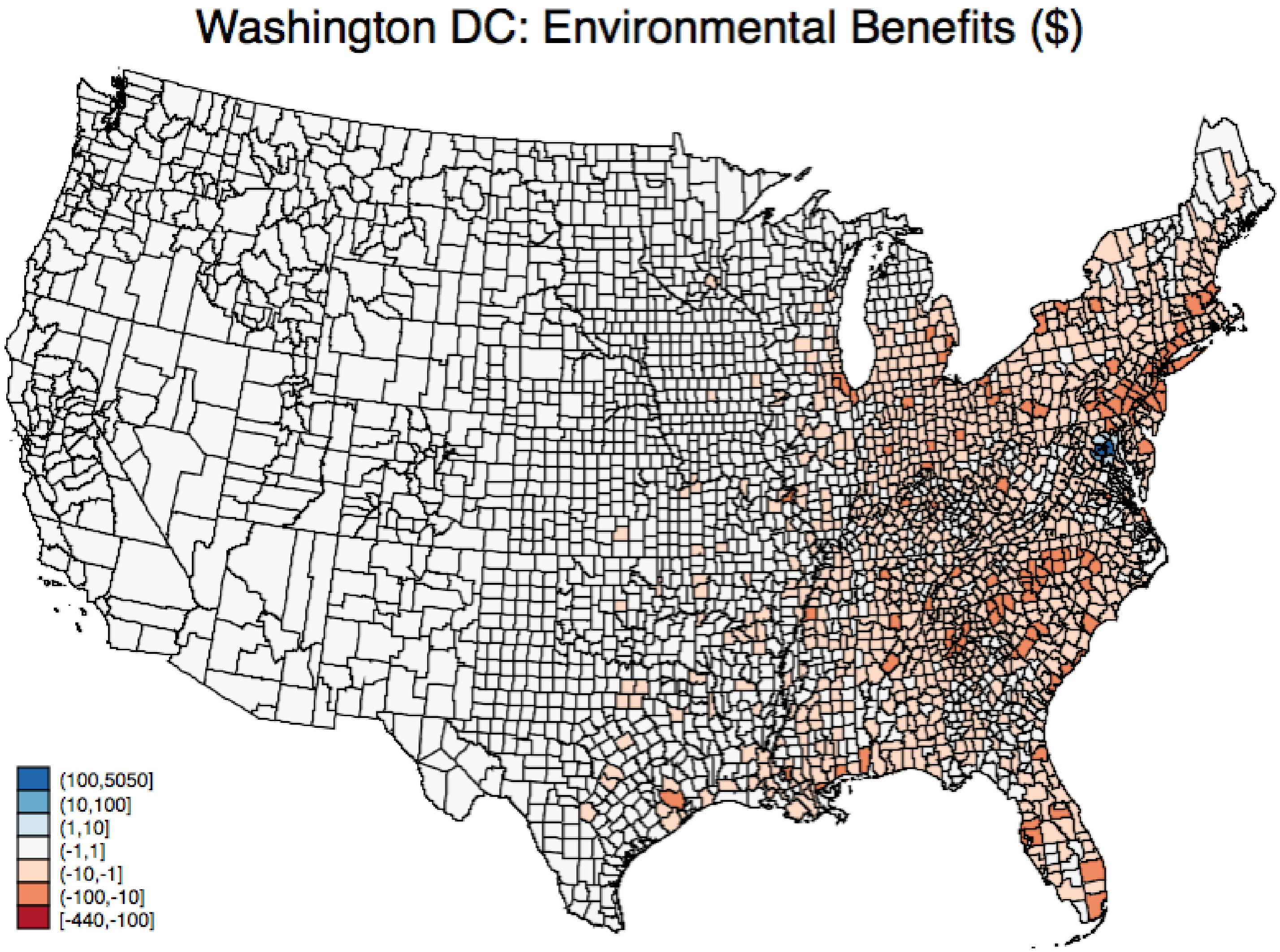
20 Tampa


Tampa: Environmental Benefits ($)
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
[-440,-100]

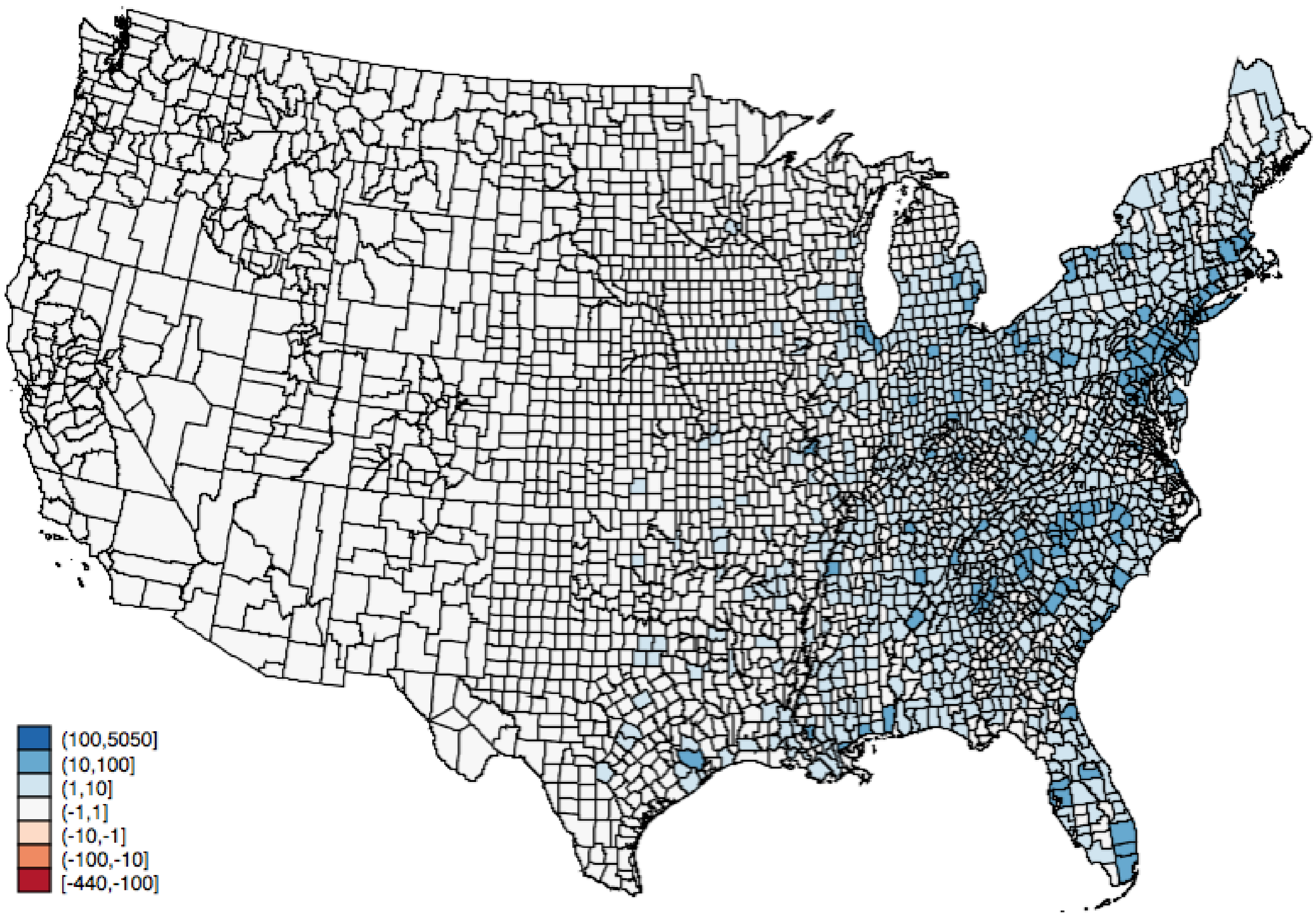

Tampa: Damages ($) from Ford Focus EV
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
[-440,-100]


Tampa: Damages ($) from gasoline Ford Focus
(100,5050]
(10,100]
(1,10]
(-1,1]
(-10,-1]
(-100,-10]
[-440,-100]

21 Washington DC



Washington DC: Damages ($) from Ford Focus EV



Washington DC: Damages ($) from gasoline Ford Focus