

Distributed Effects of Climate Policy: A Machine Learning Approach

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Abstract

We employ machine learning techniques to estimate household carbon footprints (HCFs) for the average household in each Census tract—geographic areas that represent roughly 4,000 people. We find that there is significant variation in carbon footprints across income and geography; income effects are driven by higher footprints related to transportation and consumer products and services, while geographic effects are primarily a result of the variable carbon intensity of the electricity grid. Using these footprints, we assess the net effects of various climate policies on households in the United States paying particular attention to the distribution across geography, urbanity, and income groups. Our objective is to improve the understanding of the potential for regressivity, geographic transfers, and rural-urban transfers among climate policy options and test for ways to control for transfers—preserving transfers from high-income households to low-income households, but mitigating transfers from rural areas to urban areas and from the Midwest and South to the Coasts. Our focus is on the net increase or decrease of annual household expenses under 12 different policy scenarios, which included both carbon pricing schemes and regulatory standards. We find regulatory standards tend to be regressive and, on average, are a net cost to low-income households—especially those in rural areas. Carbon pricing, when accompanied with a dividend, is progressive for urban, rural, and suburban households, with the average low-income household receiving a larger dividend check than they spend in carbon taxes. However, there are transfers from the Midwest and Plains to the Coasts when the dividend is evenly divided. We show that this can be mitigated through adjusting the dividend slightly (<8% increase or decrease). Increasing the progressive structure of a policy benefits rural households more on average, but increases the overall heterogeneity of impacts within each income group. Reducing the transfers between geographic regions and urban-rural households increases the average benefit to low-income households and reduces the heterogeneity of impacts within income groups. We encourage policy makers to assess and control for unwanted transfers between households.

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1 Introduction

How do policy makers address climate change aggressively enough to meet climate goals without harming communities and households historically reliant on fossil fuels? While economic literature has determined that a carbon tax is the most economically efficient way to fix the carbon “externality,” depending on what policy makers do with the tax revenues, the tax can be regressive. The potential regressive nature arises because low-income households spend a larger share of their income on energy, and energy-consuming, products. Therefore, ignoring how revenue is recycled, a carbon tax is likely to be regressive.¹ Furthermore, households in the industrial heartland and the Midwest are reliant on a carbon-intensive electrical grid; they also generally lack adequate public transit options and use fossil fuels to heat their homes during cold winters. Consequently, these households tend to spend a larger share of their income on energy relative to households that live in coastal areas.

These stylized facts of carbon consumption across incomes and geography imply that the details of a carbon tax policy are of utmost importance. Whether a *specific* policy that establishes a price on carbon is regressive or harms certain regions of the country depends on how the carbon revenue is recycled. An additional stylized fact with respect to energy consumption implies that a number of recycling methods will be progressive. Specifically, although low-income households spend a larger *share* of their income on energy, high-income households spend a larger *amount* on energy. Therefore, the high-income households add a larger amount to the pool of revenues than they receive back as a dividend, while low-income households, on average at least, receive a larger dividend than they pay in taxes. This implies that a simple policy that rebates revenues equally to all households, a so-called tax-and-dividend plan, will be progressive; low-income households will, on average, receive a larger dividend check than they spend in carbon taxes. However, a simple tax-and-dividend plan that does not differentiate based on geography runs the risk of benefiting the industrial heartland and the Midwest less than the Coasts.

These same concerns for geographic distribution and regressivity hold for alternative climate change policies. Historically, instead of pricing carbon, policy makers have relied on instruments such as a Corporate Average Fuel Economy (CAFE) standards and subsidies for electric vehicles in transportation and Renewable Portfolio Standards (RPS) and subsidies for wind and solar in electricity. While these policies tend to keep prices for the regulated products lower, compared to a price on carbon, they, too, can be regressive (see, for example,

1. Recent work by Goulder et al. (2019) notes that once one considers the impact of a carbon tax on inflation-adjusted transfers, wages, and capital, a carbon tax can be progressive even if one were to ignore the revenues.

Burger et al. (2020) and Davis and Knittel (2019)). Furthermore, these alternatives do not generate revenues that can provide transfers to vulnerable groups.

In this paper, we bring attention, and perhaps more importantly data, to these issues for policy making. Using data on energy consumption, transportation habits, and consumer behavior from representative samples of US households to generate predictions of those same households across all US households, we use machine learning techniques to better predict consumption of households.²

Given the estimation of energy, products, and services consumption for 72,538 of the 74,134 Census tracts in the US, we then model various policy designs to estimate the annual cost and benefit of each policy on the average household. We analyze not only carbon pricing, with a variety of different revenue recycling plans, but also regulatory policies such as CAFE and a Clean Energy Standard (CES). We add to our understanding of the importance of geography in policy outcomes, the leverage policy makers have to correct for the urban-rural divide, and the progressive outcome for a carbon price and dividend scheme compared to other regulatory approaches. We calculate the incidence in these policies across income quintiles and generate maps of the incidence across the geography. We also aggregate these effects across Congressional districts and correlate the impacts across political party.

Our results suggest that while a simple tax-and-dividend plan does a good job protecting low-income households, the distributional impacts across rural and urban households may concern policy makers. As such, we analyze alternative revenue recycling plans that vary across urbanity, income, Census regions, and electricity reliability regions. We show that allowing household dividends to depend on certain readily-observable features of the household allows policy makers to protect certain vulnerable populations.

Our analysis also points out that while all of the carbon tax-and-dividend plans we analyze are progressive, alternatives to carbon pricing are *regressive*. The negative effects of CAFE standards, as a share of income, are monotonically *decreasing* across income quintiles implying CAFE standards are regressive.³ We find that the same is true for a clean energy standard. Our modeling of the Obama Administration’s Clean Power Plan also suggests that it would have been a regressive policy. The results with respect to a CES and the CPP are not surprising. These policies increase electricity prices, but do not generate any revenues that can be used to overcome the regressivity of higher energy prices.⁴ The result

2. Our work extends past work that uses regression-based techniques. See, for example, Jihoon Min, Hausfather, and Qi Feng Lin (2010) and C. Jones and Kammen (2014).

3. This replicates the results in Davis and Knittel (2019).

4. Our analysis ignores the climate benefits and co-benefits of such policy as they cannot be properly estimated at the household level. Such costs are necessary to consider and are well covered in existing

with respect to CAFE standards is more nuanced. CAFE standards are an implicit tax-and-subsidy program, incentivizing car-makers to produce more vehicles that are more efficient and fewer cars that are less efficient. Thus, in equilibrium the car-makers implicitly tax vehicles that are worse than the standard and subsidize vehicles that are better than the standard.⁵ Therefore, the costs of CAFE to a household fall with the fuel economy of the vehicles in the household and can be negative. Because high-income households are more likely to purchase vehicles with more technology (e.g., hybrids, EVs, etc.) and middle America is more likely to own larger vehicles, high-income households are more likely to gain from CAFE standards, while low-income and Midwest households lose.

With respect to climate policy, these results underscore an important lesson: policies that generate revenue, within the policy itself, afford policy makers with more flexibility to protect certain groups. Carbon pricing affords policy makers with a direct source of revenue to shape the incidence of a policy; policies such as CAFE Standards and CESs generate regressive outcomes and large geographic differences in incidence, but not such revenues. Therefore, for policy makers to undo these negative outcomes, additional revenue sources will need to be found. This may be politically challenging, leaving the negative outcomes among low-income and Midwest households intact. To be clear, all policy creates winners and losers. Our focus is on understanding the impact on vulnerable groups and using our results to understand how climate policies can be shaped to support these vulnerable groups. Spurring the change necessary to steeply cut carbon emissions will pose significant costs and if these costs are distributed through regressive policy, the transition to a sustainable future will not be equitable or sustainable.

2 Background

In this section we discuss the existing literature pertaining to the impact of climate change policies on households and how this varies by household types. We begin discussing carbon pricing and then move to alternatives.

2.1 Carbon Taxes with and without Revenue Recycling

Ignoring the revenues generated, carbon taxation is generally thought of to be regressive to income and expenditures (Metcalf et al. (2008); Mathur and Morris (2014)). However, the

literature.

5. See Davis and Knittel (2019) and Holland, Hughes, and Knittel (2009).

revenues from carbon taxes can be used to offset regressive effects. The Energy Modeling Forum Model Inter-comparison Project Number 32 (EMF 32) convened 11 groups of academics who compared different models for the impact of a carbon tax with various revenue recycling mechanisms (Mcfarland et al. (2018)). Papers varied in terms of the underlying model assumptions, the structure of the carbon tax, and the types of recycling methods employed. They examined both the impact to individual economic actors and to the overall economy; taken together, this gives insight into the trade-off between equity and efficiency.

The first general conclusion from this work is that emission outcomes are largely insensitive to revenue recycling methods, but welfare and distributional outcomes can vary widely (Jorgenson et al. (2018)). Compared between using revenue for capital income tax reductions, labor income tax reductions, and lump sum transfers, capital tax cuts are the most efficient and the most regressive recycling method, while lump sum transfers are the least efficient and most progressive (Mcfarland et al. (2018), Goulder et al. (2019), Woollacott (2018), Jorgenson et al. (2018)). The second general result is that the use of the revenue is important in determining the incidence of a given tax, but it is also important for efficiency considerations. The best use of the revenue, from an economic efficiency standpoint, is to use it to reduce other, distortionary, taxes that exist. However, using the revenues to reduce other taxes can have important implications for incidence. For example, US capital and labor-income taxes are designed to be progressive. Therefore, if you were to replace these progressively-generated tax revenues with a regressively-generated carbon tax source, the carbon tax will necessarily be regressive. These themes are included in (Mcfarland et al. (2018), Goulder et al. (2019), Woollacott (2018), Jorgenson et al. (2018)).

A consensus within EMF 32 formed on the progressive benefits of a carbon fee-and-dividend structure and the overall economic efficiency of reducing capital taxes. Issuing payments to households through a price-and-dividend scheme, while progressive, reduces economic efficiency and increases the heterogeneity of impact within an income group (Cronin, Fullerton, and Sexton (2019)). Adopting a hybrid policy⁶ was found to have greater progressive effects and lower welfare loss compared to a pure-recycling method (Goulder et al. (2019)).

More recent work has found that the incidence of carbon taxes alone (ignoring uses of revenue) depends on the scope of the economic effects studied. A combined source- (e.g., production and transfers) and use-side (e.g., consumption) analysis can change conclusions

6. The hybrid policy consisted of implementing both tax reductions and lump-sum transfer, designed such that rebates were targeted to avoid welfare loss in the bottom two or three quintiles and the remainder of the revenue was used to reduce taxes.

compared to only a use-side study (Goulder et al. (2019)). While the use-side effects of carbon taxes is regressive and reduces welfare for each recycling option examined (in keeping with our findings and other literature), the source-side is progressive and positive for most recycling options. On net, source-side impacts outweighed the use-side.

However, the heterogeneity within an income group (whether quintile or decile) were more heterogeneous than the effects across groups. The variability of impacts within an income group can be explained, in part, by a household’s geographic region. Regional impacts tend to follow economic structures (e.g. impacts to Northeast and West Coast are similar), however capital ownership may be uncorrelated to regional impact depending on the presence of pass-through business entities (Ross (2018)). Regions also vary in terms of sources of energy used for the electric grid and for home heating. For example, many homes in New England heat with fuel oil (a relatively dirty fuel), while homes in the Midwest tend to heat with natural gas (a fuel with lower-emissions). Geography also accounts for significant variation in the co-benefits of climate policy (the benefits from reducing non-GHG contaminants such as sulfates), as well in the welfare effects of policy (Woollacott (2018)).

The heterogeneity within an income group is a critical focus of our research. Indeed, we show that where you live is nearly as strong a determinant of absolute policy impact as your income.

2.2 Previous Estimates of the Costs of Climate Policies

Regulation

A long literature in economics seeks to understand the social cost of different climate change policies per ton of CO₂ reduced from the policy. Gillingham and Stock (2018) reviews this literature and summarizes the empirical estimates of the cost per ton for a variety of policies and technologies. We will refer to these as the implicit carbon cost. These are calculated by dividing the cost of implementing the policy by the carbon emissions reduced by the policy. In many cases, the estimate range is wide because of high uncertainties in both costs and emissions avoided. Implicit carbon costs vary from negative prices for behavioral energy efficiency programs (-\$190/ton), to moderate prices (\$11/ton) for EPA regulation through the Clean Power Plan, to high prices for the Weatherization Assistance Program (\$350/ton) (Gillingham and Stock (2018)). A separate, but related question is what is the level of a carbon tax that would replace a given policy. Knittel (2019) finds that replacing all current federal regulations with a carbon tax (in 2020) would require roughly \$7 per ton to achieve equivalent emissions reductions. This price would increase to \$30 as regulations

ramp up by 2030.

Clean Energy Investments

Clean energy innovation as a method of reducing emission is widely embraced by prominent Republicans, Conservative-leaning organizations, and moderate Democrats. An optimal path for inducing clean energy innovation is a combination of research subsidies and a carbon tax (Acemoglu et al. 2014). Compared to the optimal path, implementing only carbon taxes is inefficient and would result in a welfare loss, although current US policy deviates significantly from optimal policy and under current policies, climate change dynamics will be significantly worse (Acemoglu et al. 2014).

Renewable Portfolio Standard/ Clean Energy Standard

A Renewable Portfolio Standard (RPS) has a range of implicit cost between \$0 and \$190 per ton of CO₂ (Gillingham and Stock (2018)). Other estimates of the implicit cost of an RPS is between \$130 and \$460 per ton (Greenstone and Nath 2019).

A research team at Resources for the Future modeled the effects of a Clean Energy Standard (CES) introduced in Congress. Through a cost benefit analysis, they found net benefits of \$579 billion over the 2020 - 2035 time period. However, the study did not examine welfare effects or an implicit carbon cost of a CES.

2.3 Previous Estimates of a Household Carbon Footprints

According to a multi-regional input output model, the largest aggregate contributors to HCF are private transport (26%), home energy (23%), miscellaneous goods and services (10%), health services (8%), and home food and beverages (6%). The remaining 30% of emissions are distributed across the other 7 categories (Weber and Matthews (2008)). The largest fractions of energy requirements of households (residential energy, transportation, and food)—and are also the most energy intense per dollar (Wiedenhofer, Lenzen, and Steinberger (2013)).

Previous work has found that carbon footprints vary widely by income, urbanity, and geography. With increasing income, direct energy (energy used to heat homes or drive cars) requirements raise weakly and indirect energy (energy involved in goods and services) raise strongly (Wiedenhofer, Lenzen, and Steinberger (2013); Lenzen, Dey, and Foran (2004)). As a result, emissions have a strong correlation with income (Sovacool and Brown (2010)), but the emissions intensity per dollar declines with increasing income, as necessities are more energy intense than luxuries (Lenzen (1998)). This distinction between total carbon footprints and carbon intensity per dollar is important to consider when studying the effects

of urbanization on HCFs.

Total energy use and indirect energy is higher in urban households, but direct energy use is lower than rural households (Wiedenhofer, Lenzen, and Steinberger (2013); Lenzen, Dey, and Foran (2004)). Per dollar, direct energy has higher carbon content than indirect energy consumption, leading rural households to have higher carbon intensity because more of their budget is spent on energy intensive commodities, namely private transportation and residential energy (Wiedenhofer, Lenzen, and Steinberger (2013); Munksgaard et al. (2005)). While rural households have larger footprints than urban households (Baiocchi, Minx, and Hubacek (2010)), it is not true that increasing urbanization decreases carbon footprints. As population density increases, total carbon footprints weakly increase until a threshold is met, at which point HCFs decline sharply (C. Jones and Kammen (2014); Ummel (2014)). This trend is driven by the higher incomes and the greater vehicle miles traveled in the areas outside of metropolitan centers. In result, the suburbs account for 50% of household carbon emissions (C. Jones and Kammen (2014)), despite accounting for approximately one third of the U.S. Population.

While urban areas have lower emissions than suburbs, particularly in older areas such as NYC, the differences within metropolitan areas (between city and suburbs) are smaller than across metropolitan areas (e.g. between New York and San Francisco) (C. Jones and Kammen (2014); Glaeser and Kahn (2008)). Variability in emissions depends, in part, on city age. Older cities tend to have lower transit emissions but higher heating emissions compared to newer cities (Glaeser and Kahn (2008)). Globally, urban density is not always related to small carbon footprints, as there is greater dependence on the wealth of those occupying city (Sovacool and Brown (2010)).

2.4 Policy and Policy Proposals

Carbon Pricing

Carbon pricing has gained prominence in the policy landscape over the last several years. The Baker-Schultz carbon pricing framework has provided a road-map for a market-based solution to climate change. It includes four main components: a carbon price (starting at \$40 per ton and increasing at 2% above inflation), a dividend, a border adjustment for goods traded into and out of the United States, and regulatory roll back (Baker et al. (2017)).

Seven bills introduced in the 116th Congress would implement a carbon price ranging from \$15 to \$52 per metric ton of CO₂. The legislation varies in how revenue would be used;

five of the bills propose direct payments to consumers, either as a dividend or an increase to social security; four bills include tax reform, either through a payroll tax cut or a tax credit scheme; and most bills include ancillary uses of revenue such as research funding, block grants, and infrastructure spending.⁷

Regulatory Policy

The Corporate Average Fuel Economy (CAFE) standard is a regulation that is a legacy of the 1970s Arab Oil Embargo. It has since been used with the goal of reducing carbon emissions and was the subject of a protracted battle between the Trump Administration and that State of California. CAFE mandates a certain fuel economy for the production-weighted average vehicle fleet. As noted above, this incentivizes car-makers to produce more vehicles that are more efficient, such as hybrids, and fewer cars that are less efficient, such as SUVs, which creates an implicit subsidy and tax (respectively).

A Clean Energy Standard (CES) is a regulatory framework that mandates electricity providers to acquire a certain percentage of their energy from clean or low-carbon sources. There were two CES proposals in the 116th Congress, which both used a credit trading system to create a subsidy for clean electricity and an implicit tax on more carbon intensive electricity. The way we model CES and CAFE is described in the following section.

3 Methodology

When estimating the effects of policy, the literature so far has applied economy-wide, sectoral models. Other bodies of research have quantified the size of household carbon footprints according to sources of consumption. We seek to bridge these bodies of work by estimating the impacts of climate policy on households and examining the resulting geographic and demographic variability. We seek to fill the important gap of identifying how the heterogeneity within an income group varies across the United States and its implications for policy design. We also attempt to compare household impacts of tax policies versus regulatory policies, showing that the impact to the public can be obscured and that the cost of regulatory compliance is passed on in regressive ways. This entails generating carbon footprints at a fine-geographic resolution. To do this, we will use data on representative samples of US households and build machine learning models to project the relationships in these data on the entire US.

7. Resources for the Future compiles information on carbon pricing bills here: RFF Carbon Pricing Bill Tracker.

The general process is as follows: we start with a data set that reports consumption of a commodity along with household demographics and physical characteristics of housing for a representative sample of US consumers. Next, we use machine learning techniques that train a prediction model relating household demographics, geographic characteristics, and weather data to energy consumption. Finally, we apply the model to Census data with the equivalent variables at the smallest geographic unit of analysis. For most of our analysis this is a Census tract. We developed 17 models from three federal surveys. The models predict consumption of a utility, product, or service for each household. We then use emissions factors to convert consumption to HCF.

3.1 Data Sources

The 2015 Regional Energy Consumption Survey (RECS) is used to estimate the electricity and heating fuel consumed by each household (U.S. Energy Information Administration (2018)). RECS, conducted by the Energy Information Administration is comprised of two surveys: one to households and one to energy suppliers. Together, it characterizes the energy use and expenditure across a range of physical characteristics of housing and demographic characteristics and the corresponding sample weight. Due to the lower response rate on the 2015 survey, estimates could only be characterized at the Census Division level, of which there are 9, though RECS separated the Mountain Division into North and South. The 2017 National Household Transportation Survey (NHTS) was used to estimate the vehicle miles traveled per household (Federal Highway Administration (2019)). NHTS characterizes non-commercial travel at the household level and associated demographics. The 2018 Consumer Expenditure Survey (CEX) was used to estimate household spending on products and services (U.S. Bureau of Labor Statistics (2020)). CEX is conducted quarterly and annual estimates were made by aggregating across the five quarters for which there are data for 2018, following the guidelines published by the Bureau of Labor Statistics. While a number of these data sets report demographic information at a coarser resolution than a Census tract, we are able to use Census tract level data to “fit” carbon footprints at a finer resolution.

3.2 Model

We model electricity, heating fuel use (methane, propane, and fuel oil), vehicle miles traveled, and consumer products and services (divided into the following groups: food, alcoholic beverages, housing, apparel, health, entertainment, personal care, education, tobacco products,

life insurance, cash contributions, and miscellaneous).

We use the Least Absolute Shrinkage and Selection Operator (Lasso) algorithm, which allows us to increase the predictive power of the model and improve the accuracy of our estimates by identifying which variables among all potentials are worth including.⁸ The general equation for Lasso is given by:

$$L(\lambda, \beta) = \sum_{i=1}^n (y_i - \sum_j (x_{ij}\beta_j))^2 + \lambda \sum_{j=1}^m |\beta_j|, \quad (1)$$

where n is the number of observances, m is the number of covariates in the model, β is the coefficient for variable, j , and lambda is a penalty term. The penalty term, λ , will adjust how restrictive the model will be. If $\lambda = 0$, then all variables will be selected and we have the Ordinary Least Squares result; the greater is λ fewer variables will be selected.

There are thousands of covariates among the variables and interaction terms. For example, the age of a house and source of home heating may both be predictive of energy consumption (older homes might have less insulation and tend to use more energy to heat their house, and people who heat their homes with natural gas will consume more natural gas). However, the interaction between the age of the home and home heating could also be important if, perhaps, older homes tend to have less efficient natural gas furnaces. Indeed, in our estimate for natural gas consumption, Lasso selected to include the interaction term between age of home and whether the home heats with natural gas.⁹

We tested various values of lambda using a k-fold cross-validation method. Cross validation allows us to determine the optimal trade-off between including too few variables (with a large lambda) and too many variables (with a small lambda). RECS and CEX data were given five folds (k=5) and NHTS data were given 10 (k=10), which are divided randomly.

After first determining a sequence of potential lambda values, the model is “trained” with one of the folds omitted and used for testing. The error and standard deviation are averaged over each fold. The value for lambda that minimizes cross-validation error (the difference between the predicted value using the trained model and the actual value in the kth fold) is identified. For models relating to energy and transportation use, the cross-validation error decreased monotonically with lambda, reflecting the diminishing ability of

8. The R package glmnet (Friedman, Hastie, and Robert Tibshirani (2010)) was used to conduct the Lasso regression

9. The R package glinternet (Lim and Hastie (2019)) was used to find interaction pairs.

including new variables to improve predictive power.¹⁰

The model is selected with the “1SE rule,” using the largest value of lambda that is one standard deviation above the minimum lambda. This rule increases the regularization and therefore improves the generalization of the model.¹¹

With the exception of the model for electricity use, which does not have null values in the outcome variable, a Probit model was used to transform the y and improve non-linear prediction.¹² A Probit model models the probability, p , for a variable being zero or one:

$$p_i = \Phi \left(\sum_{j=0}^{j=m} (\beta_j x_{ij}) \right), \quad (2)$$

where Φ is the function for a normal distribution on the linear model. Variables that were selected by Lasso were fed to the Probit model. The Probit model estimate was multiplied by the Lasso model estimate, which was trained on the data with positive values. The equation followed a Tobit-Type II estimate:

$$E[y|x] = E[y|x, z > 0] \times (p_{z>0}) + E[y|x, z \leq 0] \times (p_{z \leq 0}) = E[y|x, z > 0] \times (p_{z>0}), \quad (3)$$

where z is the dummy variable indicating whether y is positive or negative. In our case, there cannot be negative values of consumption as we did not account for cases such as home generation of energy through solar power.

3.3 Footprint Estimation

The American Community Survey (ACS) was used to gather average household characteristics per Census tract for each variable (U.S. Census Bureau (2019)).¹³ A Census tract is a subdivision of a County, consisting of approximately 4,000 residents. We chose to conduct our analysis at the Census tract level because tracts are drawn to have similar demographics, and when variables are standardized, they will be more reflective of the average household

10. See Fig 24 and 25 in the Appendix for the cross-validation with respect to lambda for each model.

11. See, for example, Friedman, Hastie, and Rob Tibshirani (2010) and Krstajic et al. (2014).

12. The R package `sampleSelection` (Toomet and Henningsen (2008)) was used to fit the Probit model

13. We used the five-year estimate for the year 2015 using the Census API and the R package `tidycensus` (Walker (2019))

in that tract. However, for some variables (such as number of vehicles per household), the data were sparsely populated and the county estimates were used instead.

The ACS does not have all the variables present in the other surveys, so the data were supplemented with other sources. Vehicle fuel economy per Census tract were averaged from the registry of motor vehicles (an IHS Markit report). Climate Normals (30-year averages) were provided by the National Oceanic and Atmospheric Administration (Arguez et al. (2012)),¹⁴ and the International Energy Conservation Code (IECC) climate region were provided by county from Pacific Northwest National Laboratory. NOAA Climate data were matched to counties by spacial analysis; for counties without sufficient weather data, the heating degree days and cooling degree days in each IECC climate region were averaged and applied. The residential prices of fuel oils were provided by the State Energy Data System (SEDS) (U.S. Energy Information Administration (2019)), and the residential electricity prices were collected from the Utility Rate Database and aggregated at the county level (National Renewable Energy Laboratory (2020)).

Carbon footprints were then calculated by applying an emissions factor to the estimates for consumption. The Department of Energy’s emissions & Generation Resource Integrated Database (eGRID) were used for the carbon intensity of the grid (U.S. Environmental Protection Agency (2020)). Each tract was assigned to a NERC subregion through geospatial analysis (U.S. Department of Homeland Security (2019)); if a tract fit within one or more subregion, the average emissions factor was used. The Compilation of Air Pollutant Emissions Factors, published and updated by the EPA, was used to determine emission factors for various fuel types (U.S. Environmental Protection Agency (2016)). Lifecycle emissions were also factored into the emissions factor calculations using the GREET model (Argonne National Laboratory (2019)). The emissions intensity per dollar of spending on goods and services were used from Ummel (2014) after adjusting the dollars for inflation relative to 2015.

3.4 Policy Modeled

We model the effects for a given policy on households by estimating the cost to households due to increased prices of energy and commodities with a carbon tax or regulatory cost; we assess the household benefits of a policy by estimating savings related to a decrease in energy and commodity prices due to a subsidy or a lump sum transfer, in the case of carbon dividend schemes.

14. We used the 1981-2010 Normals for Heating Degree Days and Cooling Degree Days.

We make a number of assumptions. First, our approach only accounts for use-side effects (not source-side effects) which are important to determine regressivity. Second, while there are direct benefits to climate policy such as avoiding social costs and co-benefits such as reduced emissions of nitrogen oxides, they are outside the scope of this paper. That is, we are not crediting the households for any reductions in local pollutants or climate benefits from the policies we model. Third, to model costs and benefits, we assume that consumers are inelastic in their spending, there is complete pass through of tax and policy costs, and a carbon dividend scheme would be revenue neutral. Finally, we model the average household footprint for each Census tract; therefore, we do not capture the full variance of household effects in the United States, rather, we capture the expected variance for a representative household across variables of geography, urbanity, and income. This is meant to give policy makers an idea for the distributed effects of policy, rather than a perfect calculation of such effects. We describe the distributional impacts of policy, not to assess the relative efficacy of a policy to reduce emissions or to model the distributional impacts of climate change on the United States.

There are 11 policy designs that we model listed in Table 1. We describe them in more detail below. Each of the policies assume that the shadow value of the policy is \$50 per ton of CO_2 . For the carbon tax scenarios, this is the level of the tax. For the remaining policies it is the shadow value of the constraint.

Table 1: Net Impact of Policy Scenarios by Urbanity (USD/Household Annually)

Scenario 1	Carbon tax with no revenue recycling
Scenario 2	Carbon price and dividend (CPD)
Scenario 3	CPD with an adjustment for urban and rural households
Scenario 4	CPD with an adjustment for geography
Scenario 5	CPD with an adjustment for both urbanity and geography
Scenario 6	CPD with an adjustment for NERC regions
Scenario 7	CPD with an adjustment for household income
Scenario 8	CPD with an adjustment for household income and geography
Scenario 9	Corporate Average Fuel Economy (CAFE) standard
Scenario 10	Clean Energy Standard (CES)
Scenario 11	Obama-era Clean Power Plan
Scenario 12	Combination of a CAFE standard, CES, and carbon pricing

A carbon tax with no revenue recycling is an edge case scenario where policy makers decide to fix the externality, but commit all revenue to paying down the deficit. We consider this the least likely policy to be enacted, but it nonetheless provides a baseline for consideration. CPD policy scenarios use this baseline to calculate total revenue and resulting dividend

per household.

For scenarios 2-6, the carbon footprints for households in each category (e.g., urban or rural) were averaged and the dividend was adjusted so that the average household would break even. For scenarios 7 and 8, the dividend was calculated such that the average household in each quintile would break even, then increased by 75% for the bottom quintile, 25% for the second quintile, reduced by 25% for the fourth quintile, and reduced for the fifth quintile by approximately 40% (adjusted such that the policy remained revenue neutral). Scenarios 7 and 8 were calculated differently from 2-6 because the latter were structured such that transfers between each group (e.g., urban and rural) were eliminated; if 7 and 8 followed the same procedure, we would reduce dividends to low-income households because they have a smaller absolute contribution. When adjusting for income, we are considering the scenario where policy makers want to increase the progressive outcome of the policy. Urban and Rural designations were determined following the method described in Isserman (2005) and income quintile ranges were followed the 2015 data from the Tax Policy Center. In Scenario 9, the CAFE standard calculates the implicit tax/subsidy on each vehicle owned according to the shadow price of the regulation, following Davis and Knittel (2019). Cars that get worse fuel economy than the standard get taxed, cars that get better than the standard get subsidized according to the model:

$$\text{Price of a Car} = \text{MC} + \lambda(\text{GPM of car} - \text{Standard in GPM}),$$

where MC is the observed price of the vehicle, λ is the shadow value of the constraint, GPM is the gallons of gasoline-equivalent consumed by the vehicle, and Standard in GPM is the assumed CAFE standard.¹⁵ We then multiplied the average tax by the vehicles per household. We used the estimate for vehicles per household at the county level because of poor availability in the ACS data at the finer scale.

Scenario 10 is a CES. CES policy is still a developing area of research and does not have universal characteristics, but such a standard is generally a technology-neutral portfolio standard that requires utilities to sell a give percentage of energy that is determined to be from a "clean" source. Qualifying clean energy producers are awarded credits that can be traded in a market, similar to a the operation of a renewable portfolio standard. We model this such that the policy sets an emissions standard for the electricity grid and energy providers with more carbon-intensive energy would buy credits (which would cost \$50/ton) from providers with less carbon-intense energy. Thus, areas with cleaner electricity

15. The details of this exercise are in Davis and Knittel (2019). We use the same footprint-based 2012 targets as laid out by CAFE for the targets that go into the implicit tax/subsidy calculation.

will benefit through lower rates, while areas with dirtier electricity will pay higher rates. The household cost or benefit was the implicit tax or subsidy multiplied by the electricity consumed.¹⁶

Scenario 11, the Clean Power Plan (CPP), examined the change in electricity prices and the resulting rise in costs of energy for each household. The rise in energy costs was assumed to be only due to the associated permit price in each state. Using an analysis of projected permit prices conducted by the Nicholas Institute (Ross, Hoppock, and Murray (2016)), we estimated the policy cost as follows:

$$\text{Policy Cost} = (\text{Permit Cost/MWH})(\text{MWH Consumed}).$$

where the Permit Cost in each state was based on the estimated permit costs in 2030, as to capture the full effect of the proposed policy of the CPP.

Scenario 12 combined regulatory policy costs with a carbon price and dividend scheme. Each sector of the HCF was affected by one type of climate policy to avoid compounding costs or benefits in our model. We, therefore, assumed that areas of consumption that were covered by regulation policy would be exempt from the carbon price. This scenario blended the effects of a Clean Energy Standard, CAFE Standard, and a carbon price with an evenly divided dividend. Therefore, the carbon price applied only to home heating fuels and consumer goods (to avoid double taxation) and the dividend was equally divided to all households, based on the revenue collected from heating fuels and consumer goods alone; the net policy effects were the combined effects of CES, CAFE, and the scaled-down CPD.

4 Results

4.1 Household Footprint

Figure 2 shows the distribution of carbon footprints across geography. An expanded view of New York City is included to highlight the effect of Urbanization—an average household

16. By assuming inelastic consumption of energy, we note that the associated costs and benefits will be more accurate in the short-term. This assumption is not accurate in long-run, as consumers will adapt to differentiated energy prices, for example by changing appliances. We also note that \$50 per ton is a high estimate for permit prices.

on Long Island has a footprint nearly three times larger than that of an average household in Manhattan. Across the map, there are similar trends visible; major metropolitan areas have a “donut” trend, where the city center has low carbon emissions and the suburban areas outside the city have high emissions. Some rural and suburban areas have lower than average emissions, such as, through the Carolinas, the southern Mississippi Valley, and parts of the Pacific Coast. This is driven by two different factors: the Carolinas and the southern Mississippi Valley have more households that are low income, which depresses their overall footprint. The Coast has higher income, but operates on a grid with lower emissions intensity and in a climate that does not necessitate the same level of energy required for cooling and heating.

In Figure 23 we show the contributions to total footprints by the six categories.

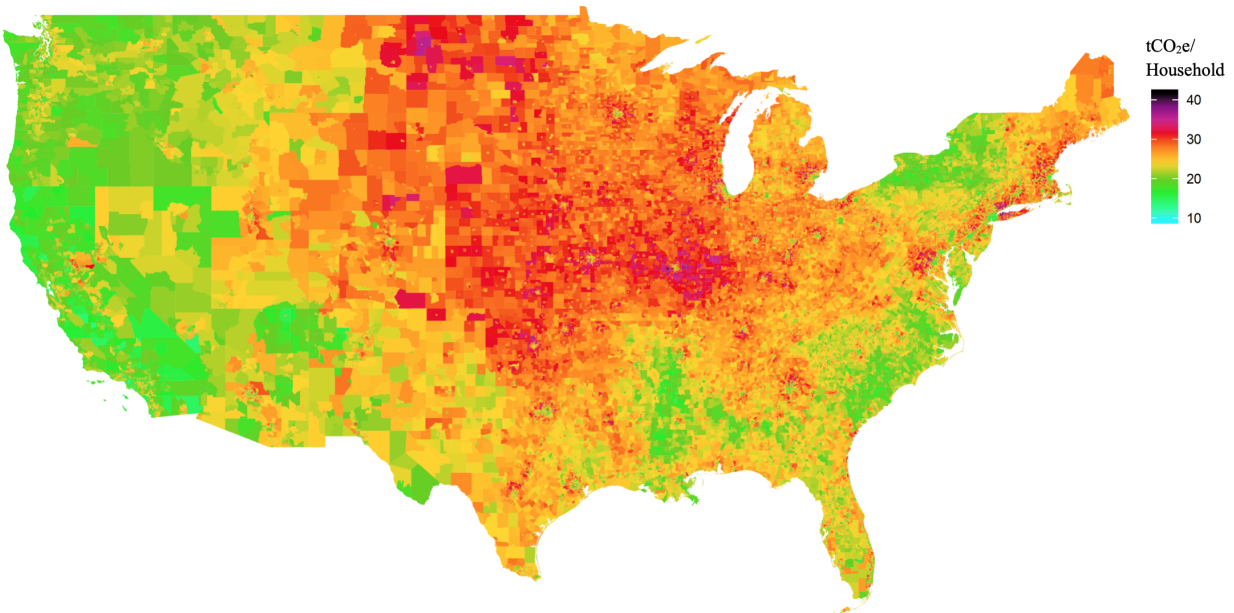


Figure 1: Total Household Carbon Footprints for the Continental United States

Our results highlight the importance of accounting for not only differences across incomes, but also differences across geography and urbanity. Across the US, the average carbon footprint is 24.2 tons per household per year.¹⁷ The bottom 20% of footprints of households generate 17.0 tons, or less, of carbon dioxide emissions, while the top 10% of households generate 30.0 tons, or more. Meaningful differences exist across both income and geography, however. The average carbon footprint of a household in the bottom 20% of income is 18.1; the average is 29.1 for households in the top-20 percent of income. Average carbon emissions

17. This is the population-weighted average across all Census tracts.

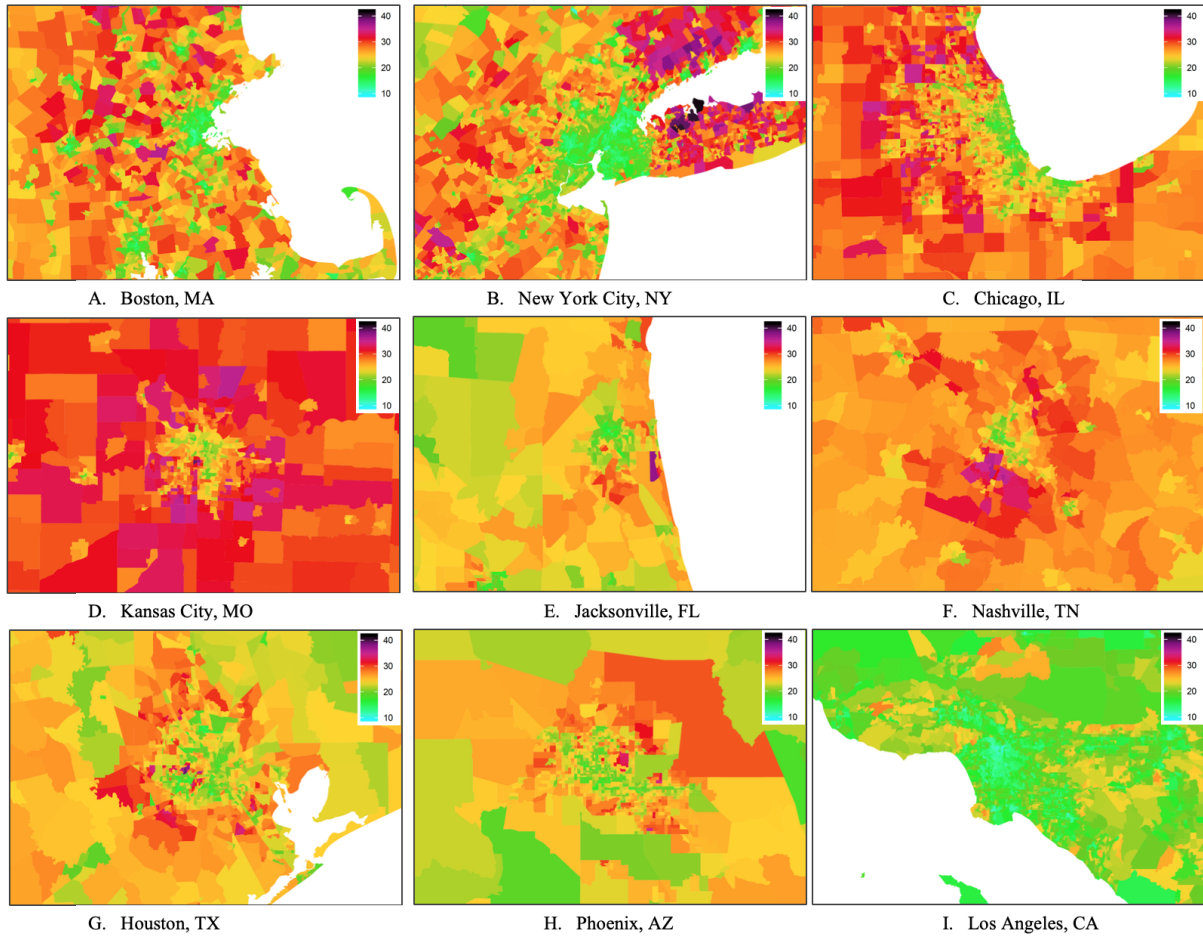


Figure 2: Total Household Carbon Footprints for the Most Populous City in Each Census Division

per dollar of income, in contrast, falls monotonically across income quintiles, with the bottom quintile producing 1.02 tons per every \$1,000 of income and the top quintile producing 0.2 tons per every \$1,000 of income.

Carbon footprints in rural communities exceed those of suburban and metropolitan areas. Average footprints are 27.7 tons per year in rural areas, but 26.0 and 21.1 tons in suburban and urban areas, respectively. There are also important differences across race. While footprints are negatively correlated with the share of residence that are African American (correlation of -0.32), emissions per \$1,000 of income is positively correlated with the share of African American residents (0.26).

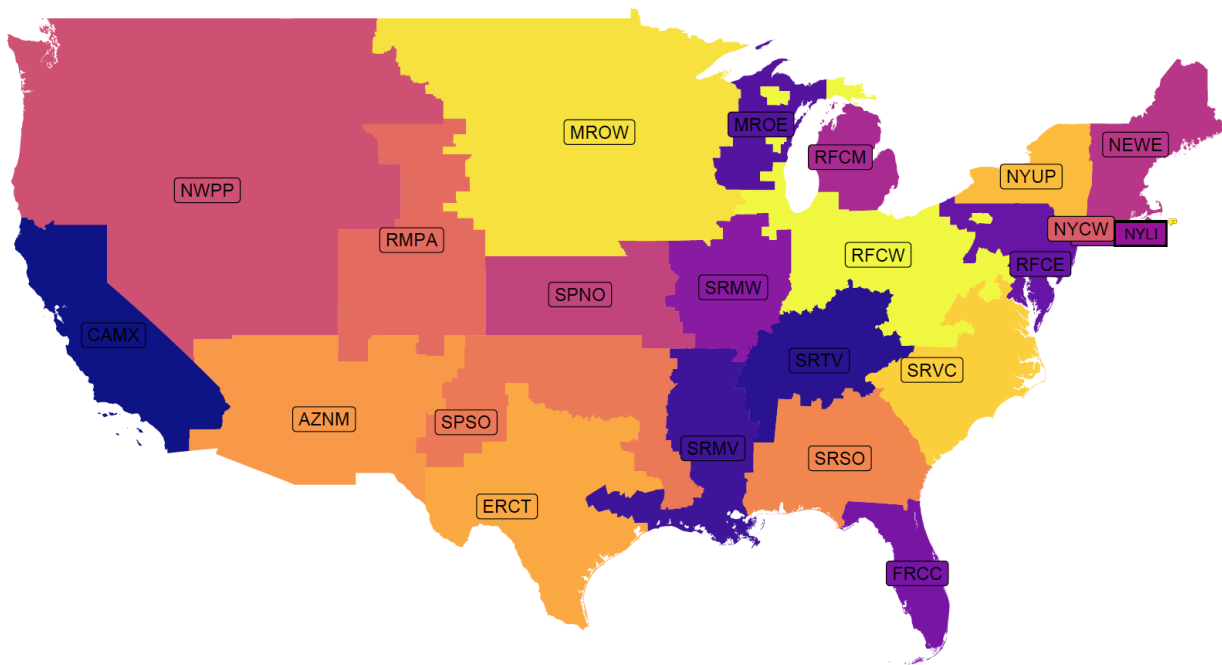


Figure 3: Subregions of the North American Electricity Reliability Corporation That Were Used to Assign Emissions Factors to Electricity Consumption)

The footprint associated with electricity consumption is heavily influenced by the emissions intensity of the associated North American Electric Reliability Corporation (NERC) subregion. Fuel oil- and methane-related carbon emissions are concentrated in regions that rely on those fuels for home heating, most notably in the Northeast where fuel oil is heavily relied upon. Transportation emissions are greater in the suburbs where households tend to have longer commutes and multiple cars. The transportation footprint is generally larger in the Midwest where fuel economy for private vehicles tends to be lower.¹⁸ Products and

18. We did not model the footprint related to public transit or air travel, which would likely increase the estimate in urban areas.

services account for a carbon footprint that was strongly correlated with income. These findings are consistent with similar studies in the literature (C. Jones and Kammen (2014), C. M. Jones and Kammen (2011), Ummel (2014), Jihoon Min, Hausfather, and Qi Feng Lin (2010)).

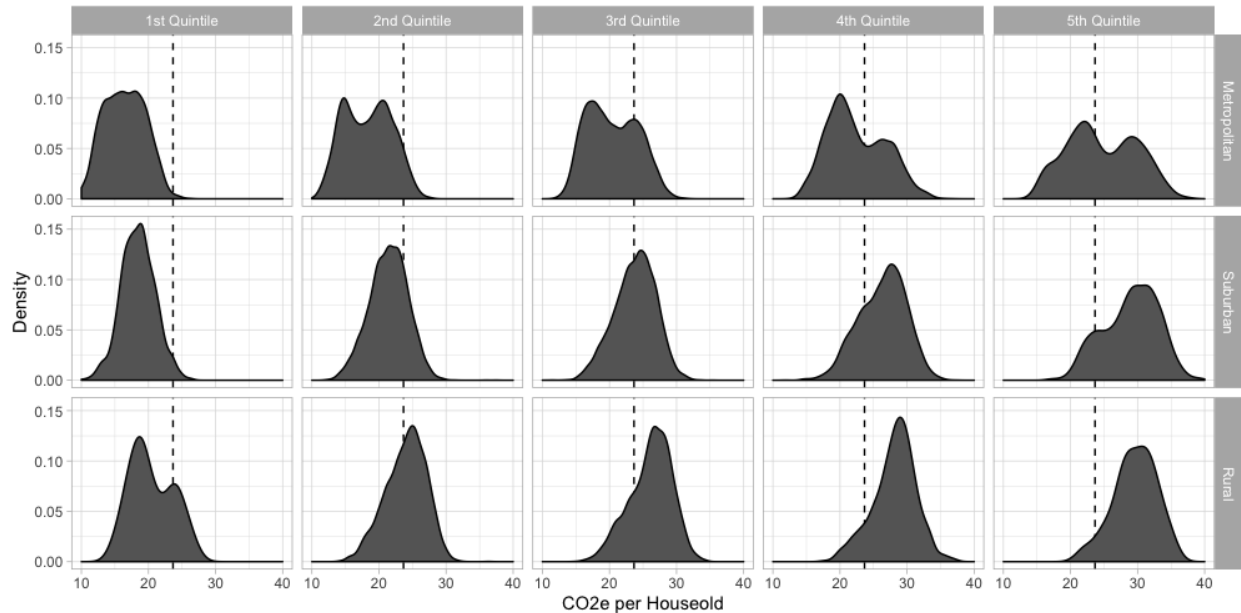


Figure 4: Total Household Carbon Footprints (in tons) Across Income quintiles and urbanity, compared to U.S. average (represented by the dashed line)

Figure 4 shows the distribution of carbon footprints across two dimensions: urbanity and income. This shows that as income increases, the footprint distribution moves right, and for a given income group, increased urbanization generally shifts the distribution left. It also shows that there can be wide and bi-modal distributions within each grouping.

Figure 5 shows the significant effect that geography and NERC Region have on footprints related to energy. While income and urbanity both influence the size of footprint, the variances across geography reduce the absolute difference between income quintiles and between urban and rural populations. That is, there are often significant differences between the urban and rural areas of one city (as seen in Figure 2) but the variances across metropolitan areas can exceed the differences within metropolitan areas.

Figure 7 shows the variation in HCFs across party affiliation, as determined by the political party of the Census tract’s House Member in the 116th Congress. While households represented by Republicans tend to have slightly higher footprints than average and households represented by Democrats tend to have slightly lower footprints than average; however, there is a wide distribution for both parties that largely overlap.

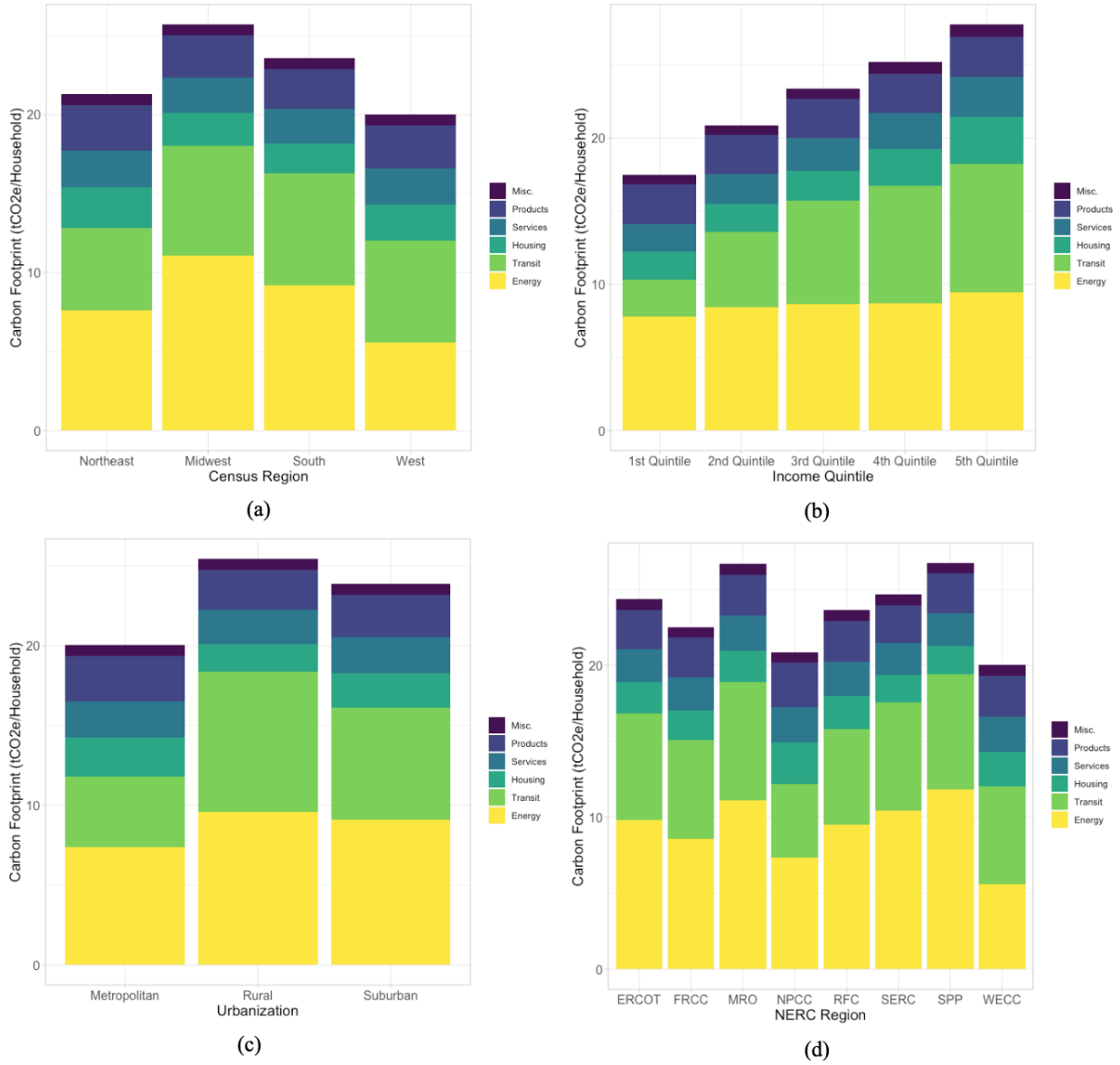


Figure 5: Total Household Carbon Footprints according to Census Region; Income Quintile; NERC Region; and Urbanization, broken out by footprint contribution

To get a sense of how carbon footprints correlate with key demographics and regional variables, Table ?? reports the results of a regression of the natural log of carbon footprints on these key variables. Column 1 omits state fixed effects while column 2 includes them. While these estimates do not reflect causal relationships, the conditional correlations are interesting and intuitive. We find that a one percent change in the number of both heating and cooling degree days is associated with a roughly a 0.05% increase in footprints when state effects are omitted; however, these elasticities fall by an order of magnitude when we include fixed state effects. Income has a similarly-sized elasticity without fixed state effects and becomes more strongly correlated when we look within states. Older households, measured by the age of the head of household, are associated with lower carbon footprints. African American and Asian households have lower footprints relative to white and multiple-race households; Hispanic households have, effectively, similar footprints. Footprints increase with education, as the omitted group is households with less than a high school education. Population density is correlated with lower footprints.

The elasticity of footprints with respect to the carbon content of the grid is nearly 0.14 without state effects and 0.06 with fixed state effects. The share of total carbon footprints coming from the electricity is 25%. These elasticities suggests that those households whose electricity has a higher carbon content also use more electricity. Homeowners have higher carbon footprints, as do households living in older homes (homes built before 1960 are the omitted group). Those homes heated with electricity, propane, and heating oil have higher carbon footprints.

	ln(CO ₂ Total), No State FEs	ln(CO ₂ Total), State FEs
ln(HDD)	0.052 (0.001)**	0.007 (0.001)**
ln(CDD)	0.031 (0.001)**	0.007 (0.001)**
ln(Household Income)	0.056 (0.002)**	0.116 (0.001)**
ln(Household Age)	-0.203 (0.003)**	-0.183 (0.002)**
Percent African American	-0.146 (0.002)**	-0.137 (0.001)**
Percent Asian	-0.230 (0.005)**	-0.087 (0.004)**
Percent Hispanic	0.008 (0.003)**	0.038 (0.002)**
Percent with HS Education	0.162 (0.007)**	0.088 (0.005)**
Percent with Some College	0.281 (0.006)**	0.235 (0.004)**
Percent with BA	0.298 (0.006)**	0.183 (0.004)**
ln(Population Density)	-0.014 (0.000)**	-0.011 (0.000)**
ln(Emissions Rate lb/mWh)	0.138 (0.001)**	-0.035 (0.008)**
Percent Owner Occupied	0.314 (0.003)**	0.245 (0.002)**
Home Built 2010 to 2015	-0.081 (0.008)**	-0.043 (0.006)**
Home Built 2000 to 2009	-0.111 (0.004)**	-0.123 (0.003)**
Home Built 1980 to 1999	-0.077 (0.003)**	-0.060 (0.002)**
Home Built 1960 to 1979	-0.025 (0.003)**	-0.024 (0.002)**
Percent Heat with Propane	-0.011 (0.005)*	-0.024 (0.004)**
Percent Heat with Electricity	0.049 (0.002)**	-0.029 (0.002)**
Percent Heat with Fuel Oil	0.113 (0.003)**	0.237 (0.003)**
Percent Heat with Other than Natural Gas	-0.219 (0.008)**	-0.174 (0.005)**
R^2	0.80	0.91
N	72,537	72,537

Notes. These represent OLS regressions of Census tract household carbon footprints on key demographics, weather conditions, and building stock variables. The first column does not include Fixed State Effects, while the second column does. Standard errors are clustered at the state level.

Table 2: Conditional Correlations of Household Carbon Footprints and Demographics, Weather Conditions, and Building Stock Variables

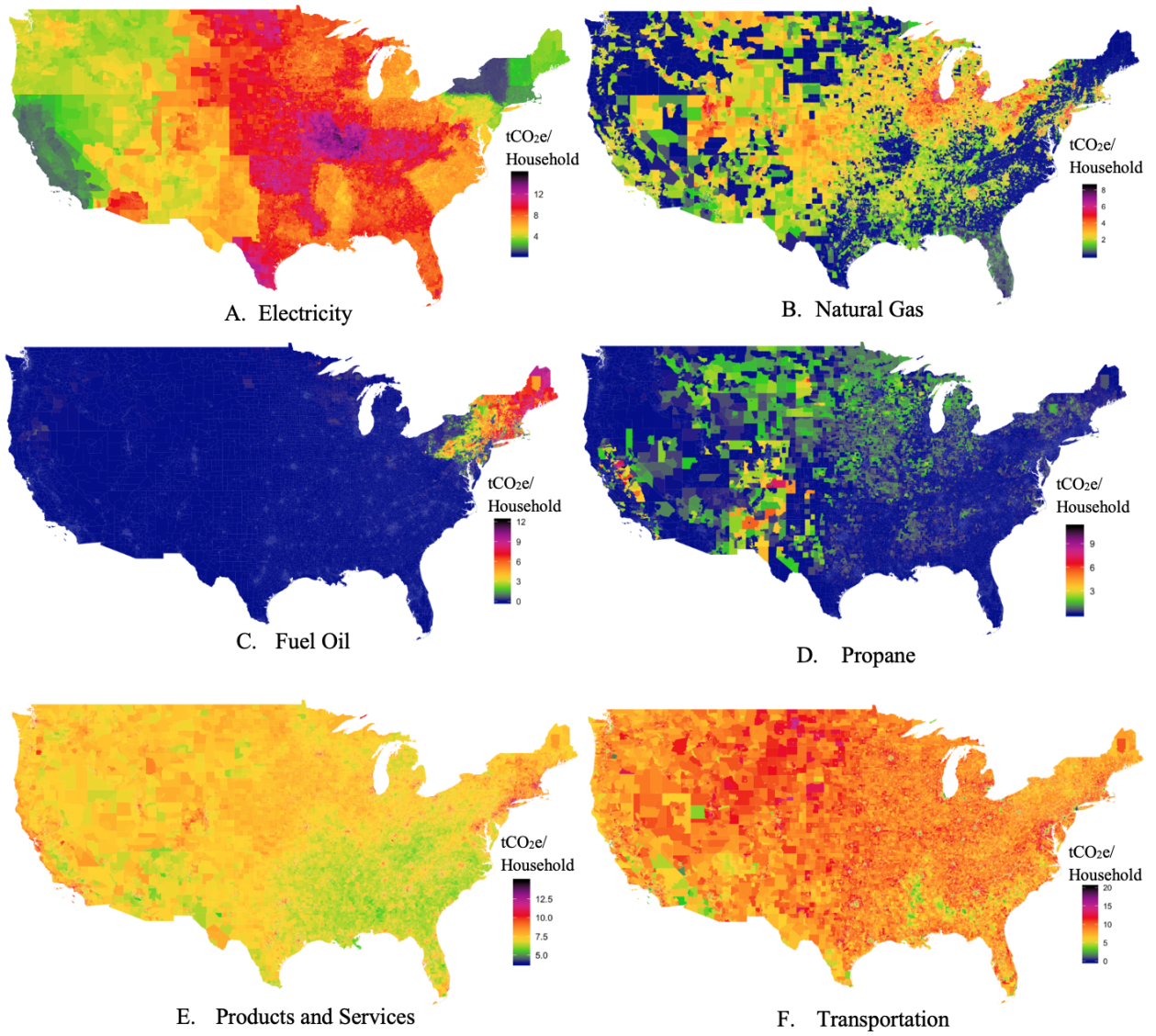


Figure 6: Carbon Footprint by Category

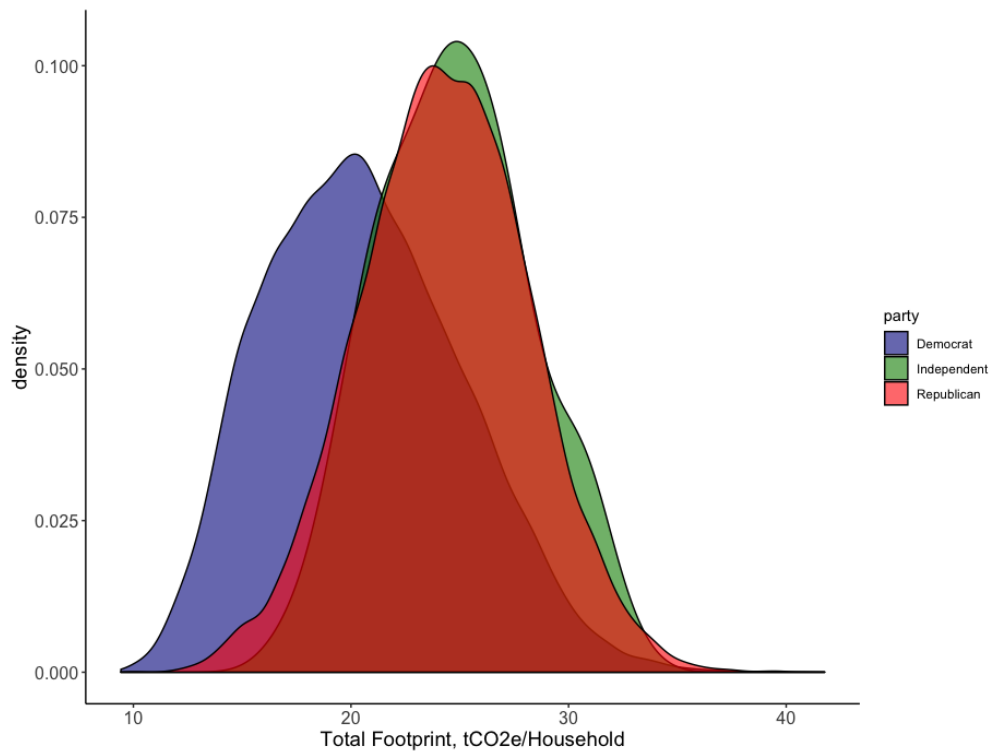


Figure 7: Distribution of Household Carbon Footprints across political parties (according to party affiliation of House Members in the 116th Congress), compared to U.S. average (represented by the dashed line)

4.2 Policy Impacts

Next we turn to analyzing the impacts of different policies on households. We begin with tax-and-dividend plans where we vary how dividends are determined. Then, we study regulatory standards. Our results highlight the large differences in incidence across policies, even within different carbon tax designs, and across geographic regions within policies. However, even the most basic tax-and-dividend plan, one that has each household within the US receiving the same dividend payment, is highly *progressive*; higher-income households receive lower net payment, the dividend amount minus carbon tax payments, especially as a share of their income.

Under a simple tax-and-dividend plan, Scenario 2 above, 96% of Census tracts with an average income in the bottom 20% of income receive a larger dividend than they pay in increased prices of energy and commodities, with an average net gain of \$307 per household per year. This is a substantial amount of income for these households. On average, a household receives over \$16.21 per year for every \$1,000 of income. Among tracts in the second income quintile, 68% of households have net gains (average gain of \$115 per year or \$3.27 per \$1,000 of income), 46% in the third quintile (-\$16 or -\$0.29 per year per \$1,000 of income), 35% in the fourth quintile (-\$115 or -\$1.32 per year per \$1,000 of income), and only 17% in the fifth quintile (-\$226 or -\$1.65 per year per \$1,000 of income).

This simple plan, however, leads to transfers from suburban and rural homes to metropolitan households. Rural households are less likely to benefit from this simple tax-and-dividend plan. Across all income levels, 31% of rural households receive a net positive dividend with an average net gain of -\$90 per household per year (-\$1.90 per \$1,000 of income). In contrast, 74.6% of metropolitan households receive net benefits, with an average net benefit of \$163 per household per year (\$2.72 per \$1,000 of income). Suburban areas lose, on average, under the simple tax-and-dividend plan. The average suburban household spends \$56 more in taxes per household per year, with over 57% of households spending more in taxes than they receive in dividends (\$1.92 per \$1,000 of income).

In the second income quintile, 70% of households benefit, with an average net dividend of \$43 per year (\$3.27 per \$1,000 of income). However, the difference among households in the second quintile is dramatic. A large share of households receive a net positive dividend (68.5%) and the average net impact is \$115 per year, but the average net impact is negative (\$-4.53 per household per year) among rural households in the second income quintile.

Households in the first quintile also see a wide distribution, although rural households still see a net positive impact, it is less than half of the net benefit to the first quintile overall

(\$122 per household per year , compared to \$307). The share of suburban tracts in the bottom 20% of income that have net benefits is 90% with an average net dividend of \$242 per household per year (\$12.80 per \$1,000 of income).¹⁹

Table 3: Net Impact of Policy Scenarios by Income Quintile (USD/Household Annually)

	1st Q.	2nd Q.	3rd Q.	4th Q.	5th Q.
Scenario 1: Carbon Tax	-907	-1088	-1219	-1322	-1457
Scenario 2: CPD	307	115	-16.2	-115	-226
Scenario 3: CPD – adjusted for urbanity	273	116	-6.96	-126	-249
Scenario 4: CPD – adjusted for geography	331	141	-10.9	-151	-289
Scenario 5: CPD – adjusted for urb. + geo.	306	136	-3.8	-153	-299
Scenario 6: CPD – adjusted for NERC Reg.	330	142	-13	-150	-281
Scenario 7: CPD – adjusted for income	676	273	0	-331	-587
Scenario 8: CPD – adjusted for inc. + geo.	676	273	0	286	571
Scenario 9: CAFE	-68.1	-87.9	-86.4	-53.4	-23.4
Scenario 10: CES	-5.06	-5.49	3.56	27.2	41.1
Scenario 11: CPP	-161	-191	-177	-145	-130
Scenario 12: CPD & Regs	-21.5	-42.2	-77.1	-99.7	-149

Table 4: Net Impact of Policy Scenarios by Urbanity (USD/Household Annually)

	Metropolitan	Rural	Suburban
Tax	-1044	-1297	-1264
Baseline	163	-89.9	-56.4
CPD – adjusted for urbanity	117	4.52	-93.2
CPD – adjusted for geography	111	-33.6	-34.7
CPD – adjusted for urb. + geo.	82.2	5.23	-57.6
CPD – adjusted for NERC Reg.	122	-56.6	-36.6
CPD – adjusted for income	192	-34.8	-67.4
CPD – adjusted for inc. + geo.	147	95.9	-95.5
CAFE	-48	-136	-74.4
CES	20.9	-20.6	1.81
CPP	-127	-204	-186
CPD & Regs	-52.0	-93.4	-88.1

19. For additional information on the net impact per \$1000 of income, percentage of households who have a net benefit, and average dividend amount in each CPD scenario, see the Appendix, section A.

4.2.1 Alternative Dividend Plans

Tables 9 and 10 display the average dividend amount per household for policy scenarios 2 through 8 according to income and urbanity, respectively. In each scenario, the revenue collected is the same (approximately \$101 Billion USD), but divided differently. In scenarios 3, 5, and 8, there is an explicit adjustment for urbanity of the household and in scenarios 7 and 8 there is an explicit adjustment for income. However, adjusting for urbanity and geography increases the dividend for the bottom three income quintiles and adjusting for income increases the dividend for rural households. Adjusting for NERC regions also increases the progressive structure of the dividend.

Figures 8, 10, and 12 show the geographic distribution of household impacts for policy scenarios 2, 5, and 7, respectively. Each figure includes an expanded view of St. Louis, Missouri to facilitate discussion on impacts to major Midwestern cities. Figures 9, 11, and 13 show the income distribution of household impacts for policy scenarios 2, 5, and 7, respectively. Each figure includes the overall effect and the cross-sectional impacts across urbanity for each income group.

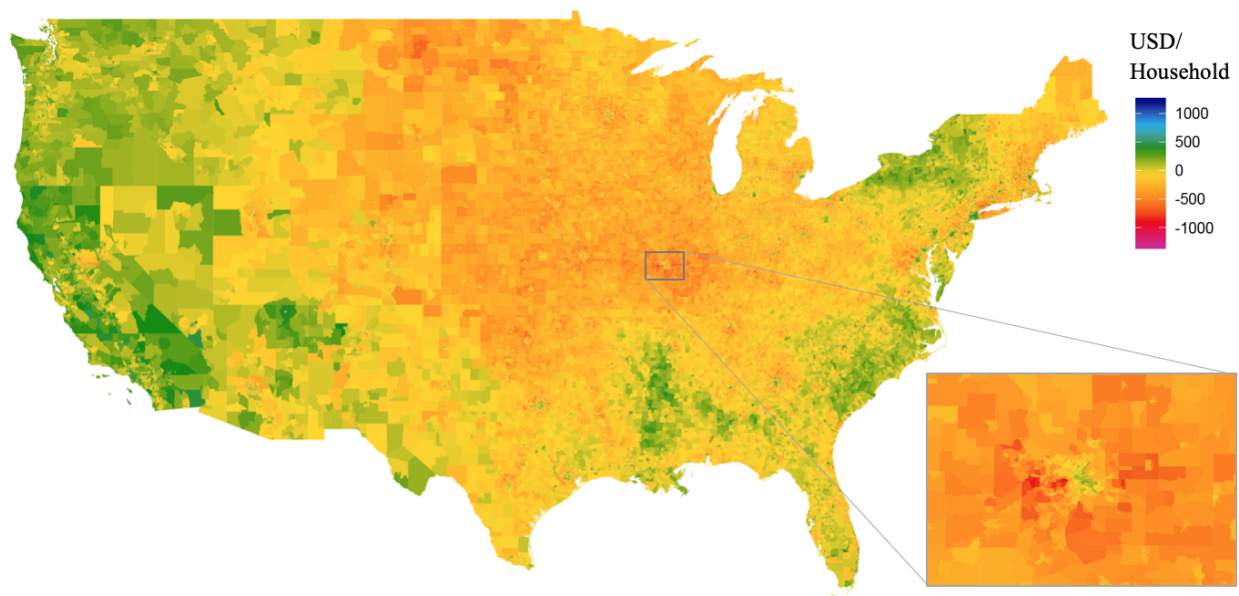


Figure 8: Net Impact of \$50 Carbon Price and Dividend

Scenario 5, a carbon price and dividend adjusted for urbanity and geography has the most homogeneous impact across the United States and the most narrow distribution of impacts within each income group. Scenario 7, a carbon price and dividend adjusted for income, has the greatest heterogeneity net effects within income groups. St. Louis is a good example of the effects of urbanization across each of these policy scenarios. In each case, there

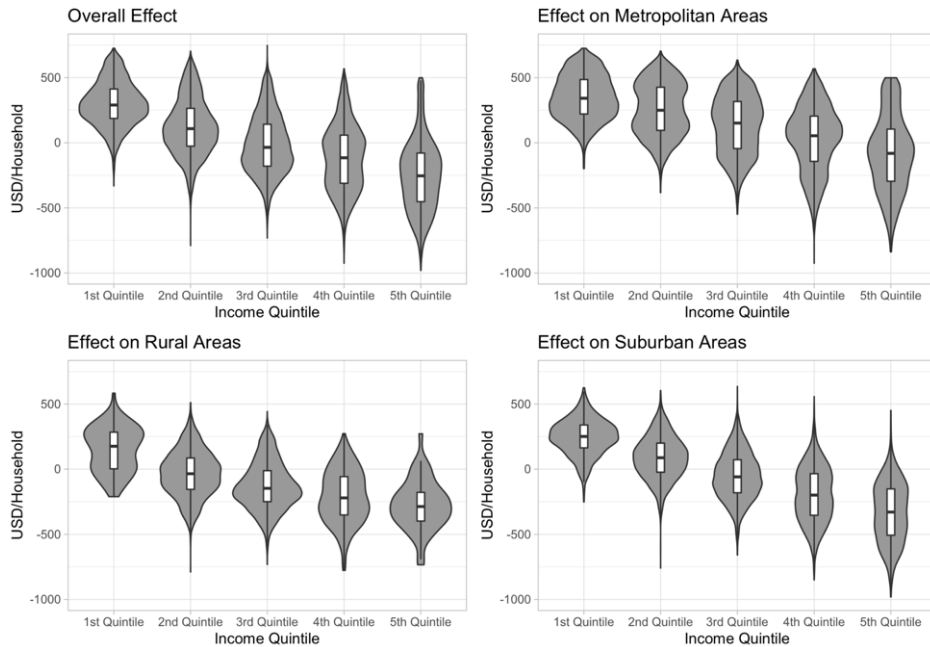


Figure 9: Net Impact of \$50 Carbon Price and Dividend - According to Income Quintile and Urbanity

are greater net benefits in the city center, lower net benefits in the suburbs, and rural areas tend to break even or lose on net. But, compared to the baseline CPD, the CPD adjusted for urbanity and geography has more homogeneous effects (a smaller absolute difference) and the CPD adjusted for income has more heterogeneous effects (a larger absolute difference). Comparing across geographic differences, when controlling for urbanity and geography, there does not seem to be clear and strong advantage for any particular state. However, when this is not controlled for, there are stronger advantages to California and New York and lower advantages to the Midwest and Mountain North.

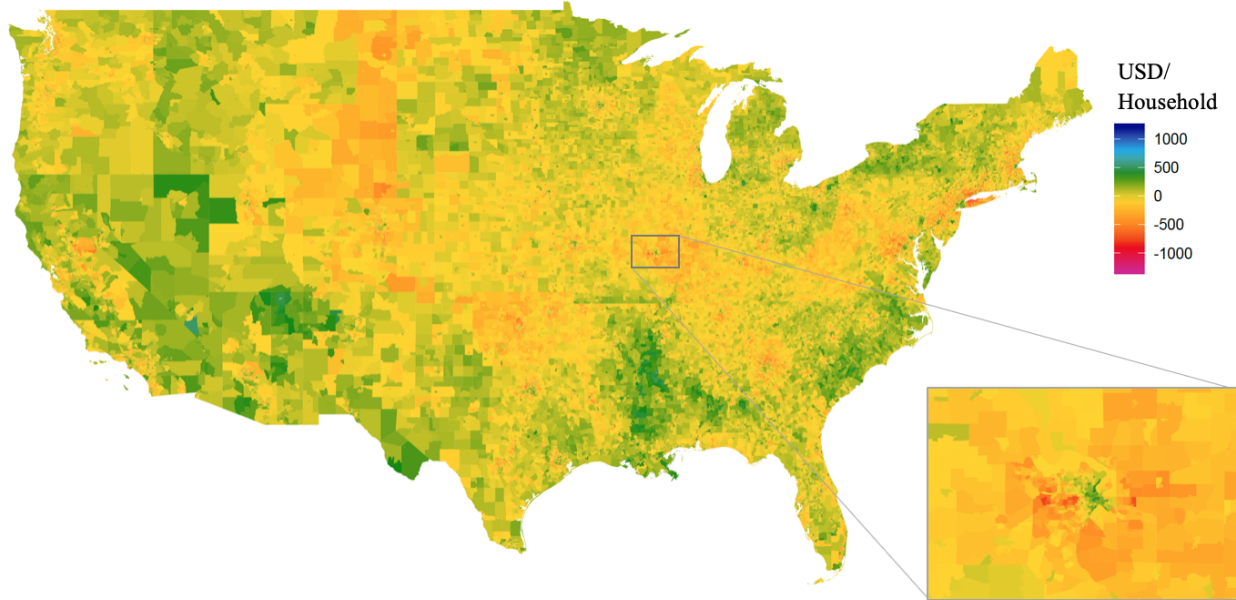


Figure 10: Net Impact of \$50 Carbon Price, Dividend adjusted for Urbanity and Geography

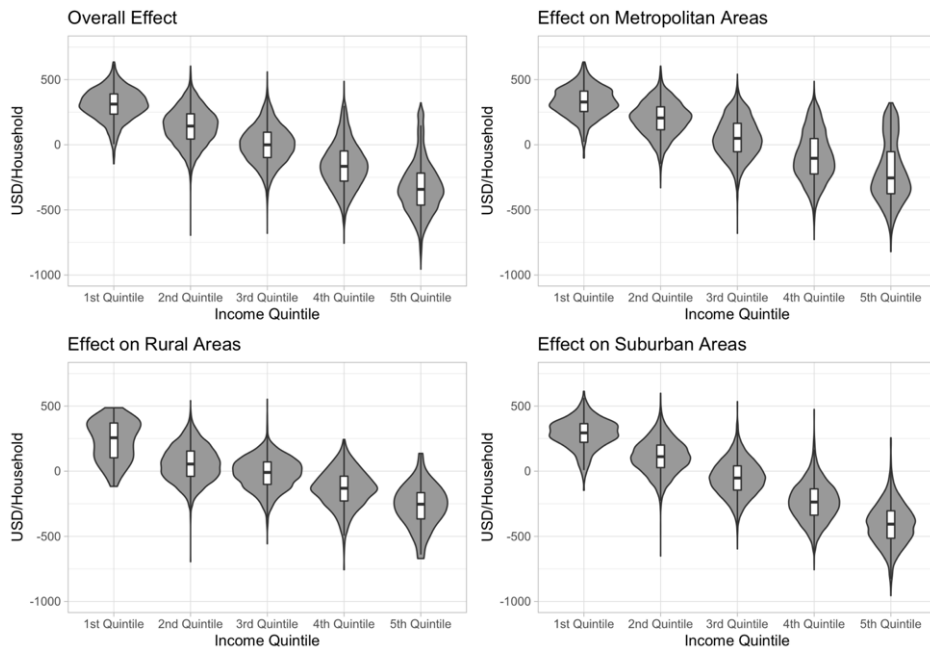


Figure 11: Net Impact of \$50 Carbon Price, Dividend adjusted for Urbanity and Geography - According to Income Quintile and Urbanity

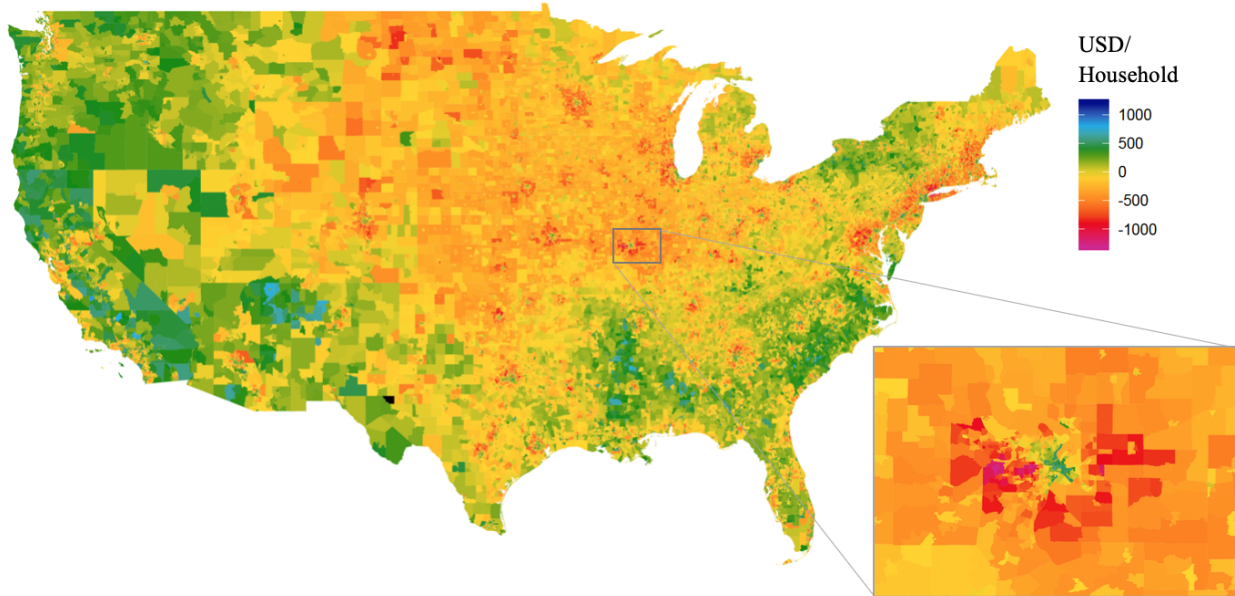


Figure 12: Net Impact of \$50 Carbon Fee, Dividend adjusted for Income

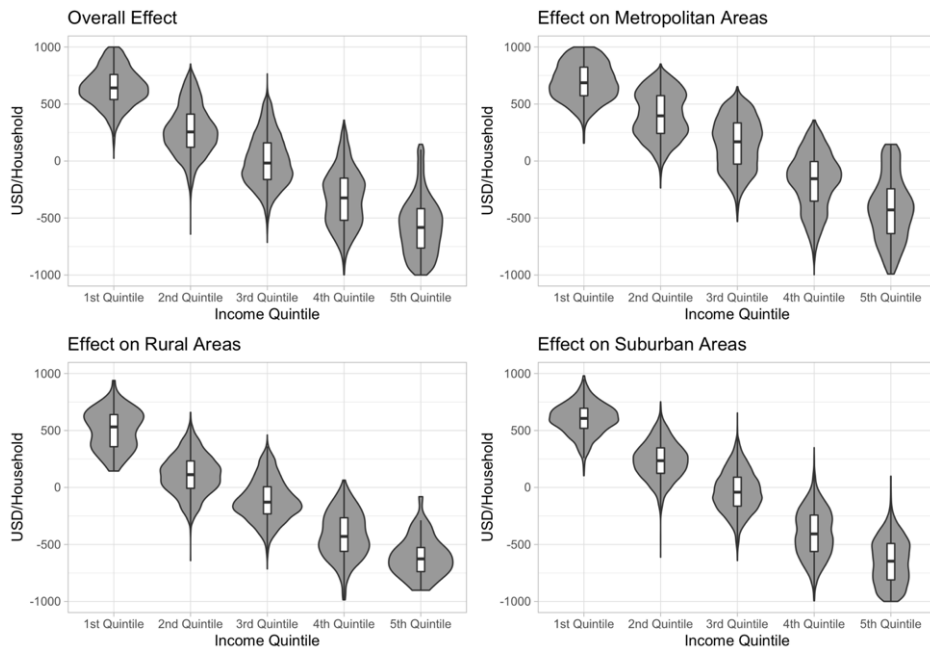


Figure 13: Net Impact of \$50 Carbon Fee, Dividend adjusted for Income - According to Income Quintile and Urbanity

4.2.2 Regulations

Figures 14, 16, and 18 show the geographic distributions for a CAFE Standard (Scenario 9), Clean Energy Standard (Scenario 10), and the Clean Power Plan (Scenario 11), respectively. Figures 15, 17, and 19 show the distribution of net effects across income groups and urbanity for each regulatory approach. As shown, CAFE standards are regressive and tend to disadvantage rural and Midwestern areas while benefiting coastal and urban areas. The conclusions for regressivity are less clear in the case of a CES, as the distribution is bi-modal, but there is a clear disadvantage to households in dirtier NERC regions, which are located in the Midwest and the Plains.

The regulatory policies we model all have net costs to the bottom two income quintiles. The Clean Power plan has the largest absolute cost per household (-\$161 per household for the lowest 20%, or -\$8.54 per \$1000 of income; and -\$191 for the second quintile, or -\$5.44 per \$1000 of income), followed by CAFE standards (-\$68 per household for the lowest 20%, or -\$3.61 per \$1000 of income; and -\$88 per household for the second quintile, or -\$2.50 per \$1000 of income). Although it followed a regressive trend, the costs associated with a Clean Energy Standard were small in comparison (-\$5.06 per household for the lowest 20%, or -\$0.27 per \$1000 of income; and -\$5.49 for the second quintile, or -\$0.16 per \$1000 of income). It should be noted that the estimated carbon emissions reduction between each regulatory policy and between the regulatory policies and the carbon pricing policies are not the same. We seek to draw attention to the general trends in regional and income effects, not only absolute impacts.

The estimation of costs and benefits for the Clean Energy Standard are based on the assumption of inelastic consumption of electricity for each household and 100% pass-through of the permit prices. If a household is connected to a part of the grid with lower carbon emissions than the national average, then they will have subsidized electricity rates and will therefore have a net benefit, scaled by the amount of consumption for that household. In areas with more carbon-intensive grids, especially in states such as Missouri, Wisconsin, and Illinois, then households will have higher electricity rates and a resulting net cost. We applied a price of \$50 per ton of CO₂-equivalents, although the permit prices are likely to be lower. Accounting for the benefits of a CES such as reduced nitrogen oxide emissions is important for policy-making but outside the scope of this paper.

The costs of the Clean Power Plan are based on the estimated permit prices for each state that would be necessary to be in compliance with the Obama-era policy by the year 2030. As with the CES, estimating the benefits of avoided emissions and the co-benefits

of lowered pollutants and their respective distribution across the country is important but outside our scope. In fact, any benefits to the CPP are not included in our framework.

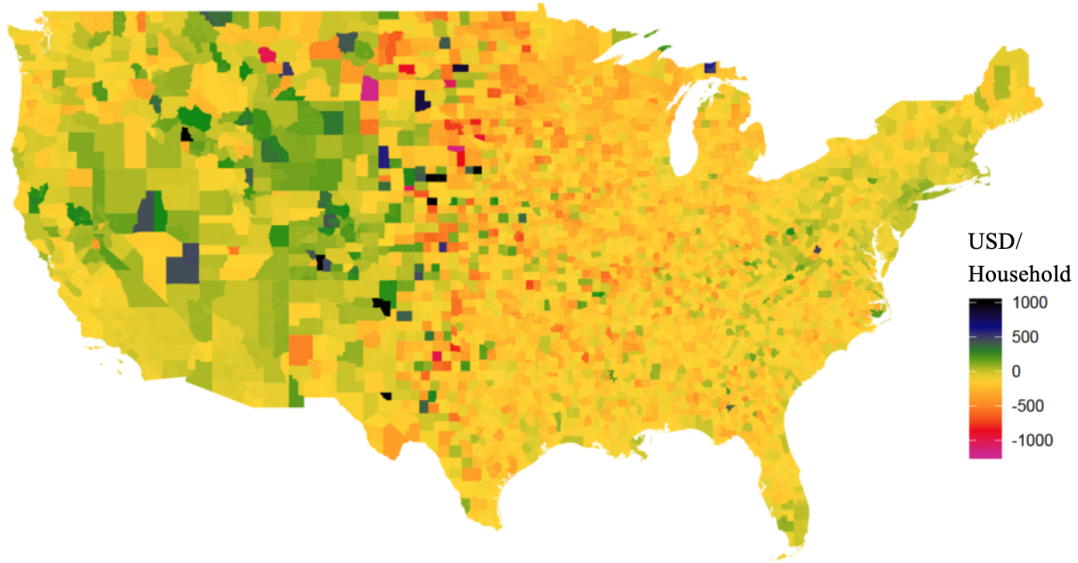


Figure 14: Net Impact of CAFE Standard

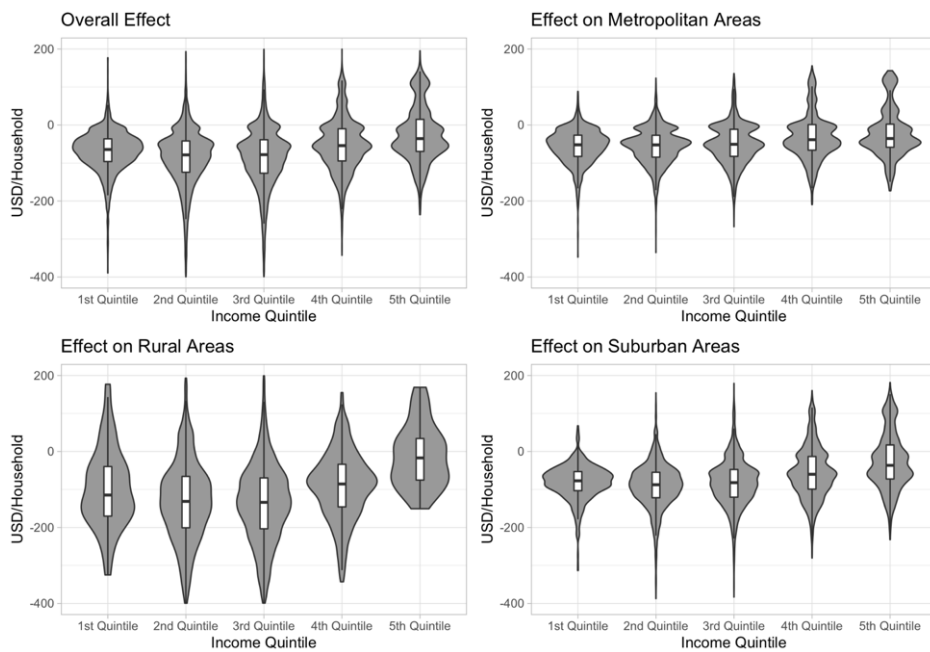


Figure 15: Net Impact of CAFE Standard - According to Urbanity and Income Quintile

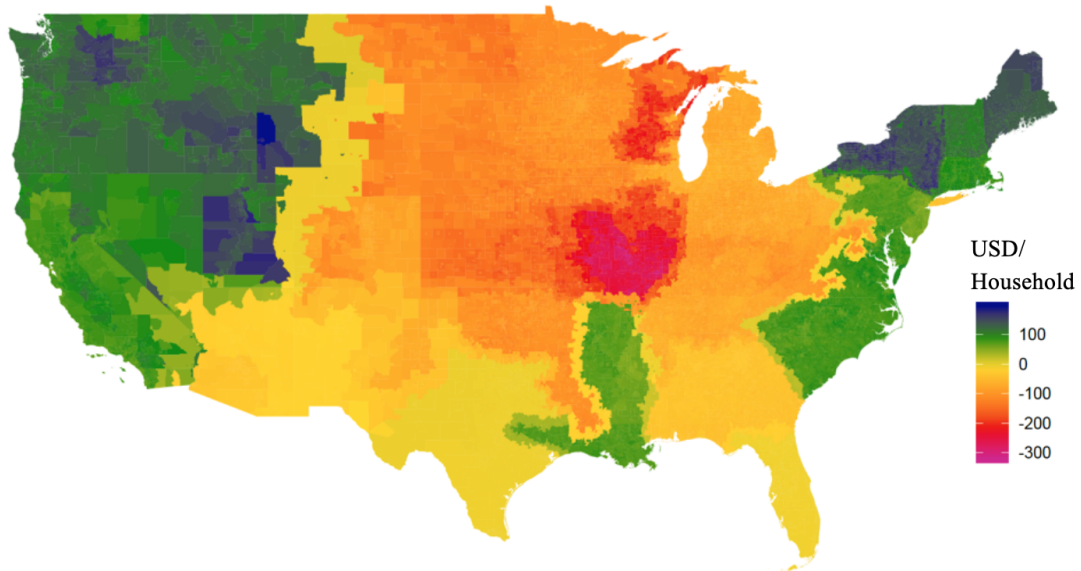


Figure 16: Net Impact of Clean Energy Standard

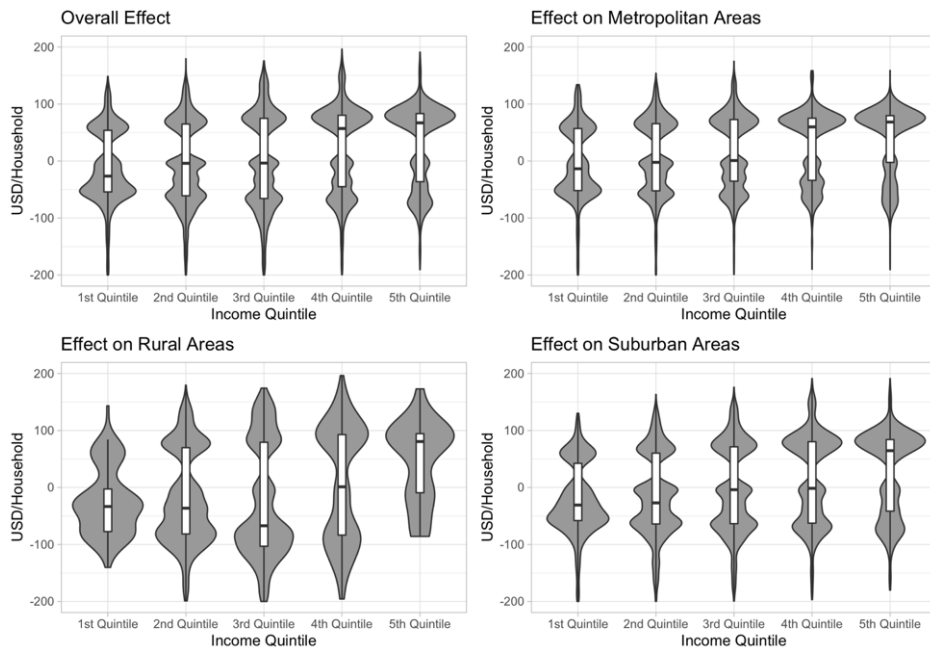


Figure 17: Net Impact of Clean Energy Standard - According to Urbanity and Income Quintile

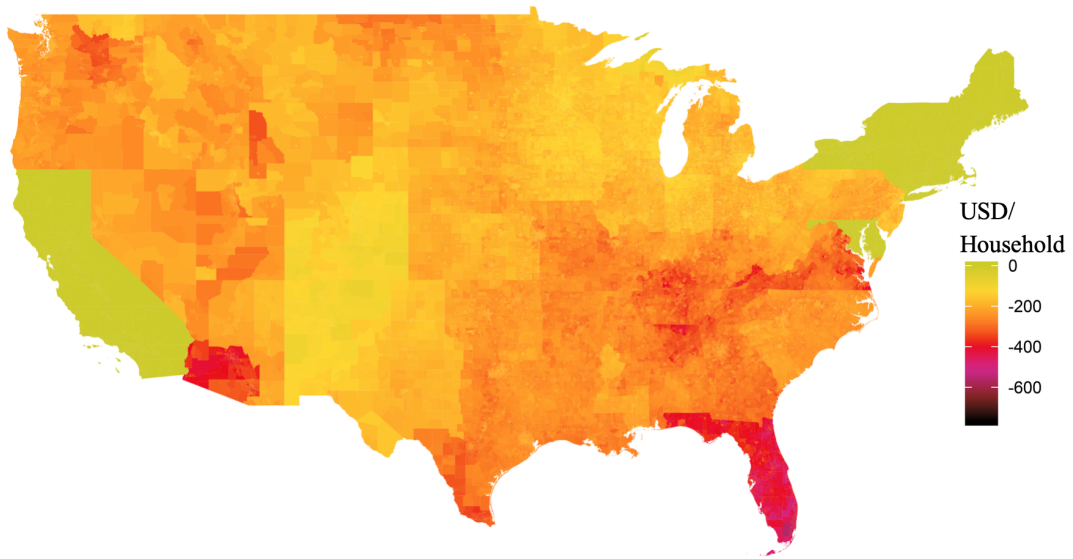


Figure 18: Net Impact of the Clean Power Plan

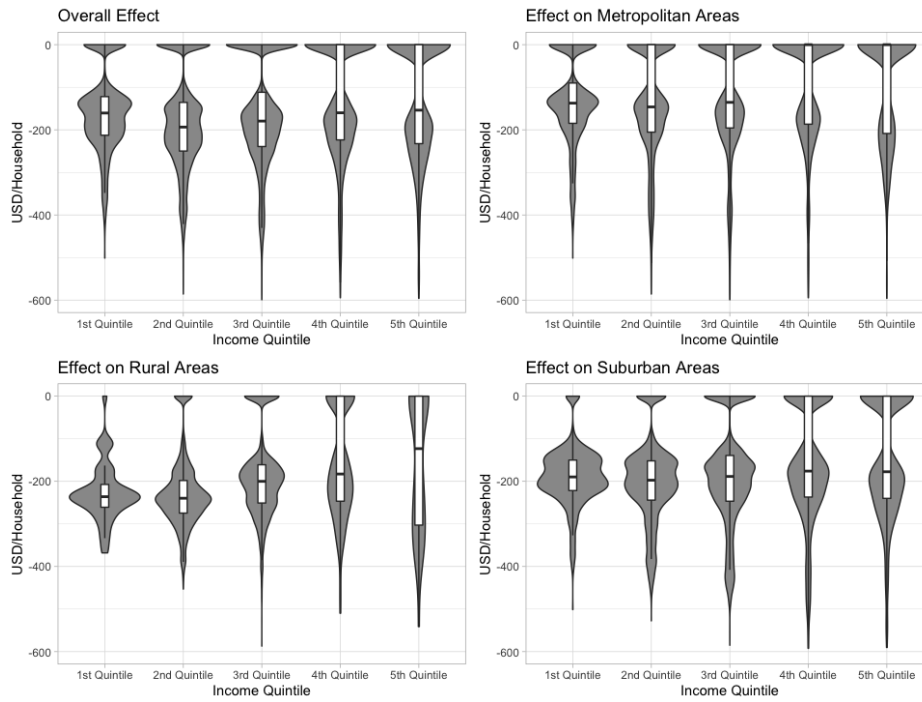


Figure 19: Net Impact of the Clean Power Plan - According to Urbanity and Income Quintile

5 Discussion

All policy creates winners and losers. Climate change policies are not different. However, our results highlight that if policy makers are not careful, winners and losers can be concentrated within certain income brackets and certain regions of the country. Given the controversial nature of climate change policy in general, policies that do not rectify these discrepancies are likely to be resisted.

We find that geography can play a role that is as significant as household income. This is largely due to the relative carbon intensity of the electricity grid. Other modeling has found that the majority of emissions reductions will come from the electric power sector (Goulder et al. (2019)), therefore this regional difference will likely be mitigated with higher amounts of renewable penetration and the retirement of coal power in Appalachia and the Midwest. As decarbonization occurs in the United States, there is potential to reduce the heterogeneous impacts of climate policy within an income group—especially through programs that will reduce consumption and emissions in rural areas. Such policy could include community solar and weatherization assistance programs and the extension of the Production Tax Credit. However, new wind and solar in the heartland will not erase the substantial advantage of the West Coast in renewable energy and efficiency measures. A carbon dividend can be an effective tool for mitigating regional transfers, while still incentivizing households everywhere to reduce emissions.

Based on the conclusions of Jorgenson et al. (2018), we can expect that all policy scenarios that assess a similar price on carbon (scenarios 1 through 8) will have similar emissions reductions. However, we cannot assume that there will be equivalent reductions through regulatory control (scenarios 9 through 12). Indeed, as discussed in Knittel (2019), existing regulations could be replaced with a \$7 per ton price on carbon. We draw attention instead to the trends in regressivity and regional transfers across policy scenarios. There is likely to be a blend of regulatory approaches and pricing policy in a comprehensive climate strategy and future work should focus on how policy can be efficiently combined, and which sectors of the economy should be decarbonized through the instruments available.²⁰

Figures 21 and 20 show that for a Carbon Price and Dividend policy, there are transfers

20. Goulder et al. (2019) showed that 64 to 68% of the emissions reduced from a carbon price come from the electric power sector. Our work shows that the electric grid accounts for the large regional differences between effects of climate policy, while higher costs to high-income households are a factor of greater transportation emissions and more product and service consumption. If a carbon price is not economy wide, or properly applied through border adjustment policy, our conclusions that a price and dividend scheme will be broadly progressive may not hold.

that exist between income quintiles, between urban and rural households, and between regions.²¹ We believe that the former is desirable, as a progressive policy will yield a transition that is equitable and resilient to change. The latter, however, is not necessary in achieving a progressive outcome and should be avoided in the design of an national climate policy. Further, we believe that dividends are the clearest and most efficient way to correct for transfers between urban and rural populations. Across incomes, the typical household in the upper quintile of income transfers \$289 per year, the fourth and third quintiles transfer \$105 and \$17 out to lower income quintiles, respectively. Across urbanity, the typical rural household transfers \$286 per year to urban households. Finally, households in the South and Midwest transfer money to the Coasts under the plain CPD program. It is these last two transfer that we seek to analyze and reduce.

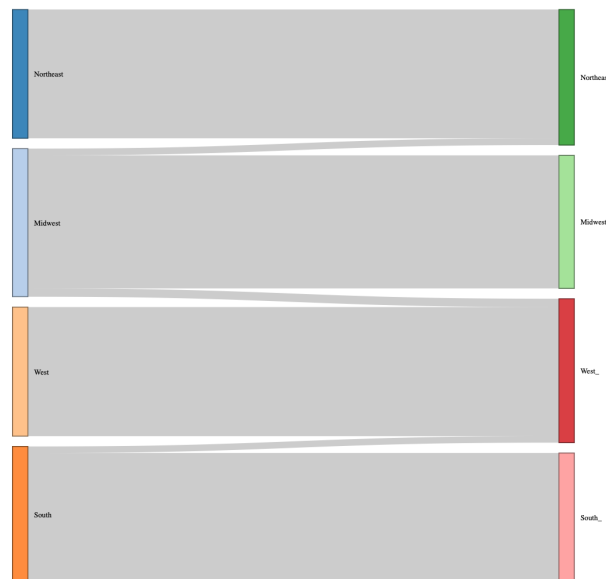


Figure 20: Transfers between households in each Census region for a Carbon Price and Dividend (the left side represents relative tax paid through a carbon price for the average household in each region, the right side represents the dividend received; the flows between regions reflect the transfers between those regions)

Policy makers can easily protect both rural populations and low-income households if a carbon dividend scheme accounts for geography and/or urbanity. Creating a ladder for the dividend, where low-income households are paid more and high-income households are paid less, can indeed increase the progressive trend of the policy, but also increases the heterogeneity of outcomes within an income group. While income-adjusted policy design might

21. While the amount of money flowing *out* of a quintile is exact, the specific mix of *where* the dollars flow is arbitrary. We show the results for one mix.

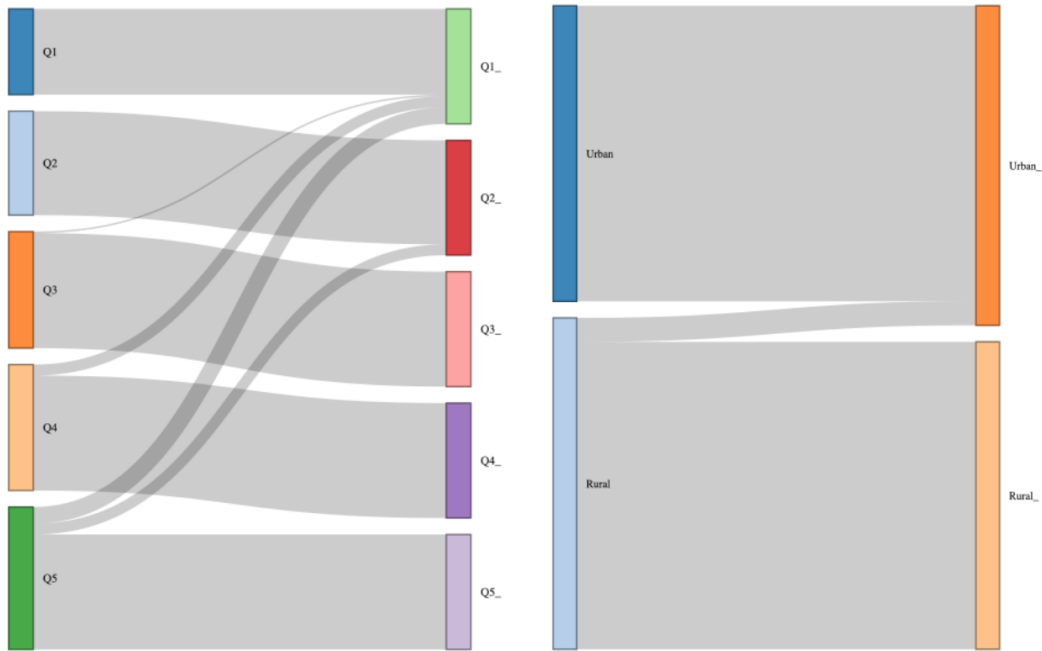


Figure 21: Transfers between income quintiles and urban-rural households for a Carbon Price and Dividend

have more natural political support, mitigating the negative effects for some households in low-income brackets (even while an income group as a whole benefits) is also likely a goal for policy makers. That is, it is not enough to examine the effects to the average household within an income group, the distribution of outcomes by geography must also be considered. Therefore, policy makers must also consider heterogeneity of impacts and their geographic distribution.

Accounting for both geography (determined by the Census divisions of the country) and urbanity (determined by population density and Census classifications) produce an outcome that is significantly less heterogeneous and more progressive than an equal dividend given to all households. Such a policy could be a good bipartisan “win-win” that will benefit constituents in progressive districts and conservative alike.

There will be a trade-off between the simplicity of policy, and thus administratively simple, and fixing regional transfers; and there is also a trade-off between protecting vulnerable populations who could be adversely affected by a policy and maintaining the incentive to reduce emissions. For example, carbon tax revenues could be adjusted based on state boundaries so that households in more carbon-intense states would receive higher dividends than states that have lower emissions. However, such a policy could create an adverse incen-

tive for state policy makers to maintain a higher carbon footprint so that their constituents would continue to receive a higher dividend.

There is more to do. The interaction between command-and-control regulation and a carbon price and dividend should be explored in further depth with a computational and general equilibrium model. Other components of a carbon pricing proposals, such as border adjustments, deserve attention and modeling. Finally, the distribution of source-side effects, costs to industry and business, and costs to local governments also warrants exploration.

6 Conclusion

The results from our work underscore the high variability in household carbon footprints across a number of dimensions. Two dimensions warrant focus. First, our results suggest that largely driven by consumption of goods and services, low-income consumers are likely to spend more on carbon taxes, as a share of their income. We are not the first to find this result. The regressivity of carbon taxes, ignoring the use of the revenues, is a well-known argument against their use. While recent work suggests that after accounting for the impact of carbon taxes on transfers, firms, and employment (known as source-side effects), carbon taxes are no longer regressive, but the regressivity of carbon taxes on the consumption dimension (use-side effects) is likely to be a major political obstacle.

Our work highlights a second dimension that is likely to be just as large, if not larger, of a political obstacle: the wide range in carbon footprints across rural and urban communities. Indeed, the geographic effect of carbon footprints is nearly as significant as the variability across income levels.

These results highlight the importance of how revenues from a carbon tax are recycled into the economy. From an economic efficiency perspective, the best use of the revenue is to reduce existing taxes that are a drain on economic activity and efficiency, such as income or sales taxes. The intuition here is that as we replace economically inefficient (e.g., income) taxes with efficiency-enhancing taxes (such as carbon taxes), we not only help mitigate climate change, but we also improve the overall efficiency of the macro economy. The drawback of such a carbon tax policy is that it requires jointly adopting a carbon tax together with larger tax reforms, as well as the commitment of policy makers to not increase the income or sales taxes in the future. We suspect that the political hurdles of such a system are insurmountable.

A more simple policy design refunds the revenues collected by the carbon tax in the

form of household “dividends,” so-called tax-and-dividend plans (Baker et al. (2017)). Most tax-and-dividend plans that we are aware of do not differentiate across households; each household receives the same dividend amount each year. While a policy such as this has the advantage of being simple and straightforward, this ignores the large geographic differences in carbon footprints that we document, particularly across rural and urban settings.

We show that correcting for heterogeneity can also improve the progressive outcome of policy. However, one important result to note is that when adjusting the dividend to increase the amount for low-income households and reduce the amount for high-income households benefits rural households more on average but increases the overall heterogeneity of impacts within each income group. Adjusting the dividend for both geography and urbanity increases the average benefit to low-income households and reduces the heterogeneity of impacts within income groups.

We recommend a tax-and-dividend policy design that accounts for the rural-urban divide in carbon footprints. There are many ways to do this. The basic structure is to condition the level of the dividend on some information about the type of the household. It is of utmost importance that households have limited ability to alter their type themselves. If a household can take strategic actions to affect their dividend level, then they will have less of an incentive to reduce their carbon footprints. In addition, the dividends cannot be state specific. Having them be based on the average carbon content of a given state will reduce the incentives of state policy makers to adopt carbon-reducing policies. We leave the details of such a plan for future policy discussions, but we hope that our results can aid policy makers in weighing the different trade-offs associated with designing a carbon tax-and-dividend policy.

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A Additional Tables

Table 5: Net Impact of Policy Scenarios per \$1000 of Income by Income Quintile

	1st	2nd	3rd	4th	5th
Carbon Tax	-48.10	-31.00	-21.70	-15.10	-10.60
CPD	16.30	3.27	-0.29	-1.32	-1.65
CPD – adjusted for urbanity	14.50	3.30	-0.12	-1.44	-1.81
CPD – adjusted for geography	17.60	4.01	-0.20	-1.72	-2.10
CPD – adjusted for urb. + geo.	16.20	3.87	-0.07	-1.74	-2.17
CPD – adjusted for NERC Reg.	17.50	4.04	-0.23	-1.71	-2.04
CPD – adjusted for income	35.90	7.78	0.00	-3.78	-4.27
CPD – adjusted for inc. + geo.	35.90	7.78	0.00	3.26	4.15
CAFE	-3.61	-2.50	-1.54	-0.61	-0.17
CES	-0.27	-0.16	0.06	0.31	0.30
CPP	-8.54	-5.44	-3.15	-1.66	-0.95
CPD & Regs	-1.14	-1.20	-1.38	-1.14	-1.09

Table 6: Net Impact of Policy Scenarios per \$1000 of Income by Urbanity

	Metropolitan	Rural	Suburban
Carbon Tax	-18.10	-26.10	-19.50
CPD	2.72	-1.90	-1.14
CPD – adjusted for urbanity	1.91	0.00	-1.73
CPD – adjusted for geography	1.80	-0.76	-0.80
CPD – adjusted for urb. + geo.	1.30	0.00	-1.17
CPD – adjusted for NERC Reg.	2.00	-1.20	-0.82
CPD – adjusted for income	2.97	-0.83	-1.56
CPD – adjusted for inc. + geo.	2.22	1.76	-1.99
CAFE	-0.81	-2.73	-1.15
CES	0.39	-0.39	0.04
CPP	-2.27	-4.15	-2.91
CPD & Regs	-0.904	0	-1.36

Table 7: Fraction of Households with Positive Net Impact by Income Quintile

	1st	2nd	3rd	4th	5th
CPD	0.962	0.685	0.459	0.348	0.172
CPD – adjusted for urbanity	0.95	0.7	0.494	0.336	0.15
CPD – adjusted for geography	0.989	0.802	0.479	0.189	0.0803
CPD – adjusted for urb. + geo.	0.986	0.808	0.509	0.199	0.0789
CPD – adjusted for NERC Reg.	0.98	0.798	0.467	0.226	0.0913
CPD – adjusted for income	1	0.892	0.486	0.104	0.0333
CPD – adjusted for inc. + geo.	1	0.915	0.509	0.133	0.0338
CAFE	0.0487	0.0854	0.114	0.201	0.31
CES	0.331	0.356	0.411	0.541	0.619
CPP	0	0	0	0	0
CPD & Regs	0.463	0.450	0.366	0.276	0.113

Table 8: Fraction of Households with Positive Net Impact by Urbanity

	Metropolitan	Rural	Suburban	
CPD	0.746	0.313	0.434	
CPD – adjusted for urbanity	0.689	0.501	0.373	
CPD – adjusted for geography	0.709	0.427	0.456	
CPD – adjusted for urb. + geo.	0.669	0.529	0.419	
CPD – adjusted for NERC Reg.	0.73	0.366	0.461	
CPD – adjusted for income	0.711	0.433	0.465	height
CPD – adjusted for inc. + geo.	0.681	0.637	0.415	
CAFE	0.161	0.104	0.113	
CES	0.496	0.336	0.386	
CPP	0	0	0	
CPD & Regs	0.415	0.343	0.327	height

Table 9: Average Household Dividend by Income Quintile

	1st	2nd	3rd	4th	5th
CPD	1208	1208	1208	1208	1208
CPD – adjusted for urbanity	1174	1209	1217	1197	1185
CPD – adjusted for geography	1232	1233	1213	1172	1145
CPD – adjusted for urb. + geo.	1207	1228	1220	1170	1135
CPD – adjusted for NERC Reg.	1231	1235	1211	1173	1153
CPD – adjusted for income	1577	1366	1224	992	847
CPD – adjusted for inc. + geo.	1577	1366	1224	1037	863
CPD & Regs	523	523	523	523	523

Table 10: Average Household Dividend by Urbanity

	Metropolitan	Rural	Suburban
CPD	1208	1208	1208
CPD – adjusted for urbanity	1161	1302	1169
CPD – adjusted for geography	1155	1264	1229
CPD – adjusted for urb. + geo.	1126	1302	1205
CPD – adjusted for NERC Reg.	1166	1242	1228
CPD – adjusted for income	1222	1261	1180
CPD – adjusted for inc. + geo.	1179	1390	1152
CPD & Regs	523	523	523

B Additional Figures

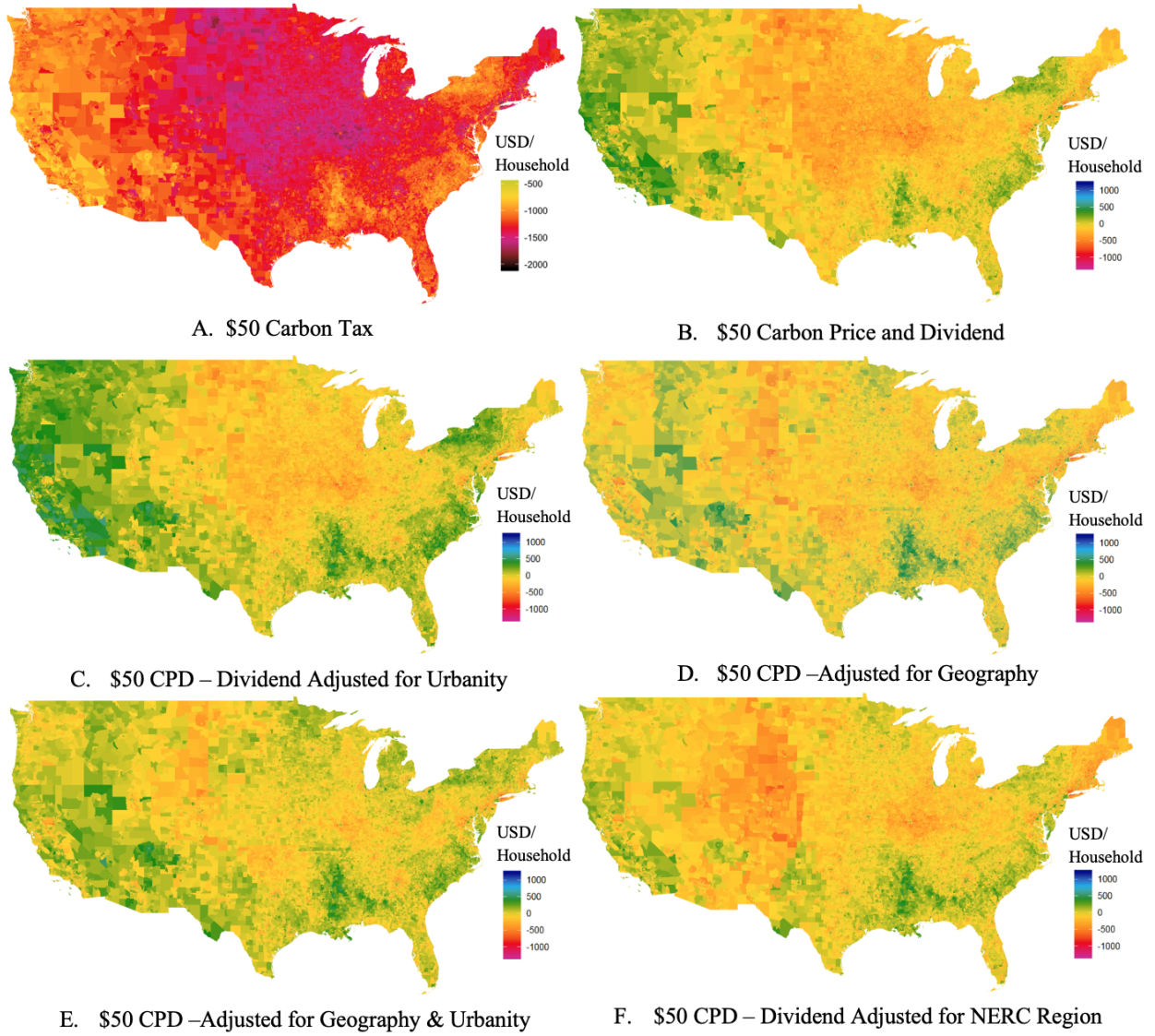


Figure 22: Policy Scenarios 1 - 6

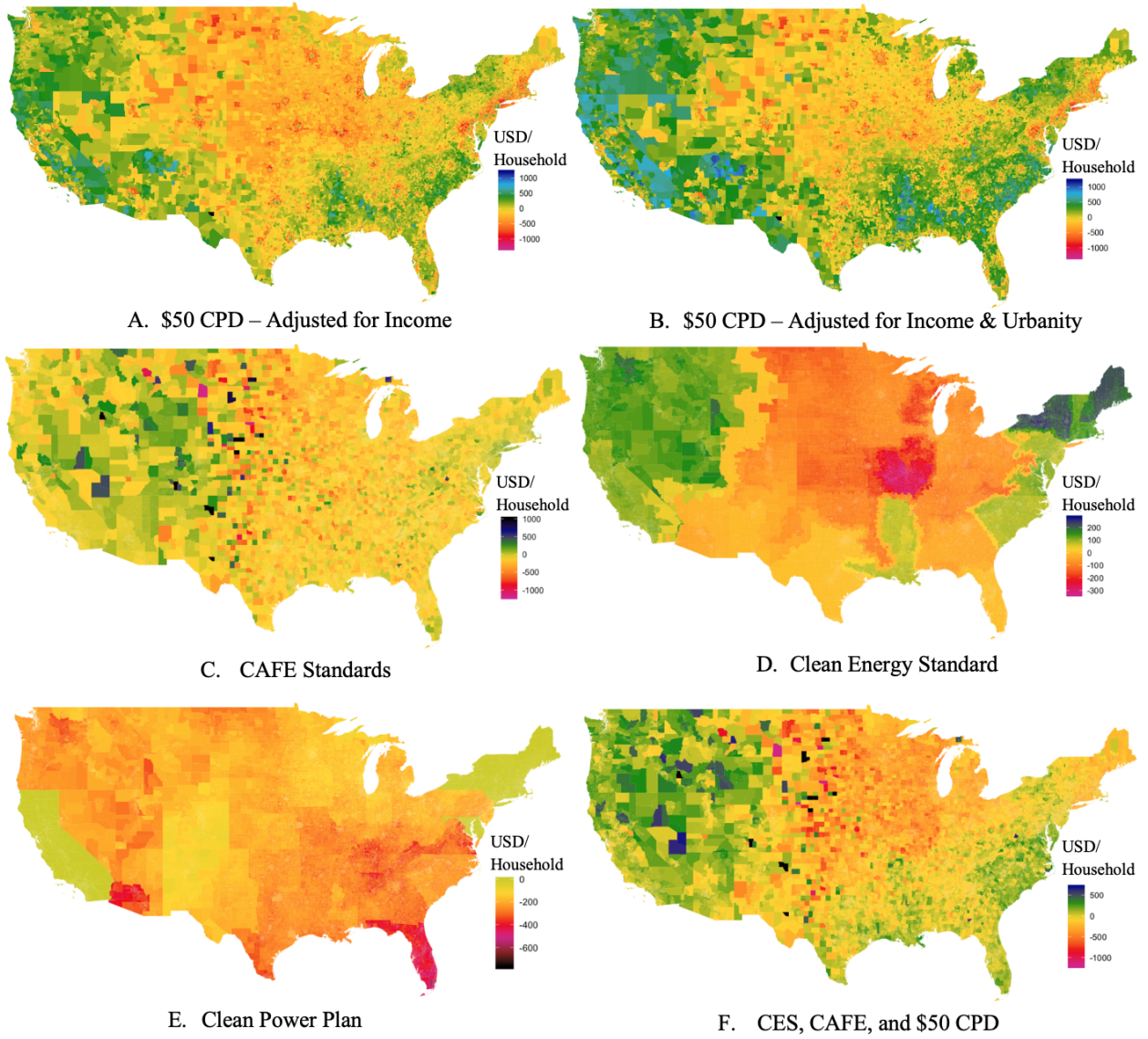


Figure 23: Policy Scenarios 7 - 12

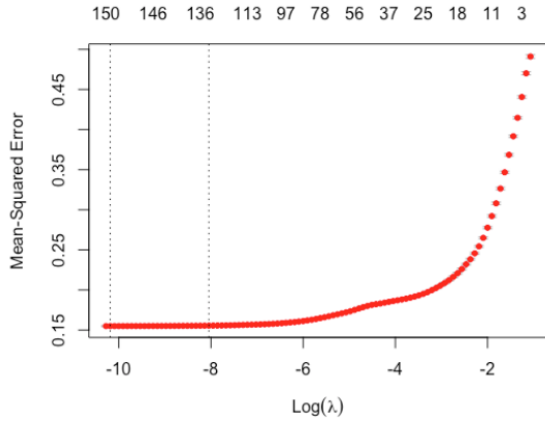
C Model Performance

Table 11: R-Squared Values for models

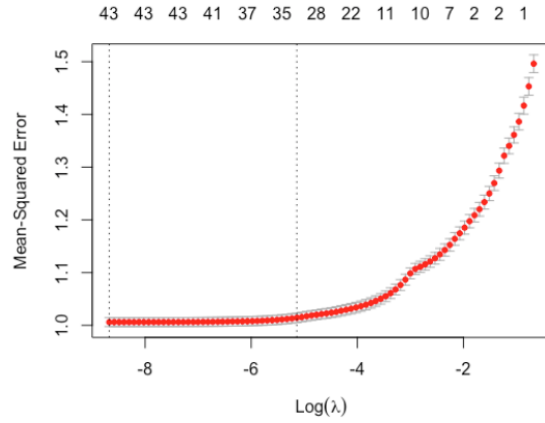
Jones and Kammen (Reported)	Lasso Only	Lasso & Probit
Electricity 0.608	0.687	0.623
Natural Gas 0.471	0.674	0.835
Propane	0.646	0.614
Fuel Oil 0.206	0.604	0.812
Vehicle Miles Traveled 0.324	0.324	0.277
Food Cons.	0.332	0.248
Alcoholic Bev. Cons.	0.0716	0.0503
Housing Costs	0.243	0.184
Apparel Cons.	0	0.00221
Healthcare Costs	0.142	0.0849
Entertainment Costs	0	0.00349
Personal Care Cons.	0.115	0.0610
Education Costs	0.0131	0.00513
Tobacco Prod. Cons.	0.0195	0.0133
Life Insurance Costs	0	0.0111
Misc. Cons.	0	0.00239
Cash Contributions	0	0.00373

D Model Development

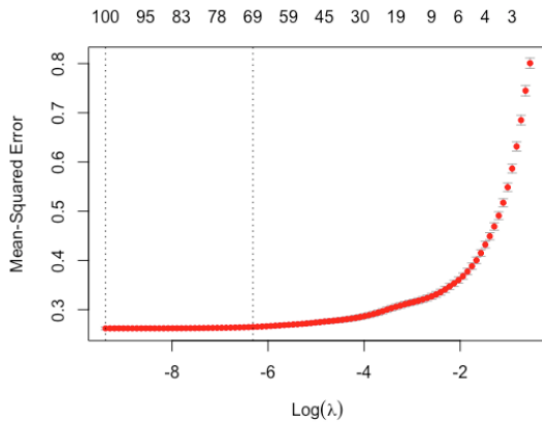
The cross validation errors for 12 models is shown below. Two dotted lines show the minimum CV error for all tested values of lambda and the CV error that is one standard deviation above the minimum.



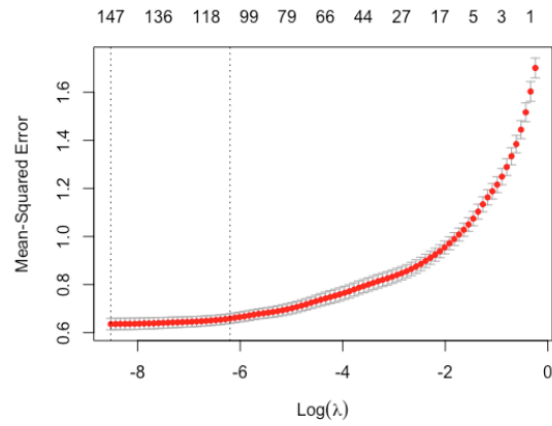
A. Log-KWHs



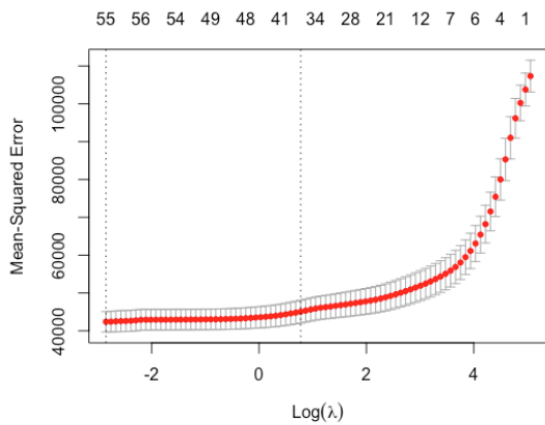
B. Log-VMTs



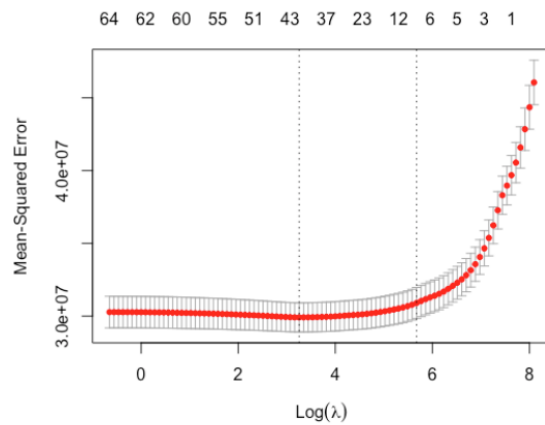
C. Log-BTUs of Methane



D. Log-BTUs of Propane

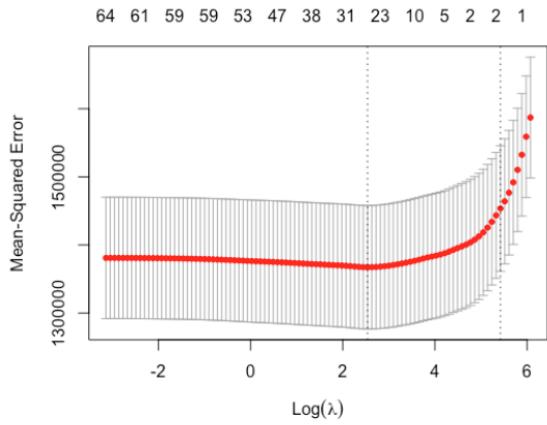


E. Gallons of Fuel Oil

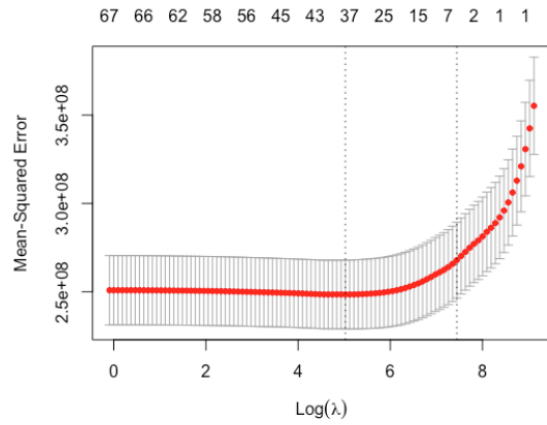


F. Spending on Food Consumption

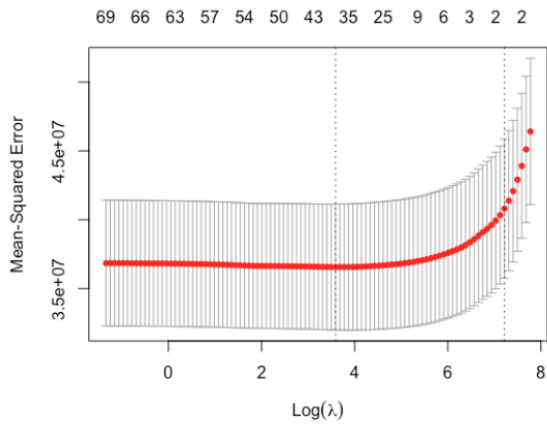
Figure 24: Cross-Validation Errors for Lasso Models



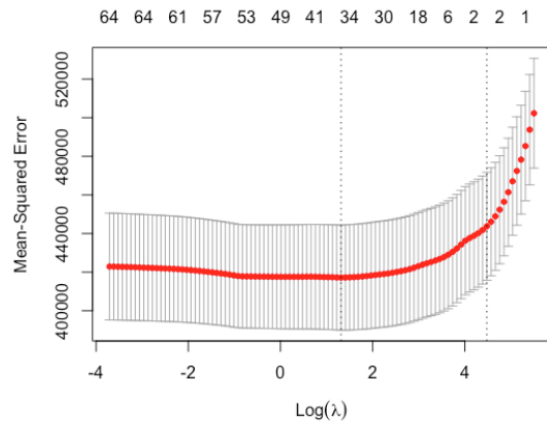
G. Spending on Food Consumption



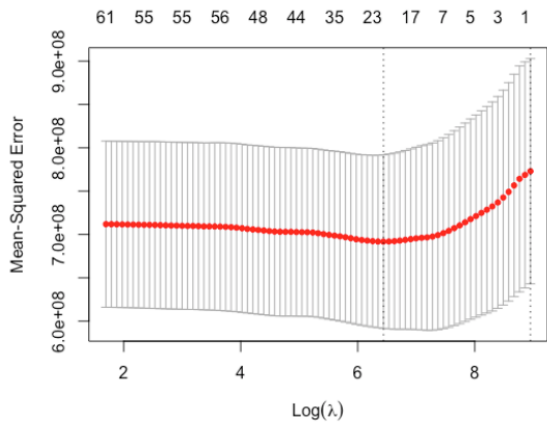
H. Spending on Housing



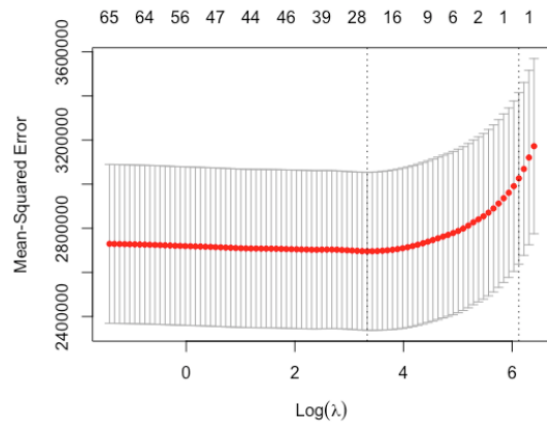
I. Spending on Healthcare



J. Spending on Personal Care



K. Spending on Education



L. Spending on Tobacco Products

Figure 25: Cross-Validation Errors for Lasso Models (Continued)



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