Distributed Household Effects of Climate Policy in the United States

by

Tomas W. Green

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Abstract

The net effects of various climate policies on households in the United States are assessed, with particular attention to the distribution of economic outcomes across geography, urbanity, and income groups. Climate policy has the potential to assess more costs to low-income households than high-income households (regressive) as well as more costs to rural households than metropolitan. The objective of this study was to improve the understanding of the potential for regressivity, geographic transfers, and rural-urban transfers among climate policy options and to test for ways to mitigate regressivity and unwanted transfers.

Using different machine learning algorithms, I created a statistical model of the household carbon footprint (HCF) for an average household in each US Census tract. Policy outcomes were assessed by quantifying the net increase or decrease of annual household expenses (e.g. electricity, utilities, and gasoline consumption) under 12 different policy scenarios, which included carbon pricing schemes, regulatory standards (Corporate Average Fuel Economy Standards, Clean Energy Standards, and the Clean Power Plan), and a scenario that combined carbon pricing and command-and-control regulation.

I found that there is significant variation in carbon footprints with income and geography; income effects are mostly driven by higher footprints related to transportation and consumer products and services, while geographic effects are affected by the carbon intensity of the electricity grid. Carbon pricing, when accompanied with a dividend, is progressive for urban, rural, and suburban households. There are transfers from the Midwest and Plains to the Coasts when the dividend is evenly divided, but this can be mitigated though adjusting the dividend slightly (<8% increase or decrease). 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 carbon dividend for both geography and urbanity increases the average benefit to low-income households and reduces the heterogeneity of impacts within income groups. The effects of the regulatory policy tends to be regressive and are, on average, a net cost to households who are low income – especially those in rural areas. Combining a carbon price and dividend with regulatory standards can remove the regressive trend of regulations, but regional and urban-rural transfers are harder to mitigate.

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Chapter 1

Introduction

How do policy makers address climate change aggressively enough to meet stated climate goals (keeping global temperatures below 1.5°C) without harming communities and households reliant on fossil fuels? While economic literature has determined that a carbon tax is the most economically efficient way to fix the carbon emission externality, depending on what policy makers do with the tax revenues, this policy can be regressive. The potential regressivity arises because low-income households spend a larger share of their income on energy, and energy-intensive, products. Furthermore, households in the industrial heartland and the Midwest are reliant on a carbon-intensive electrical grid for their power; 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 structural facts of carbon consumption across incomes and geography signifies the preeminent challenge of designing equitable climate policy. 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 (Goulder et al. 2019). A second structural fact with respect to energy consumption demonstrates that a number of recycling methods will be progressive. Namely, that a policy that rebates revenues equally to all households, a "tax-and-dividend" plan, will be progressive. 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 contribute more to the pool of revenues than they receive back as a dividend, while low-income households, on average, receive a larger dividend than they pay in taxes. However, a simple tax-and-dividend plan that is geographically agnostic could benefit the Coasts more than the industrial heartland and the Midwest, which is contrary to stated policy goals.

These same concerns for geographic distribution and regressivity hold for alternative climate policies. Historically, instead of pricing carbon, policy makers have relied on instruments that disguise the costs to the consumer–such as the Corporate Average Fuel Economy (CAFE) standard, subsidies for electric vehicles, Renewable Portfolio Standards (RPS), and subsidies for wind and solar power. While these policies tend to keep prices for the regulated products lower, when compared to a price on carbon they also can be regressive (Burger et al. 2020). Furthermore, these alternatives do not generate revenues that can provide transfers to vulnerable groups.

In this thesis, I seek to demonstrate the importance of these issues for policy-making. I use data on energy consumption, transportation habits, and consumer behavior from representative samples of US households to predict carbon footprints. This extends past work (C. Jones and Kammen 2014, Jihoon Min, Hausfather, and Qi Feng Lin 2010) by utilizing machine learning techniques to better predict energy, fuel, and product consumption of households and fills in a gap in climate policy literature (Goulder et al. 2019, McFarland et al. 2018, Woollacott 2018) by describing the nature of heterogeneous impacts within income groups.

Given the estimation for consumption of energy, fuel, products, and services for the 72,538 Census tracts in the continental US, I then model various policy designs to estimate the cost and benefit of each policy on the average household in terms of the change to their annual budget. I 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). I add to the 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. I calculate the incidence in these policies across income quintiles and generate maps of the incidence across the geography. I also aggregate these effects across Congressional districts and correlate the impacts across political party.

My results suggest that while a simple tax-and-dividend plan adequately protects low-income households, the impacts of these policies across rural and urban households may concern policy makers. I analyze six alternative revenue recycling plans that vary across urbanity, income, Census regions, and electricity reliability regions. I show that relatively slight changes to household dividends (less than an eight percent increase or decrease) that depend on certain, readily observable, features of the household allows policy makers to protect vulnerable populations.[1]

My analysis also reveals that, while all of the carbon tax-and-dividend plans I analyze are progressive, the alternative policies are *regressive*. The negative effects of CAFE standards, as a share of income, are monotonically *decreasing* across income quintiles, implying CAFE standards are regressive.[2] I find that the same is true for a clean energy standard. My model of the Obama Administration's Clean Power Plan also suggests that it too 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. The result with respect to CAFE standards is more nuanced. CAFE standards are an implicit tax-and-subsidy program, taxing vehicles that are

[1] Such adjustments, for the sake of policy implementation, need to be already known by the Federal Government and not easily changed by individual actors. The factors used in each policy scenario fit both requirements.

[2] This replicates the results in Davis and C. R. Knittel 2019

worse than the standard and subsidizing vehicles that are better than the standard (Davis and C. R. Knittel 2019; Holland, Hughes, and C. R. Knittel 2009). Therefore, the costs of CAFE to a household fall with the fuel economy of the vehicles in the household. Because high-income households are more likely to purchase vehicles with more technology (e.g., hybrids, EVs, etc.) and low-income households are more likely to own larger vehicles (e.g., vans, trucks), high-income households are more likely to gain from CAFE standards, while low-income households lose.

Understanding how the costs of policy are distributed in the economy and among households should be of utmost importance for policy makers. If policy is intended to be equitable, it is not enough to examine whether the policy is progressive. The distribution within an income group can be greater than the distribution across groups. Dimensions such as geography, urbanity, race, and ethnicity need to also be examined and the public should be given transparent information about the cost associated with policy options.

Chapter 2

Background and Literature Review

2.1 Distributed Effects of Carbon Pricing

Ignoring the revenues generated, carbon taxation is generally determined to be regressive to income and expenditures (Metcalf et al. 2008; Mathur and Morris 2014). However, the 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). Their 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 report 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 among 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, the 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 divided 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 policy[1] 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 use-side (e.g., consumption) analysis can change conclusions compared to only a use-side study (Goulder et al. 2019). While the use-side effect of carbon taxes is regressive and reduces welfare for each recycling option examined (in keeping with my findings and other literature), the source-side effect is progressive and positive for most recycling options. On net, source-side impacts outweighed the use-side.

However, the effects within an income group (whether quintile or decile) were

[1]In this paper, the hybrid policy consiseted 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.

more heterogeneous than the effects across groups. The variability of impacts within an income group can be partially explained 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 (M. T. Ross 2018). There are also significant differences in consumer behavior across geography, due to factors like reliance on cars and size of homes (Wiedenhofer, Lenzen, and Steinberger 2013). 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).

Additionally, there is temporal variability in welfare benefits for labor versus capital income tax cuts. That is, labor tax cuts are better in short term, while capital tax cuts are better in later term (Zhu et al. 2018). Variability in the generational effects of carbon tax designs are also significant. The generation that first sees the implementation of a carbon tax would fare worse, but welfare losses diminish with time after introduction (Rausch and Yonezawa 2018). Using the revenue from a carbon tax for a household dividend favors older generations, while reducing labor taxes favors younger generations (Rausch and Yonezawa 2018).

While I do not attempt to model temporal transfers, the heterogeneity within an income group is a critical focus of my research. Indeed, I show that where you live is nearly as strong a determinant of absolute policy impact as income.

2.2 Effects and Costs of Other Climate Policies

2.2.1 Regulation

The implicit carbon tax[2] of regulations and policy measures vary from negative prices for behavioral energy efficiency programs (-$190/ton), to moderate prices ($11/ton) for EPA regulation though the Clean Power Plan, to high prices for the Weatherization Assistance Program ($350/ton) (Gillingham and Stock 2018). Replacing all current federal regulations with a carbon tax (in 2020) would require roughly $7 per ton to achieve equivalent emissions reductions (C. Knittel 2019). This price would increase to approximately $30 as some regulations such as CAFE Standards ramp up by 2030.

2.2.2 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)).

2.2.3 Renewable Portfolio Standard/ Clean Energy Standard

A Renewable Portfolio Standard (RPS) has a range of implicit costs between $0 and $190 per ton of CO_2 (Gillingham and Stock 2018). Other estimates of the implicit cost of an RPS is between $130 and $460 per ton (Greenstone and Ishan (2019)),

[2]These implicit costs 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.

although this study received criticism for overestimating the upper bound of the cost by not adequately isolating the effects of an RPS or defining a realistic counterfactual for carbon emissions without an RPS.[3]

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 price of CES.

2.3 Estimating a Household Carbon Footprint (HCF)

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 seven categories (Weber and Matthews 2008). The largest fractions of energy requirements of households (residential energy, transportation, and food) are also the most energy intense per dollar (Wiedenhofer, Lenzen, and Steinberger 2013).

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

[3] Many states passed their version of an RPS as part of a larger energy package, including policy that would conceivably increase emissions. These accompanying policies were not isolated in the Greenstone paper.

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 footprint weakly increases until a threshold is met, at which point HFCs 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 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

2.4.1 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 annually), 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 CO_2. 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.[4]

2.4.2 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. This incents car-markers 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 electric-

[4] Resources for the Future compiles information on carbon pricing bills here: RFF Carbon Pricing Bill Tracker

ity 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 on a credit trading system to create a subsidy for clean electricity and an implicit tax on more carbon intensive electricity. The way I model CES and CAFE is described in the following section.

2.5 Objectives

When estimating the effects of policy, the literature hitherto has applied economy-wide, sectoral models. Other bodies of research have quantified the size of household carbon footprints according to sources of consumption. I seek to bridge these bodies of work by estimating the impacts of climate policy on households and examining the way that the resulting costs of these policies vary with geography and demography. Further, I endeavor 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. Finally, I also 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.

Chapter 3

Methodology

The general process is as follows: I start with a data set that tracks consumption of a commodity for a representative sample of US consumer units (households), along with household demographics, and physical characteristics of housing. Next, I use machine learning techniques that trains a prediction model relating household demographics, geographic, and weather data to energy consumption. Finally, I apply the model to Census data with the equivalent variables at the smallest geographic unit of analysis. This analysis is repeated for transportation data and consumer expenditure data.

3.1 Data Sources

The 2015 Regional Energy Consumption Survey (RECS) was 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, comprises 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.

3.2 Model

I developed a model for consumption of electricity, heating fuel (methane, propane, and fuel oil), miles traveled, and consumer products and services (food, alcoholic beverages, housing, apparel, health, entertainment, personal care, education, tobacco products, life insurance, cash contributions, and miscellaneous).

I tested three variations of a linear model: Least Absolute Shrinkage and Selection Operator (Lasso) regression, Ridge Regression, and Elastic Net, which combines Lasso and Ridge. Elastic Net allows me to increase the predictive power of the model and improve the accuracy the estimates by identifying which variables among all potentials are worth including.

$$L(\lambda_1, \lambda_2, \beta) = \sum_{i=1}^{n}(y_i - \sum_{j}(x_{ij}\beta_j))^2 + \frac{1-\alpha}{2}\lambda_2 \sum_{j=1}^{m} \beta_j^2 + \lambda_1 \alpha \sum_{j=1}^{m} |\beta_j| \tag{3.1}$$

Where n is the number of observances, m is the number of variables (and coefficients) in the model, β is the coefficient for variable, j, λ is a penalty term, and α is the tuning parameter between ℓ_2 regularization and ℓ_2 regularization. The penalty term, λ, will adjust how restrictive the model will be. If $\lambda = 0$, then all variables will be selected; if $\lambda = \infty$, then no variables will be selected.

The tuning parameter, α, is the differentiation between Lasso and Ridge regressions. If $\alpha = 1$, then we only have ℓ_2 regularization, which is a Lasso regression. If $\alpha = 0$, then we only have ℓ_1 regularization, which is a Ridge regression. The R package "caret" (Kuhn 2020) was used to find the alpha parameters for Elastic Net. The R package "glmnet" (Friedman, Hastie, and Tibshirani 2010) was used to solve the below optimization equation:

$$\hat{\beta} = argmin\{L(\lambda_1, \lambda_2, \beta)\} \tag{3.2}$$

The variables were all mean-standardized before the optimization is conducted so that the magnitude of a variable does not affect its selection. The coefficients are returned for the non-standardized variables after the optimal soultion is found.

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 my estimate for natural gas consumption, Lasso selected to include the interaction term between age of home and whether the home heats with natural gas.[1]

I tested various values of lambda using a k-fold cross-validation method. Cross validation allows me to determine the optimal trade-off 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

[1] The R package glinternet (Lim and Hastie 2019) was used to find interaction pairs

are randomly divided.

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 including new variables to improve predictive power.[2] 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.

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. The R package "sampleSelection" (Toomet and Henningsen 2008) was used to fit the Probit model. Probit models the probability, p, of a variable being positive or negative:

$$p_i = \Phi\left(\sum_{j=0}^{j=m}(\beta_j x_{ij})\right) \tag{3.3}$$

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, and variables were removed that caused separation in the data. The Probit model was multiplied by the Lasso estimate, conditional on values being positive:

[2]See Fig B-3, B-4, and B-5 in the Appendix for the cross-validation with respect to lambda for each model.

$$E[y|x] = E[y|x, z > 0] \times (p_{z>0}) + E[y|x, z \leq 0] \times (p_{z\leq 0}) \tag{3.4}$$

$$= E[y|x, z > 0] \times (p_{z>0}) \tag{3.5}$$

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

3.2.1 Model Performance

Table 3.1: Alpha Values Selected and Used in Elastic Net Model

	α
Electricity	0.29
Natural Gas	0.24
Propane	0.91
Fuel Oil	1.0
Vehicle Miles Traveled	0.10
Food Cons.	0.70
Alcoholic Bev. Cons.	0.40
Housing Costs	0.20
Apparel Cons.	0.10
Healthcare Costs	0.20
Entertainment Cons.	0.20
Personal Care Cons.	0.60
Education Costs	0.50
Tobacco Products Cons.	0.10
Life Insurance Cons.	0.70
Miscellaneous COns.	0.70
Cash Contributions	0.20

Table 3.2: R-Squared Values for Linear Models (Positive-values Only)

	Lasso	Ridge	Elastic Net
Electricity	0.687	0.631	0.683
Natural Gas	0.674	0.663	0.670
Propane	0.646	0.608	0.651
Fuel Oil	0.604	0.578	0.615
Vehicle Miles Traveled	0.324	0.311	0.317
Food Cons.	0.332	0.335	0.352
Alcoholic Bev. Cons.	0.0716	0.0767	0.144
Housing Costs	0.243	0.266	0.303
Apparel Cons.	0	0	0.0701
Healthcare Costs	0.142	0.141	0.214
Entertainment Cons.	0	0	0.0821
Personal Care Cons.	0.115	0.135	0.168
Education Costs	0.0131	0	0.146
Tobacco Products Cons.	0.0195	0.00330	0.147
Life Insurance Cons.	0	0	0.116
Miscellaneous Cons.	0	0	0.0255
Cash Contributions	0	0	0.0758

Table 3.3: R-Squared Values for Combined Linear and Non-Linear Models

	Lasso	Ridge	Elnet 2	Jones & Kammen
Electricity	0.623	0.620	0.659	0.608
Natural Gas	0.835	0.819	0.841	0.471
Propane	0.614	0.462	0.622	
Fuel Oil	0.812	0.642	0.852	0.206
Vehicle Miles Traveled	0.277	0.281	0.284	0.324
Food Cons.	0.248	0.242	0.254	
Alcoholic Bev. Cons.	0.0503	0.0465	0.0487	
Housing Costs	0.184	0.162	0.116	
Apparel Cons.	0.00221	0.00221	0.00220	
Healthcare Costs	0.0849	0.0922	0.0772	
Entertainment Cons.	0.00349	0.00349	0.00355	
Personal Care Cons.	0.0610	0.0796	0.0738	
Education Costs	0.00513	0.00513	0.00480	
Tobacco Products Cons.	0.0133	0.0130	0.0123	
Life Insurance Cons.	0.0111	0.0111	0.0112	
Miscellaneous Cons.	0.00239	0.00239	0.00232	
Cash Contributions	0.00373	0.00373	0.236	

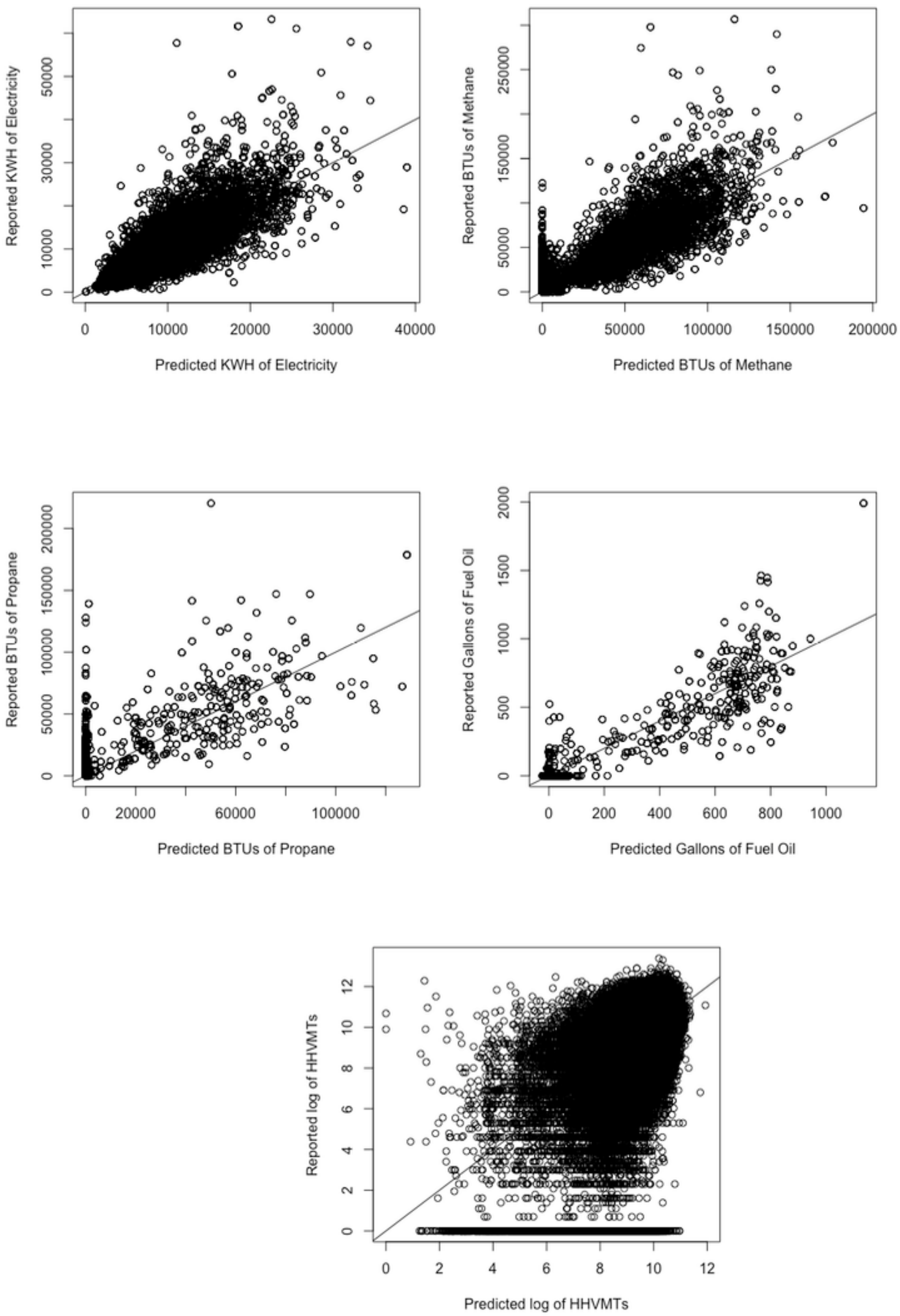


Figure 3-1: Predicted versus Actual Values using Elastic Net Models

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).[3] A Census tract is a subdivision of a County, consisting of approximately 4,000 residents. I chose to conduct the 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 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)[4] 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 using the estimates for consumption using the Lasso models. The Department of Energy's Emissions Generation Resource Integrated Database (eGRID) were used for the carbon intensity of the grid (U.S.

[3] I used the five-year estimate for the year 2015 using the Census API and the R package tidycensus (Walker 2019)

[4] I used the 1981-2010 Normals for Heating Degree Days and Cooling Degree Days

Environmental Protection Agency 2020). Each tract was assigned to a NERC subregion through geospacial analysis (U.S. Department of Homeland Security 2019); if a tract fit within one or more subregion, the average emissions factor was used. The Complication 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.

3.4 Policy Modeled

I model the effects on household budgets for a given policy by estimating the cost to households due to increased prices of energy and commodities with a carbon tax or regulatory cost; I assess the benefits of a policy by estimating savings related to a decrease energy and commodity prices due to a subsidy or a lump sum transfer, in the case of carbon dividend schemes. My approach only accounts for use-side effects, not source-side effects, which are important to determine regressivity. 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 work. To model costs and benefits, I 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. I model the average household footprint for each Census tract; therefore, I do not capture the full variance of household effects in the United States. Rather, I capture the expected variance for a representative household across variables of geography, urbanity, and income. This is meant to inform policy makers of the distributed effects of policy, rather than provide a perfect calculation of such effects. I intend to 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. I would argue that a policy of "do nothing" is the worst of all alternatives and will have severe consequences for households who are low-income and vulnerable to disruption.

There are 12 policy designs that I model: (1) A carbon tax with no revenue recycling; (2) a carbon price and dividend (CPD); (3) CPD with an adjustment for urban and rural households; (4) CPD with an adjustment for geography; (5) CPD with an adjustment for both urbanity and geography; (6) CPD with an adjustment for NERC regions; (7) CPD with an adjustment for household income; (8) CPD with an adjustment for household income and geography; (9) the Corporate Average Fuel Economy (CAFE) standard; (10) a Clean Energy Standard (CES); (11) the Obama-era Clean Power Plan; and (12) a combination of a CAFE standard, CES, and carbon pricing. I took a baseline of $50 per ton of Carbon for all applicable scenarios.

A carbon tax with no revenue recycling is an edge case in the scenario that policymaker decide to fix the externality, but commit all revenue to paying down the deficit. I 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 footprint 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, it would reduce dividends to low income households because they have a smaller absolute contribution. When adjusting for income, I am 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. Scenario 9, the CAFE standard calculated the implicit tax/subsidy on each vehicle owned according to the shadow price of the regulation. Cars that get worse fuel economy than the standard get taxed and cars that get better than the standard get subsidized according to the model:

$$\text{Price of a Car} \;=\; \text{MC} + \alpha(\text{GPM of car} - \text{Standard in GPM}) \tag{3.6}$$

I then multiplied the average tax by the vehicles per household. I 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, a CES, assumed the policy will set 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. The household cost or benefit was the implicit tax or subsidy multiplied by the electricity consumed.[5] Scenario 11, the Clean Power Plan (CPP), was based on a study of permit prices, conducted by the Nicholas Institute (M. Ross, Hoppock, and Murray 2016). The policy cost was calculated as follows:

$$\text{Policy Cost} \;= (\text{Permit Cost/MWH})(\text{MWH Consumed}) \tag{3.7}$$

Scenario 12 combined regulatory policy costs with a carbon price and dividend scheme. In this case, I assumed that areas of consumption that were covered by

[5] By assuming inelastic consumption of energy, I 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. I also note that $50 per ton is a high estimate for permit prices.

regulation policy would be exempt from the carbon price. This scenario blended the effects of a Clean Energy Standard, CAFE Standards, and a carbon price with an evenly divided dividend. Therefore, the carbon price applied only to home heating fuels and consumer goods and the net policy effects were the combined costs of CES, CAFE, and the refined CPD.

Chapter 4

Results

4.1 Household Footprint

My 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 23.8 tons per year per household.[1] The bottom 20% of households generate 17.1 tons, or less, of carbon dioxide emissions, while the top 10% of households generate 30.1 tons, or more. Meaningful differences exist across both income and geography. There is significant variation in HCF with income. The average carbon footprint of a household in the bottom 20% of income is 18.5 tons; the average is 28.2 tons, 52% greater, for households in the top 20% of income. Average carbon emissions per dollar of income, in contrast, falls monotonically across income quintiles, with the bottom quintile producing 1.04 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, though the differences are not as extreme as the variation with income. Average footprints are 25.7 tons per year in rural areas, but 24.5 tons in urban areas and 21.0 tons in metropolitan areas. The difference in HCF across regions and states is especially significant. The average HCF in California is 18.8 tons, while the aver-

[1] This is the population weighted average across all Census tracts.

age HCF in Missouri is 30.6 – a difference greater than the difference across income groups. That difference holds across Census divisions. The average HCF in the Pacific Division is 19.3 tons (which includes California, Oregon, and Washington) while the average is 27.4 tons in the West-North Central Division (which includes Kansas, Missouri, Nebraska, Iowa, Minnesota, and the Dakotas). There are also important differences across race. While footprints are negatively correlated with the share of residence that are African American or Hispanic (correlation of -0.31 and -0.30 respectively), emissions are positively correlated with the share of White residents (0.49).

The footprint associated with electricity consumption is heavily influenced by the emissions intensity of the associated North American Electric Reliability Corporation (NERC) region. Fuel oil- and methane-related carbon emissions are concentrated in regions that rely on those fuels for home heating, most notably, in the North East 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 the fuel economy for private vehicles tends to be lower. [2] Products and services account for a carbon footprint that was strongly correlated with income. These findings are consistent with similar studies in literature (C. Jones and Kammen 2014, C. M. Jones and Kammen 2011, Ummel 2014, Jihoon Min, Hausfather, and Qi Feng Lin 2010).

[2] I did not model the footprint related to public transit or air travel, which would likely increase the estimate in urban areas.

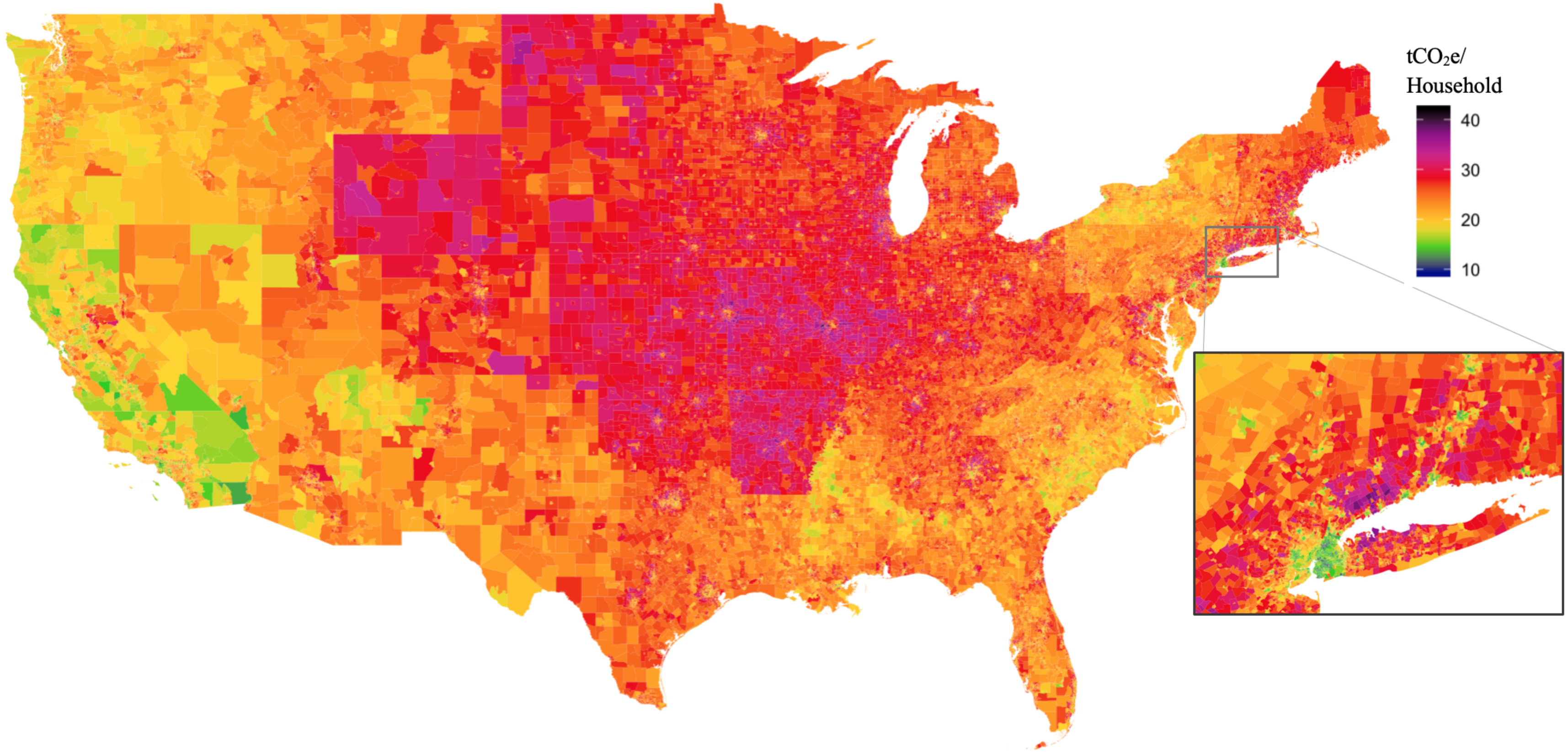


Figure 4-1: Total Household Carbon Footprint for the Continental United States

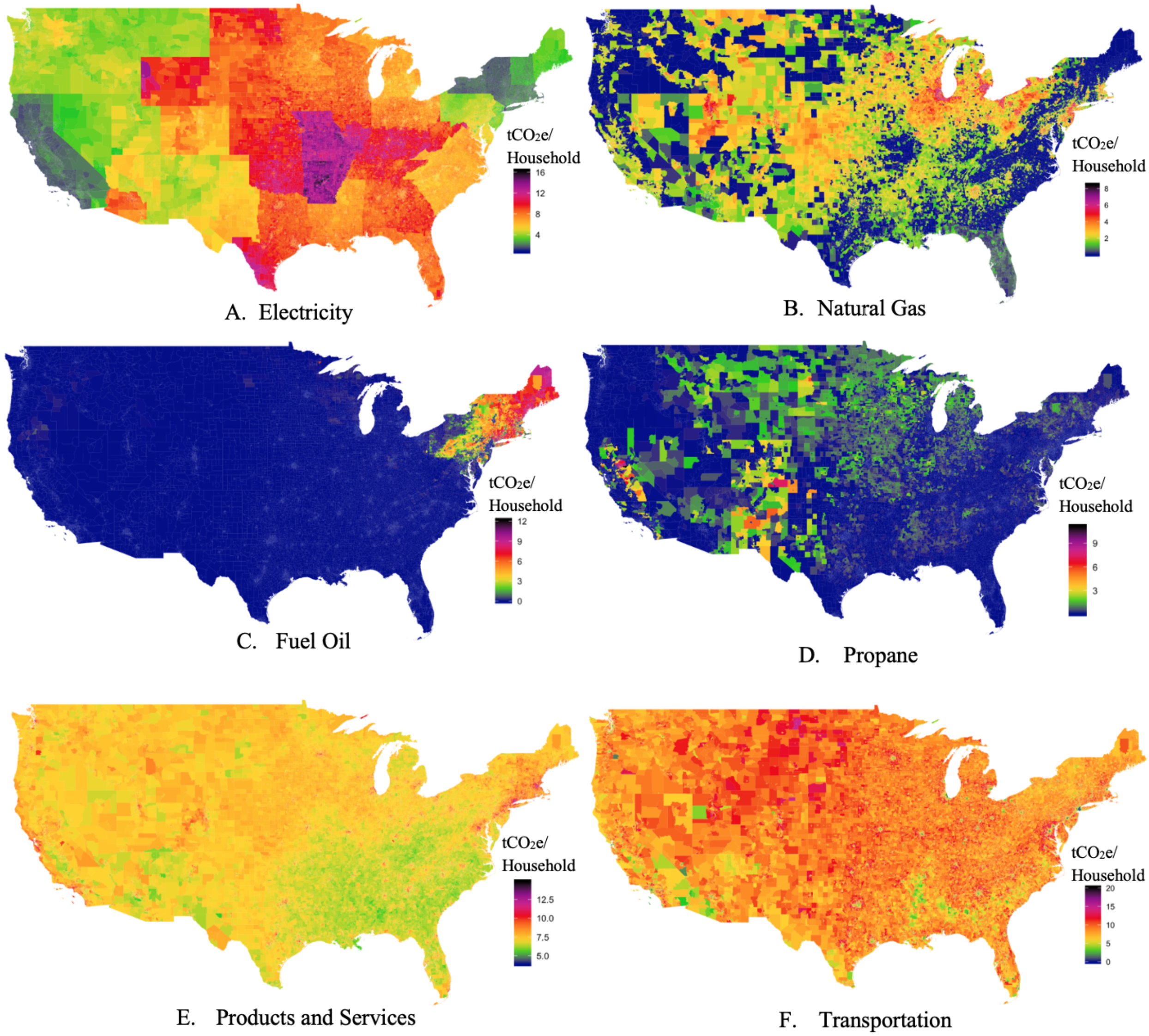


Figure 4-2: Carbon Footprint by Modeled Component

Figure 4-1 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 on Long Island has a footprint nearly three times larger than that of an average household in Manhattan. Across the map, 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.

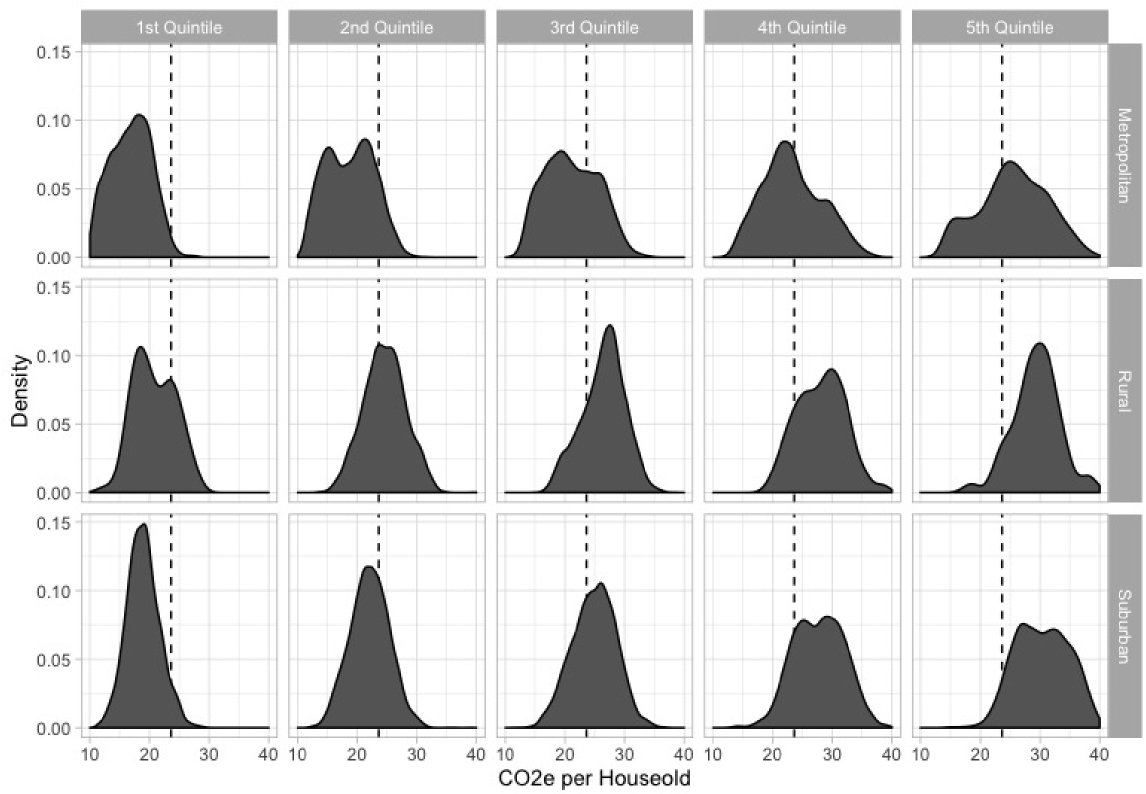


Figure 4-3: Total Household Carbon Footprint (in tons) across income quintiles and urbanity, compared to U.S. average (represented by the dashed line)

Figure 4-3 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 4-4 shows the significant effect that geography and NERC Region have on footprints related to energy. While income and urbanity both influence the size

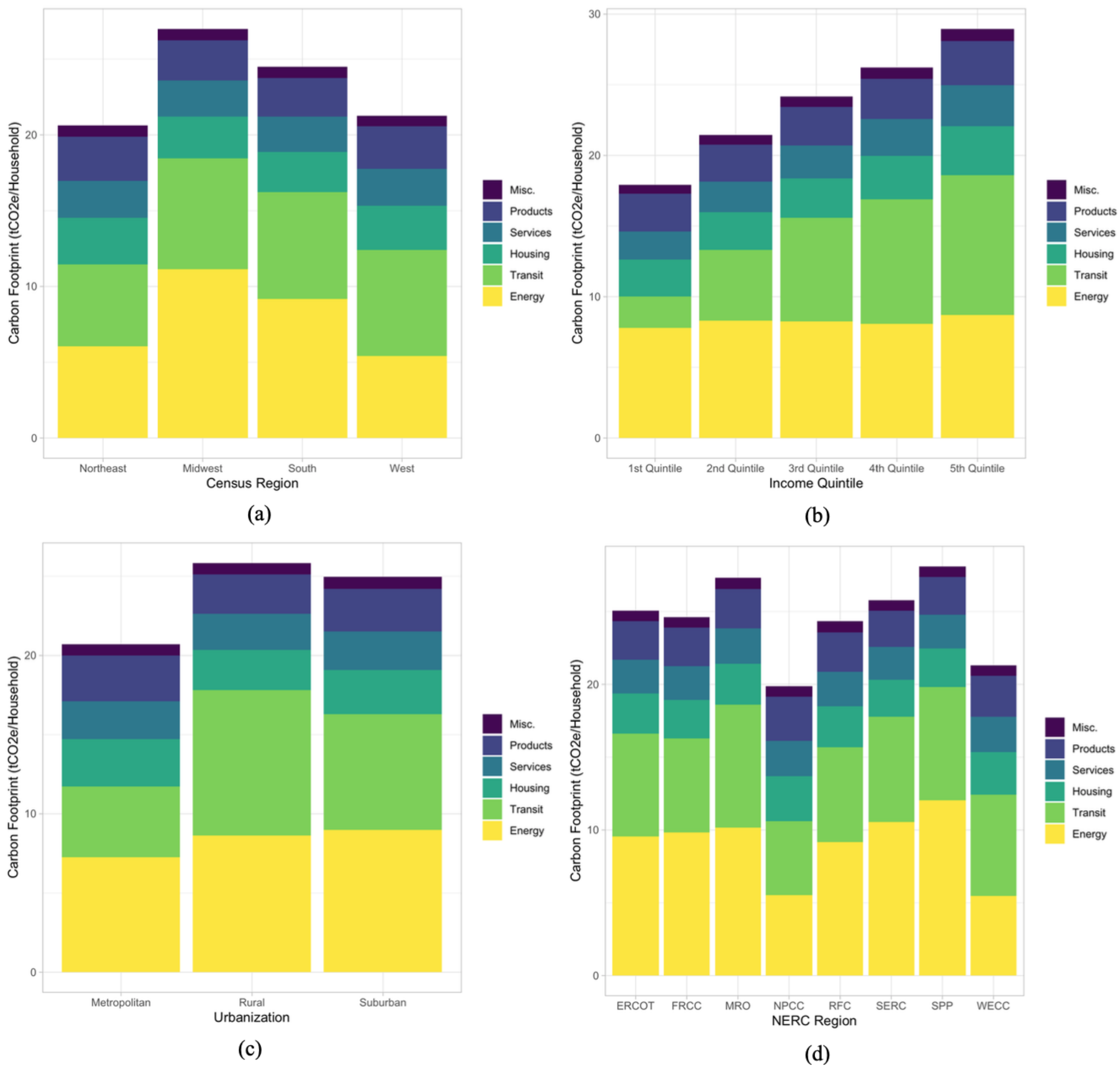


Figure 4-4: Total Household Carbon Footprint according to a) Census Region; b) Income Quintile; c) Urbanization; and, d) NERC Region, broken out by footprint contribution

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 Fig. 4-1), but the variances across metropolitan areas can exceed the differences within metropolitan areas. Figure 4-5 shows the variation in HCF across party affiliation, as determined by households represented by Members of the House of Representatives in the 116th Congress. While households represented by Republicans tend to have a slightly higher footprint than average and households represented by Democrats tend to have a slightly lower footprint than average, there is a wide distribution for both parties.

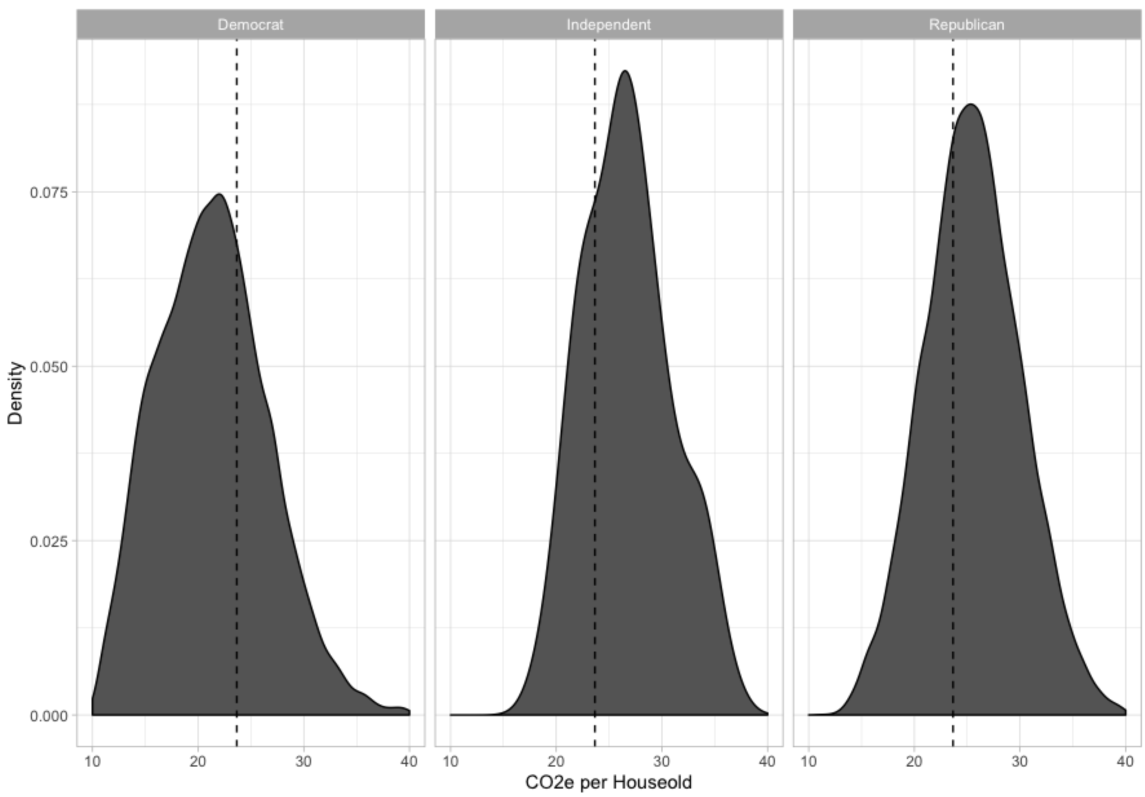


Figure 4-5: Distribution of Household Carbon Footprints across political parties (according to party affiliation of House Members in the 116th Congress), compared to U.S. average (represented by the dashed line)

4.2 Policy Impacts

My 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, 96% of 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 $284 per household per year. This is a substantial amount of income for these households. On average, a household receives over $15.1 for every $1,000 of income. Among tracts in the second income quintile, 69% of households have net gains (average gain of $106 or $3.01 per $1,000 of income), 43% in the third quintile (-$16 or -$0.29 per $1,000 of income), 33% in the fourth quintile (-$104 or -$1.18 per $1,000 of income), and only 20% in the fifth quintile (-$226 or -$1.51 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, only 25% of rural households receive a net positive dividend with an average net gain of -$121 per household per year (-$2.44 per $1,000 of income). In contrast, 76.1% of metropolitan households receive net benefits, with an average net benefit of $152 per household per year ($2.64 per $1,000 if income). Suburban areas lose, on average, under the simple tax-and-dividend plan. The average suburban household spends $57 more in taxes per household per year, with over 57% of households spending more in taxes than they receive in dividends.

Table 4.1: Net Impact of Policy Scenarios by Income Quintile (USD/Household)

	1st Q.	2nd Q.	3rd Q.	4th Q.	5th Q.
Carbon Tax	-866	-1040	-1170	-1250	-1360
CPD	284	106	-16.3	-104	-208
CPD – adjusted for urbanity	247	108	-5.73	-117	-234
CPD – adjusted for geography	309	123	-9.86	-132	-262
CPD – adjusted for urb. + geo.	278	119	-1.07	-136	-276
CPD – adjusted for NERC Reg.	304	122	-12.6	-128	-244
CPD – adjusted for income	650	261	0	-313	-556
CPD – adjusted for inc. + urb.	650	261	0	-271	-541
CAFE	-68.1	-87.9	-86.4	-53.4	-23.4
CES	-6.21	-6.85	-1.56	18.6	32.2
CPP	-139	-165	-154	-126	-114
CPD & Regs	-21.5	-42.2	-77.1	-99.7	-149

Table 4.2: Net Impact of Policy Scenarios by Urbanity (USD/Household)

	Metropolitan	Rural	Suburban
Carbon Tax	-998	-1270	-1210
CPD	152	-121	-56.6
CPD – adjusted for urbanity	99.9	0	-100
CPD – adjusted for geography	106	-68.2	-39.1
CPD – adjusted for urb. + geo.	70.9	0	-70.7
CPD – adjusted for NERC Reg.	112	-74.3	-43.2
CPD – adjusted for income	167	-68.7	-82.2
CPD – adjusted for inc. + urb.	119	83.8	-116
CAFE	-46.7	-136	-74.7
CES	17.9	-24.6	-1.64
CPP	-109	-192	-160
CPD & Regs	-52.0	-93.4	-88.1

However, the difference among households in the first and second quintile is dramatic. A large share of households receive a net positive dividend (68.5%) and the average net impact is $106, but the average net impact is about a third ($33.7) among rural households in the second income quintile. Rural households in the first quintile have less than 40% of the net benefit compared to the quintile overall ($109 per household, compared to $284).

There are significant differences in the effects for households in these policy scenarios. The best policy for rural households is a carbon price and dividend with the dividend adjusted for both income and urbanity. The effects are often negative on average for rural households, except for when adjusted for urbanity in which case the net effect is zero by construction. When only adjusting the dividend for income, the effect is negative for 60% of rural hosueholds (-$68.7 on average, or -$1.38 per $1000 of income), while the effect is positive for 62% of rural hosueholds ($83.8 on average, or $1.68 per $1000 of income) when adjusting for both household income *and* urbanity.

Regulations had negative costs for most households, as I only examined the distributed effects with respect to energy and commodity prices and ignored all other benefits of regulation that would typically factor into a cost-benefit analysis. It is difficult to compare across regulatory scenarios, because they do not all reduce carbon emissions by the same amounts and the magnitudes of each would vary if controlling for carbon reduction. That said, examining the distributional effects, especially the potential for regressive outcomes, carries important lessons.

CAFE Standards and the Clean Power Plan are both regressive. For CAFE, the average effect on households in the first quintile is -$68, while the average effect on households in the top quintile is about a third the size, -$23. Hardly any households in the first quntile see positive net effects from CAFE Standards (5%), while 31% of the wealthiest households have positive effects. CAFE also benefits those in metropolitan areas more (-$47 on average) compared to rural households (-$136). In the case of CPP, households in the second quintile have a net effect of -\$165, compared to -\$114 for households in the top quintile. CPP is worse for rural households (-\$192 on average or -\$3.9 per \$1000 of income) compared to households in metropolitan areas (-\$109 on average or -\$1.9 per \$1000 of income).

A blended approach that combines a carbon price and dividend with regulations preserves the progressive nature of carbon dividends. The net effect for this policy scenario is -\$21.5 for the bottom income quintile and -\$149 for the top income quintile. However, this scenario was worse for rural households (-\$93.4 on average) than for metropolitan households (-\$52 on average).

Table 4.3: Net Impact of Policy Scenarios per \$1000 of Income by Income Quintile

	1st	2nd	3rd	4th	5th
Carbon Tax	-46.3	-29.7	-20.8	-14.3	-10.0
CPD	15.1	3.01	-0.291	-1.18	-1.51
CPD – adjusted for urbanity	13.1	3.07	-0.102	-1.33	-1.70
CPD – adjusted for geography	16.4	3.51	-0.176	-1.51	-1.91
CPD – adjusted for urb. + geo.	14.7	3.38	-0.0191	-1.56	-2.00
CPD – adjusted for NERC Reg.	16.1	3.47	-0.226	-1.46	-1.77
CPD – adjusted for income	34.5	7.44	0	-3.58	-4.04
CPD – adjusted for inc. + urb.	34.5	7.44	0	-3.09	-3.93
CAFE	-3.61	-2.50	-1.54	-0.610	-0.17
CES	-0.330	-0.195	-0.0279	0.213	0.234
CPP	-7.38	-4.69	-2.75	-1.44	-0.826
CPD & Regs	-1.14	-1.20	-1.38	-1.14	-1.09

Table 4.4: Net Impact of Policy Scenarios per $1000 of Income by Urbanity

	Metropolitan	Rural	Suburban
Carbon Tax	-17.2	-25.5	-18.4
CPD	2.64	-2.44	-0.875
CPD – adjusted for urbanity	1.73	0	-1.55
CPD – adjusted for geography	1.85	-1.37	-0.605
CPD – adjusted for urb. + geo.	1.23	0	-1.09
CPD – adjusted for NERC Reg.	1.95	-1.49	-0.667
CPD – adjusted for income	2.90	-1.38	-1.27
CPD – adjusted for inc. + urb.	2.06	1.68	-1.79
CAFE	-0.812	-2.73	-1.15
CES	0.311	-0.493	-0.0253
CPP	-1.9	-3.86	-2.48
CPD & Regs	-0.904	0	-1.36

Table 4.5: Fraction of Households with Positive Net Impact by Income Quintile

	1st	2nd	3rd	4th	5th
Carbon Tax	0	0	0	0	0
CPD	0.959	0.693	0.432	0.325	0.198
CPD – adjusted for urbanity	0.947	0.714	0.466	0.307	0.156
CPD – adjusted for geography	0.991	0.815	0.453	0.174	0.074
CPD – adjusted for urb. + geo.	0.987	0.833	0.503	0.163	0.0682
CPD – adjusted for NERC Reg.	0.985	0.789	0.447	0.237	0.0930
CPD – adjusted for income	1.00	0.917	0.463	0.0976	0.0182
CPD – adjusted for inc. + urb.	1.00	0.938	0.48	0.12	0.0184
CAFE	0.0487	0.0854	0.114	0.201	0.310
CES	0.331	0.356	0.411	0.541	0.619
CPP	0	0	0	0	0
CPD & Regs	0.463	0.45	0.366	0.276	0.113

Table 4.6: Fraction of Households with Positive Net Impact by Urbanity

	Metropolitan	Rural	Suburban
Carbon Tax	0	0	0
CPD	0.761	0.254	0.433
CPD – adjusted for urbanity	0.689	0.479	0.354
CPD – adjusted for geography	0.738	0.309	0.465
CPD – adjusted for urb. + geo.	0.682	0.529	0.403
CPD – adjusted for NERC Reg.	0.741	0.308	0.461
CPD – adjusted for income	0.719	0.395	0.471
CPD – adjusted for inc. + urb.	0.679	0.620	0.407
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

4.2.1 Carbon Pricing

Tables 4.7 and 4.8 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 $141 Billion), 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.

Table 4.7: Average Household Dividend by Income Quintile

	1st	2nd	3rd	4th	5th
CPD	1150	1150	1150	1150	1150
CPD – adjusted for urbanity	1110	1150	1160	1140	1120
CPD – adjusted for geography	1180	1170	1160	1120	1100
CPD – adjusted for urb. + geo.	1140	1160	1170	1120	1080
CPD – adjusted for NERC Reg.	1170	1166	1154	1126	1114
CPD – adjusted for income	1520	1310	1170	940	802
CPD – adjusted for inc. + urb.	1520	1310	1170	983	817
CPD & Regs	523	523	523	523	523

Table 4.8: Average Household Dividend by Urbanity

	Metropolitan	Rural	Suburban
CPD	1150	1150	1150
CPD – adjusted for urbanity	1100	1270	1110
CPD – adjusted for geography	1110	1200	1170
CPD – adjusted for urb. + geo.	1070	1270	1140
CPD – adjusted for NERC Reg.	1110	1200	1160
CPD – adjusted for income	1170	1200	1130
CPD – adjusted for inc. + urb.	1120	1360	1090
CPD & Regs	523	523	523

Figures 4-6, 4-8, and 4-10 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 4-7, 4-9, and 4-11 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.

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 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 controlled 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.

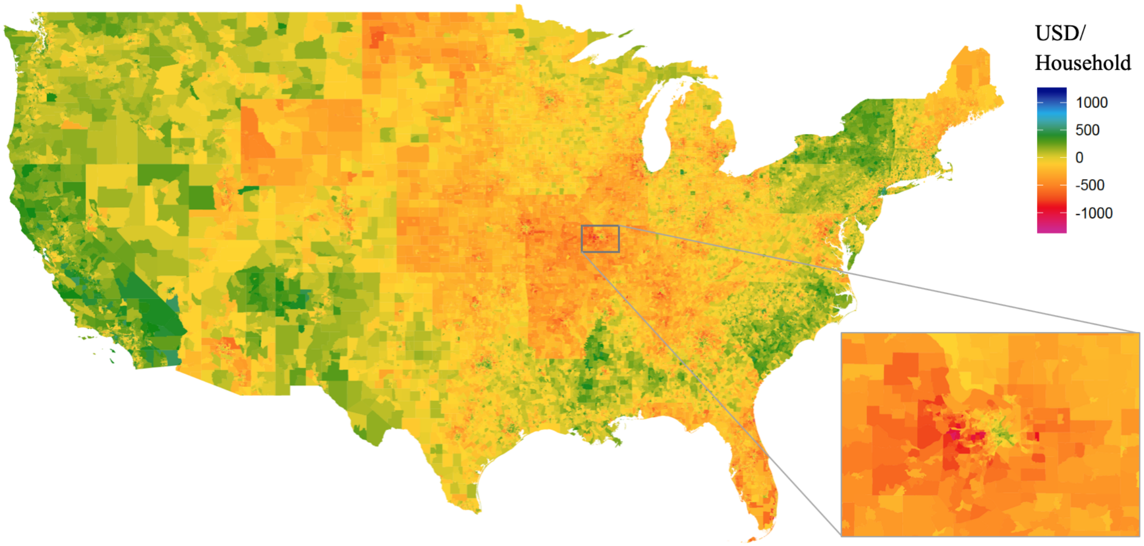


Figure 4-6: Net Impact of $50 Carbon Price and Dividend

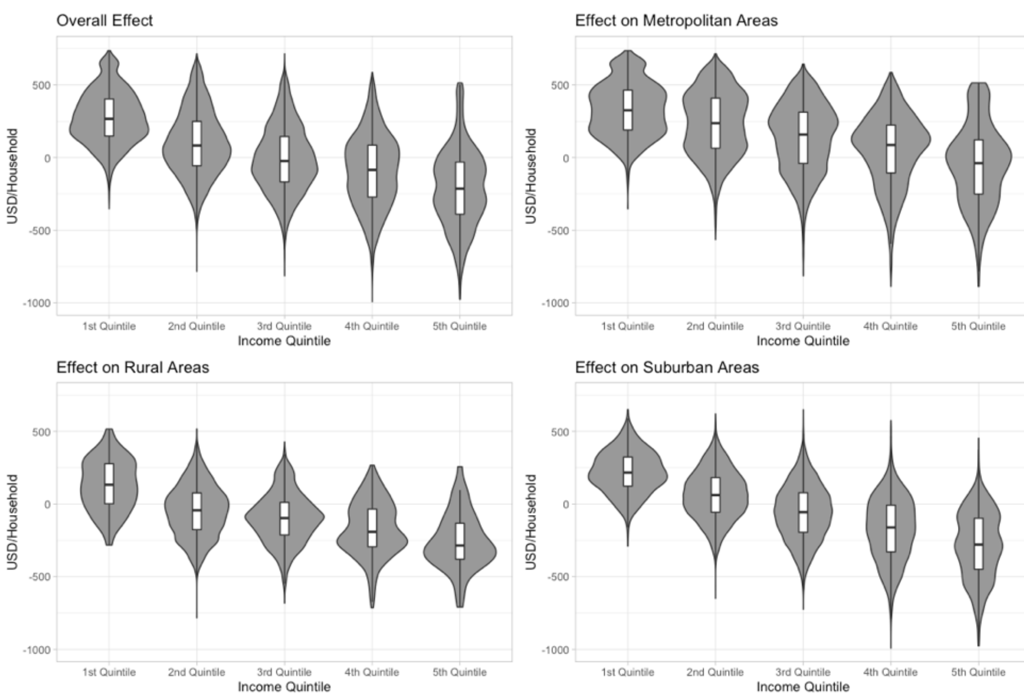


Figure 4-7: Net Impact of $50 Carbon Price and Dividend - According to Income Quintiles and Urbanity Classifications

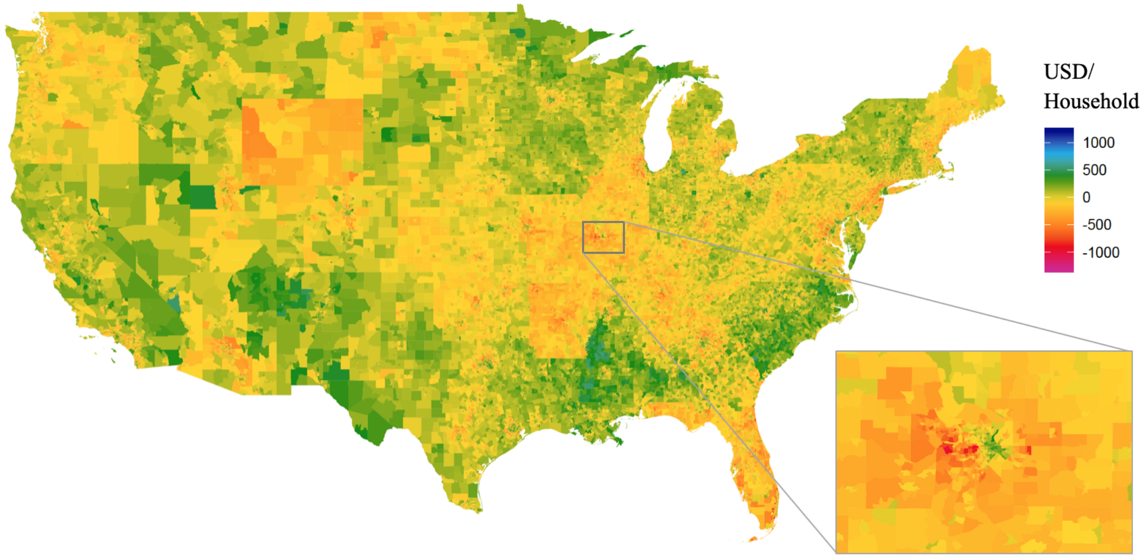


Figure 4-8: Net Impact of $50 Carbon Price, Dividend adjusted for Urbanity and Geography

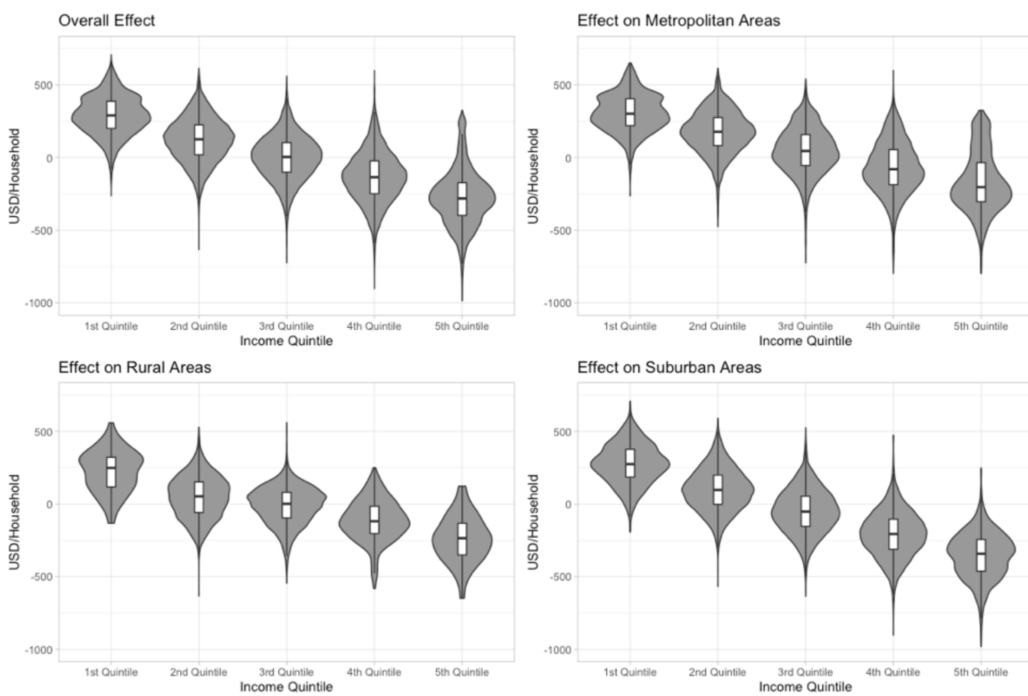


Figure 4-9: Net Impact of $50 Carbon Price, Dividend adjusted for Urbanity and Geography - According to Income Quintile and Urbanity

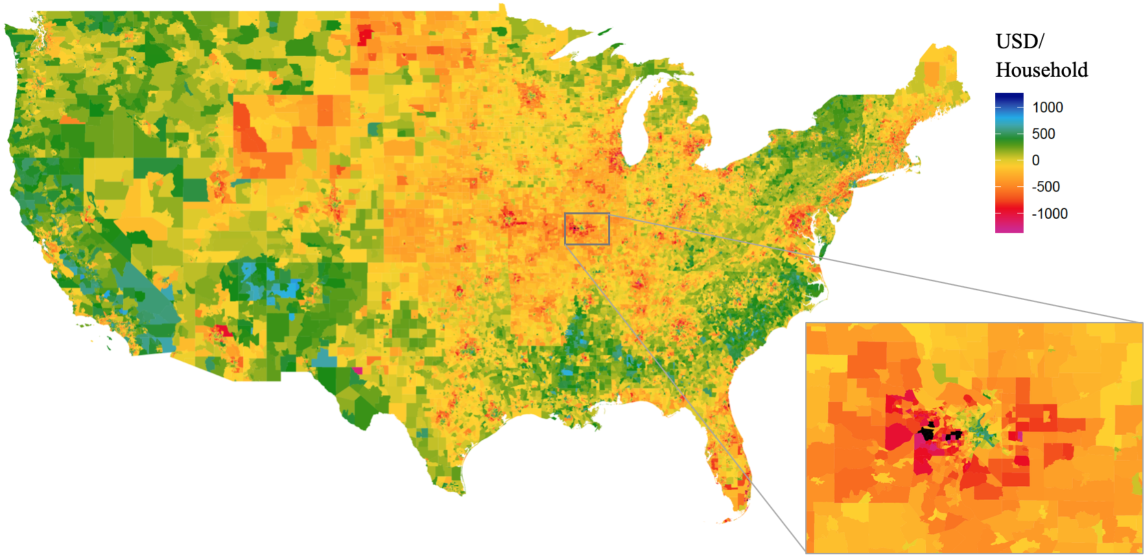


Figure 4-10: Net Impact of $50 Carbon Fee, Dividend adjusted for Income

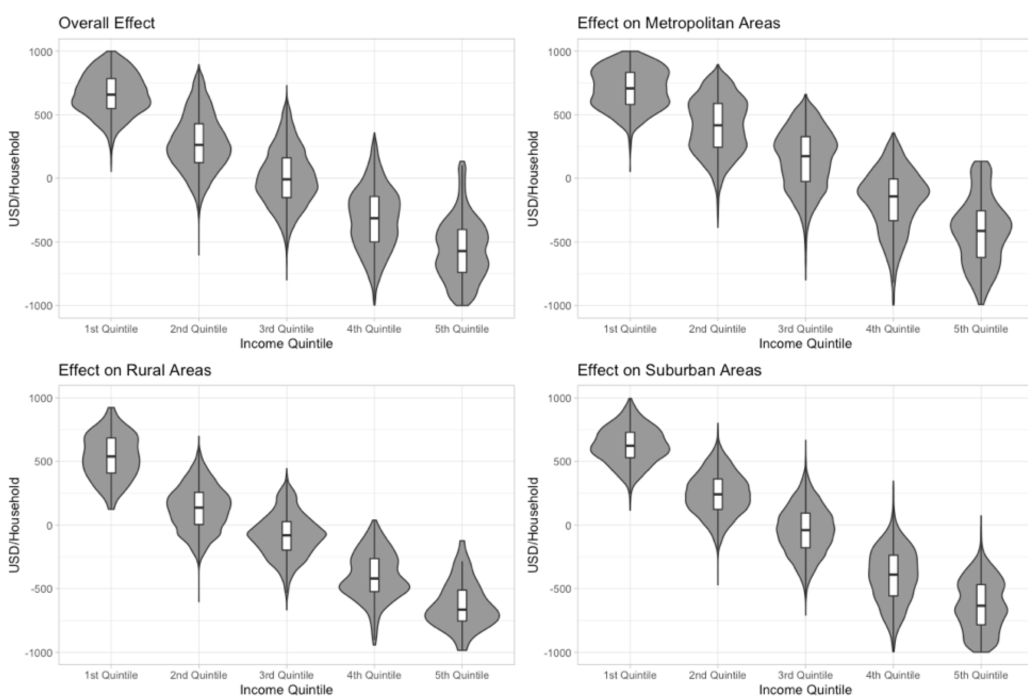


Figure 4-11: Net Impact of $50 Carbon Price, Dividend adjusted for Income

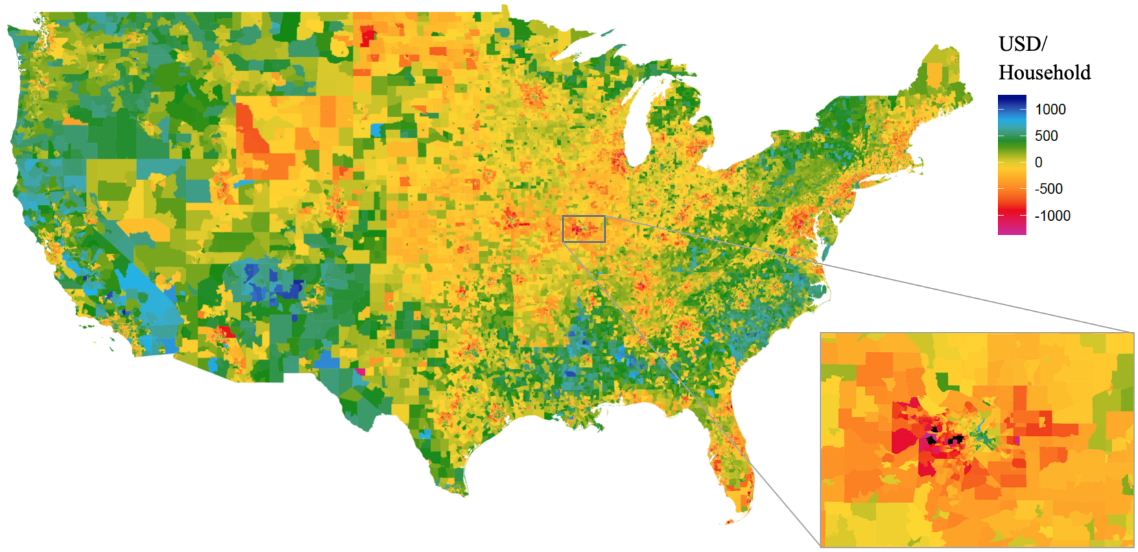


Figure 4-12: Net Impact of $50 Carbon Price, Dividend Adjusted for Income and Urbanity

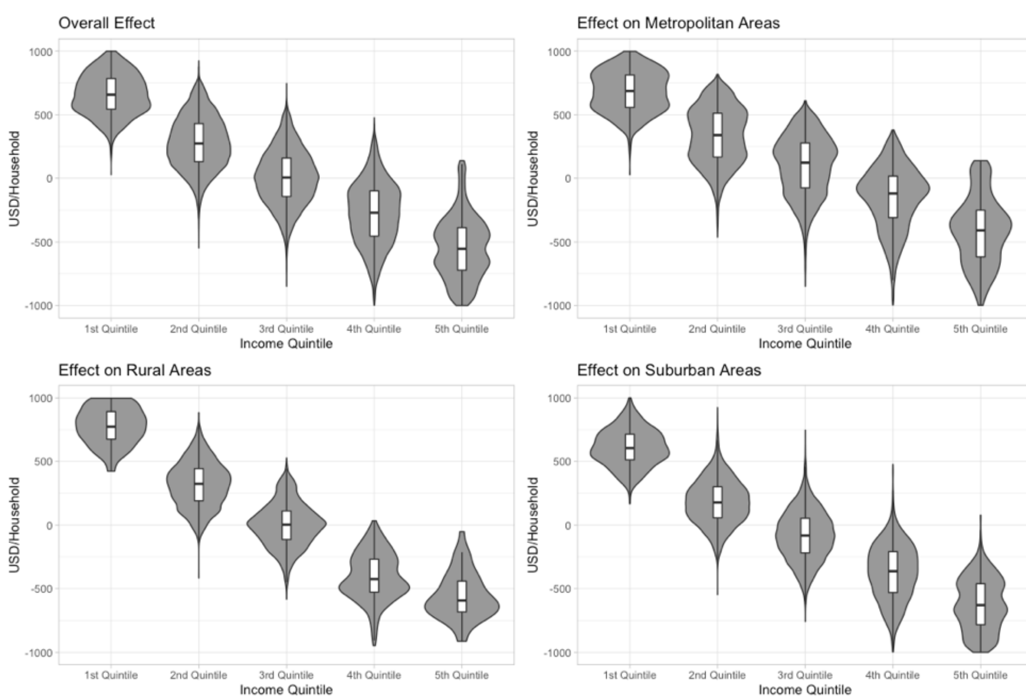


Figure 4-13: Net Impact of $50 Carbon Price, Dividend Adjusted for Income and Urbanity

4.2.2 Regulations

Figures 4-14, 4-16, 4-18 show the geographic distributions for regulatory policy, CAFE Standards, Clean Energy Standards, and the Clean Power Plan, respectively. Figures 4-15, 4-17, 4-19 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.

All the regulatory policy I modeled had net costs to the bottom two income quintiles. The Clean Power plan has the largest absolute cost per household (-$139 per household for the lowest 20%, or -$7.38 per $1000 in income; and -$165 for the second quintile, or -$4.69 per $1000 in income), followed by CAFE standards (-$68 per household for the lowest 20%, or -$3.61 per $1000 in income; and -$88 per household for the second quintile, or -$2.50 per $1000 in income). Although it followed a regressive trend, the costs associated with a Clean Energy Standard were small in comparison (-$6.21 per household for the lowest 20%, or -$0.33 per $1000 in income, and -$6.85 for the second quintile, or -$0.20 per $1000 in 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. I 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. If a household is in a NERC region with lower carbon emissions than the national average, then they will subsidized electricity rates and therefore will have a net benefit, scaled by the amount of consumption for that household. In areas with more carbon-intensive NERC regions, especially in states such as Missouri, Wisconsin, and Illinois, then households pay more and have a net cost associated with them. Accounting for distributed benefits of a Clean Energy Standard such as reduced NO_X emissions is important but outside the scope of this study.[3]

A Clean Energy Standard follows a regressive trend for rural and suburban households, while the trend is less clear overall and for metropolitan areas due to the multi-modal distribution. Rural areas tend to have a higher median cost and see a wider distribution of effects compared to metropolitan and suburban households. There is a large swath of the country that relies on coal and natural gas for power and these are where the households who bear greater costs for a CES are located. The rapid development of wind power and the displacement of coal with natural gas are changing the carbon landscape of the United States; however, households in the Midwest and Industrial Heartland could see mitigated costs if this trend continues.

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. As with the Clean Energy Standard, estimating the benefits of avoided emissions and the co-benefits of lowered pollutants and their respective distribution across the country is important but outside the scope of this study.

Rural and suburban households have higher costs on average than metropolitan households. Regardless of urbanity, the Clean Power Plan has a regressive costs, as households in the top quintile have lower average and median costs than that of households in the bottom two qunitiles.

[3]This analysis should be understood as a compliment to the study by Resources for the Future (Projected Effects of the Clean Energy Standard Act of 2019) which accounted for the direct benefits of avoided emissions as well as co-benefits of air pollution reduced.

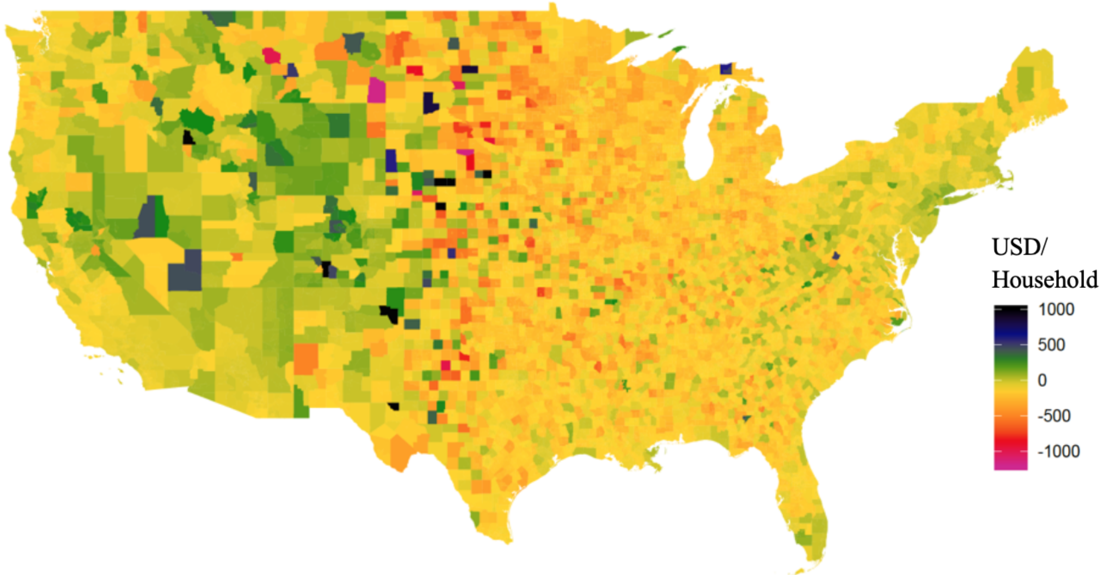


Figure 4-14: Net Impact of CAFE Standard

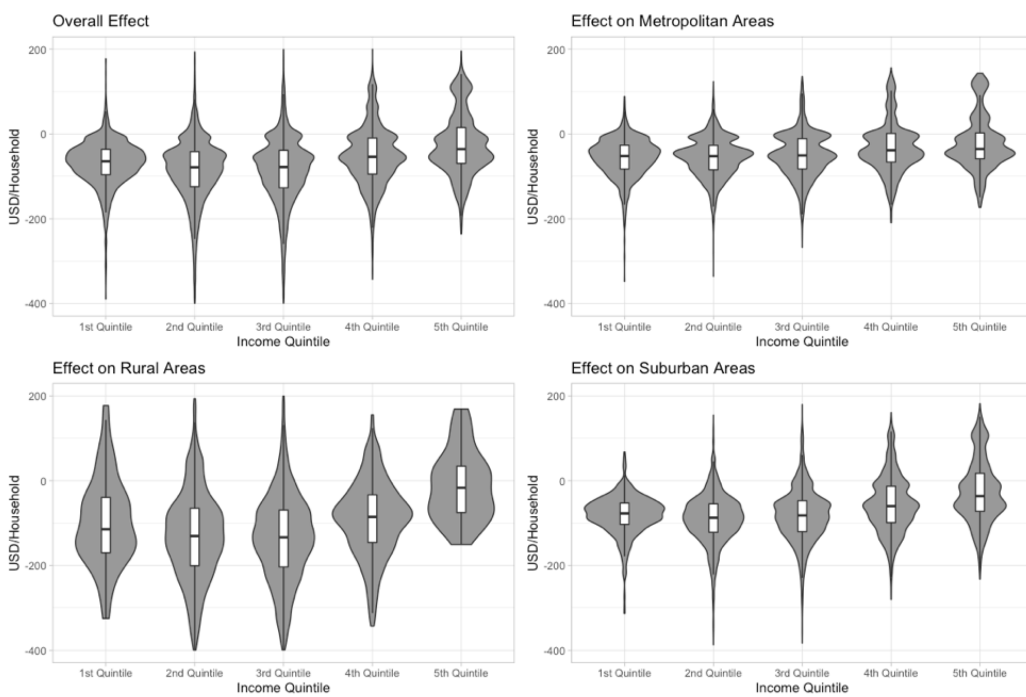


Figure 4-15: Net Impact of CAFE Standard - According to Urbanity and Income Quintile

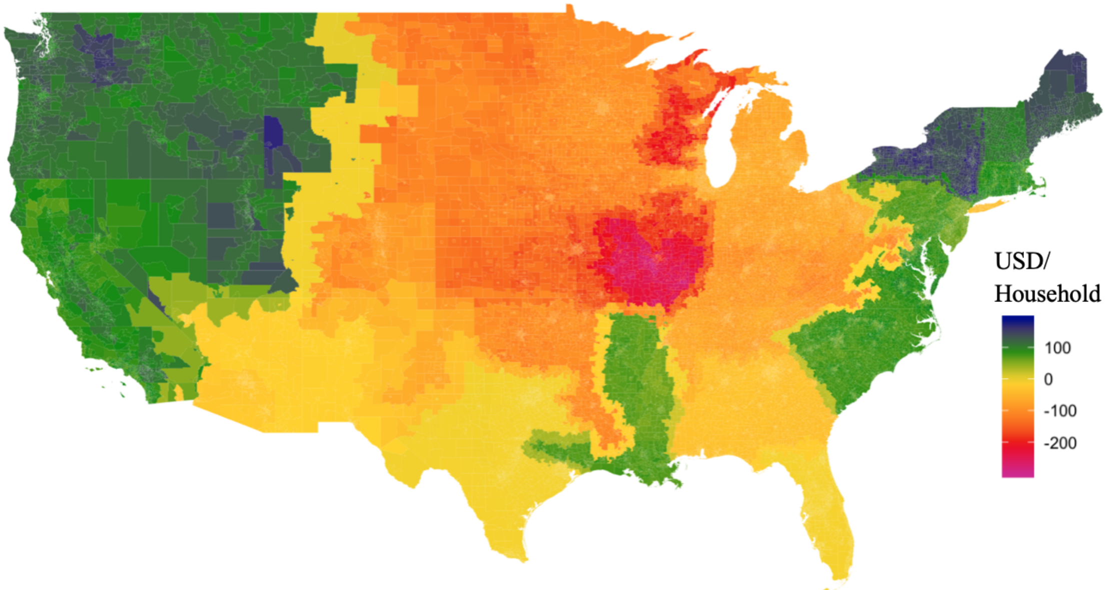


Figure 4-16: Net Impact of Clean Energy Standard

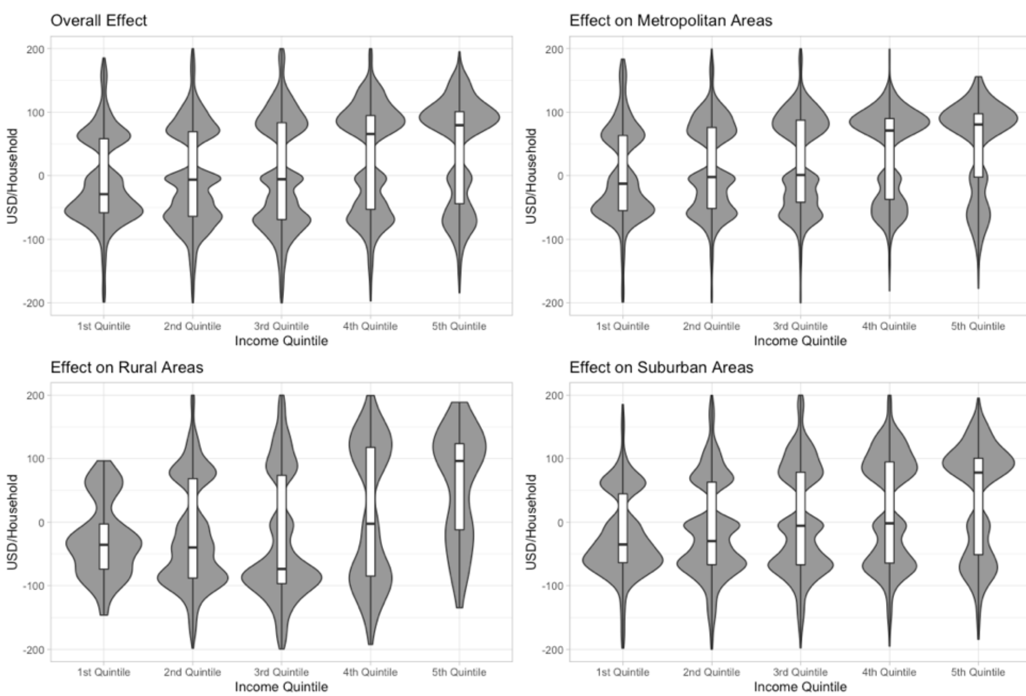


Figure 4-17: Net Impact of Clean Energy Standard - According to Urbanity and Income Quintile

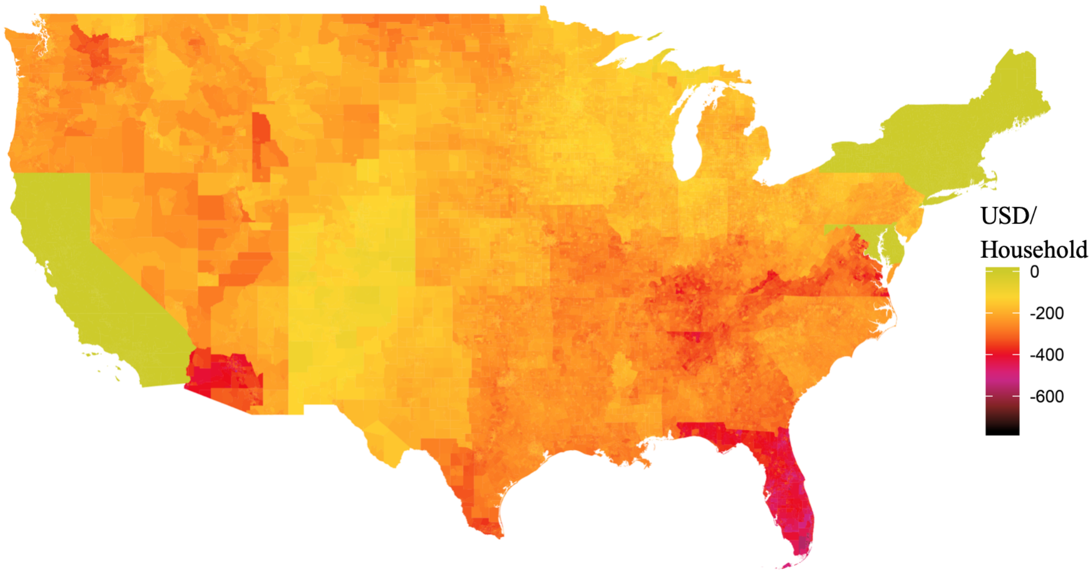


Figure 4-18: Net Impact of the Clean Power Plan

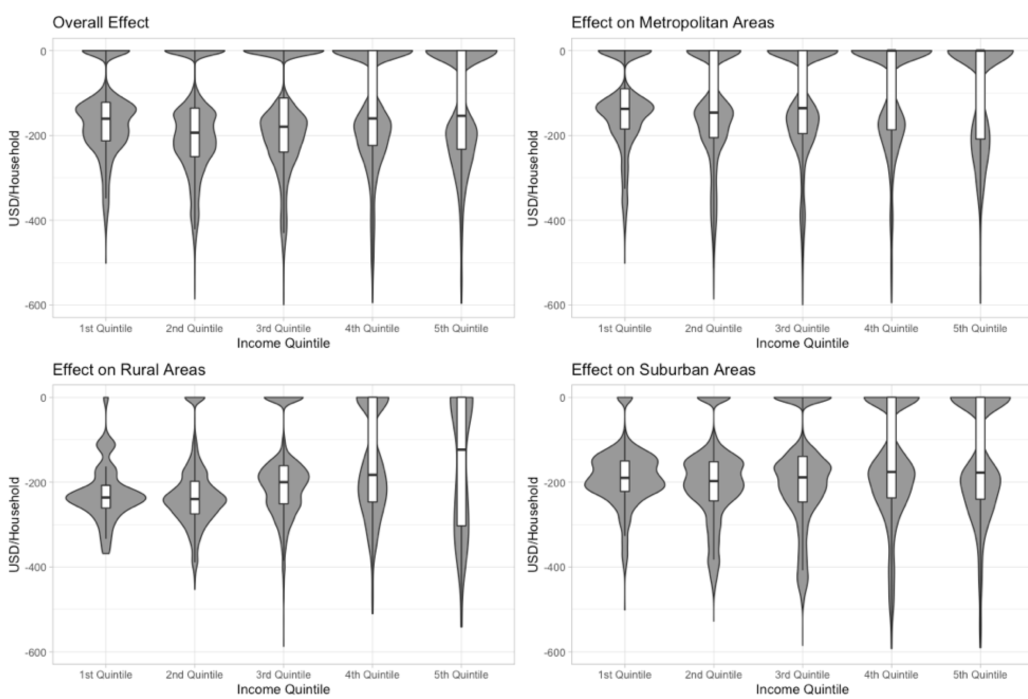


Figure 4-19: Net Impact of the Clean Power Plan - According to Urbanity and Income Quintile

Chapter 5

Discussion and Conclusion

5.1 Discussion

The models I developed analyzed regional and geographic variability in household carbon footprints with greater granularity in comparison to existing literature. When comparing carbon footprints, I found that the correlation with geography is as significant as household income. The relationship between footprint and geographic region is largely due to the relative carbon intensity of the electricity grid. Other modeling has found that the majority of emissions reduction will come from changes in 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 a 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 incenting households everywhere to reduce emissions.

Based on the conclusions of Jorgenson et al. 2018, I can expect that all policy scenarios that assess a similar price on carbon (scenarios 1 through 8) will have similar emissions reductions. However, I 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. I 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.[1]

Figure 5-1 shows that, for a carbon price and dividend policy, there are transfers between income quintiles and between urban and rural households. I 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, I believe that dividends are the clearest and most efficient way to correct for transfers between urban and rural populations.

I found that policy makers can 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 laid 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 have more natural political support, I believe that reducing the heterogeneity of net effects should be a goal for policy makers.

[1]Goulder et al. 2019 showed that 64 to 68% of the emissions reduced from a carbon price come from the electric power sector. My 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, my conclusions that a price and dividend scheme will be broadly progressive may not hold.

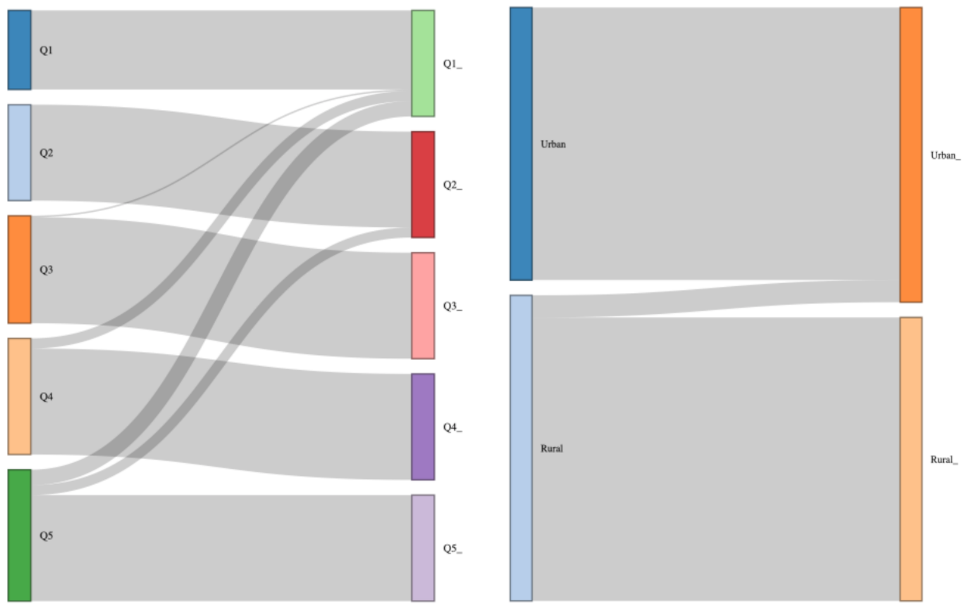


Figure 5-1: Transfers between income quintiles and urban-rural households for Carbon Price and Dividend (the left side represents relative tax paid through a carbon price, the right side represents the dividend received)

That is, it is not enough to examine the effects to the average household within an income group, but the distribution of outcomes must also be considered.

I found that accounting for both geography (determined by the Census divisions of the country) and urbanity (determined by population density and Census classifications) produces 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 and conservative districts alike.

There will be a trade-off between the simplicity of policy 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. I believe that such a policy could create an adverse incentive for state policy makers to maintain a higher carbon footprint so that their constituents would continue to receive a higher dividend.

Future work would benefit from a quantification of error propagation. Developing precision in modeling will be important in predicting the effects of proposed policy and the efficacy of potential solutions to correct for the mismatch between goals and outcomes. The interaction between command-and-control regulation and a market-based carbon price should also be explored in further depth with a computational general equilibrium model. Other components of carbon price policy proposals also deserve more attention, particularly border adjustments and their effect on trade and local economies. Finally, the distribution of source-side effects, costs to business, and costs to local governments also warrants examination.

5.2 Conclusion

The results from my work underscore the high variability in household carbon footprints across a number of dimensions. Two dimensions warrant focus. First, my results suggest that based on consumption of goods and services, low income consumers are likely to spend more on carbon taxes, as a share of their income. I am 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 firms and employment (known as source-side effects), carbon taxes are no longer regressive, the regressivity of carbon taxes on the consumption dimension is likely to be a major political obstacle.

My work highlights a second dimension that is likely to pose a political obstacle that is just as large, if not larger, than the regressivity of carbon taxes: the wide range in carbon footprints across rural and urban communities. Indeed, the geographic correlation of carbon footprints is nearly as significant as the variability across income levels. For example, the difference in average household emissions between the top and bottom quintile is smaller than the difference between the average household in California and Missouri.

These results accentuate 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. As inefficient (e.g., income) taxes are replaced with efficiency-enhancing taxes, such as carbon taxes, we not only help reduce 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. As tax reform packages are seen once per generation and are often political hot potatoes, I 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 I am aware of do not differentiate across households; each household receives the same dividend amount each year. While such a policy has the advantage of being straightforward, it ignores the large geographic differences in carbon footprints that I document, particularly across rural and urban settings.

I showed that correcting for heterogeneity can also improve the progressive outcome of policy. When I adjusted the dividend to increase the amount for low-income households and reduced the amount for high-income households, I found that the benefits for rural households increased on average but that the impacts within each income group were more heterogeneous. When I adjusted the dividend for both geography and urbanity, there was an increase in the average benefit to low-income households and a reduction in the heterogeneity of impacts within income groups.

I recommend a tax-and-dividend policy design that accounts for the rural-urban divide in carbon footprints. There are many ways to achieve this outcome. The basic structure is to condition the level of the dividend on some information about the type of the household. It is of upmost 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. I leave the details of such a plan for future policy discussions.

My results underscore an important lesson: climate policies that generate revenue within the policy itself afford policy makers the flexibility to protect disadvantaged groups. There is need for transparency in the impact to the public of each policy option – "do nothing" is the worst option, but all policy has a cost on some portion of the public. Vulnerable groups should be supported by public policy rather than burdened by it. 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.

Appendix A

Additional Tables

Note: Standard errors and Log-Likelihood are not included because the probit model involved variables that cause separation in the data and therefore the errors are not interpretable. This was deemed acceptable for predictive purposes as the variables that caused separation intuitively explain consumption (e.g., houses that heat with propane will consume propane) and our sample size was large.

Table A.1: Probit Model Coefficients (1)

	(LNBTUNG >0)	(LNBTULP >0)	(GALLONFO >0)	(LNHHVMT >0)
PRICEKWH	3.120	0.003	0.682	
PRICEKWH.SQ	0.593		1.532	
BEDROOMS	−0.054	−0.436	−0.211	
TOTROOMS	0.143	0.064	0.143	
TOTROOMS.SQ	−0.002	−0.029	−0.003	
LNHHAGE	0.133		2.494	−2.740
LNNHSLD	0.185	0.812	0.488	
POPDEN				−0.00004
LNPOPDEN				0.041
HHVEHCNT				0.814
HHVEHCNT.SQ				−0.071
TIMETOWK				0.001
LNTIMETOWK				−0.126
REG_Midwest				0.012
REG_West	−1.239	−0.149	−2.307	0.036
DIV_MiddleAtlantic	0.598	−0.015		−0.020
DIV_NECentral	0.237		−0.591	
DIV_NWCentral	0.291	0.055	−2.327	−0.050
DIV_SouthAtlantic	−1.571		0.336	
DIV_SECentral		0.325		−0.119
DIV_SWCentral	−0.156	−0.040	0.022	−0.112
DIV_MountainSouth	0.298			
DIV_Pacific	−1.152		0.185	−0.174
DIV_MountainNorth		−0.104		
TYP_Mobile	−0.797	0.900	0.489	
TYP_SingleDetached	−0.311	1.209	0.539	
TYP_SingleAttached	0.005	−0.108	−1.327	
TYP_Apartment2to4	−0.026	0.205	−1.013	
Rented	−0.052	−0.451	−0.545	
LNMADE_age	0.165	0.133	0.225	
PRICENG		0.393		
OCC_age	0.0001	−0.037		
PRICEFO.SQ		0.001		
LNOCC_age	−0.050	−0.001	−0.171	
HSLDINC	0.00000	0.00001	−0.00000	
lessHS				0.056
LNHSLDINC	−0.626	−0.309		0.027
Observations	31,407	31,407	31,407	269,128
Deg. Freedom	85	128	43	38

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.2: Probit Model Coefficients (2)

	(LNBTUNG >0)	(LNBTULP >0)	(GALLONFO >0)	(LNHHVMT >0)
CDD65	−0.001	−0.0004		
LNCDD65	0.396	−0.614	−0.315	
CDD65.SQ	0.00000	0.00000		
HDD65	−0.0001	−0.0001		
LNHDD65	0.270	0.571	0.628	
HEAT_NaturalGas	0.907	−0.940		
HEAT_FuelOil	−0.602	−1.292	6.686	
HEAT_Electricity	−0.858	−0.493	−0.002	
HHVEHCNT:LNHSLDINC				0.013
HHAGE:LNHHAGE				−0.059
POPDEN:HHVEHCNT				0.00004
HHVEHCNT:TIMETOWK				−0.0002
lessHS:NotHispanic				0.014
lessHS:Black				−0.128
BA:WRKDRV				−0.030
HHVEHCNT:WRKDRV				−0.337
HHVEHCNT.SQ:lessHS				0.028
Hispanic	−0.244	−0.244	0.453	−0.182
NotHispanic				0.147
Black	0.363	−0.238	0.007	−0.631
Asian	0.274	−0.767	0.631	−0.459
TwoRaces	0.498	−0.283	0.735	
WRKDRV				0.936
WRKHOME				0.100
WRK_PublicTransit				0.502
WRK_Walk				0.235
WRK_Bike				0.155
HS	0.170	−0.087	0.381	0.387
BA	−0.212	0.124	−0.151	0.830
IECC_1A2A	−0.836	0.142		
PRICEFO		−0.043		
Owned		−0.198		
IECC_2B	−0.456	−0.333		
IECC_3A	−0.964	−0.095	0.234	
IECC_3C	−0.046	−0.187		
IECC_5A	−0.919	0.319	−0.621	
IECC_4C		−0.624	−0.919	
IECC_5B5C	0.506	0.282		
Observations	31,407	31,407	31,407	269,128
Deg. Freedom	85	128	43	38

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.3: Probit Model Coefficients (3)

	(LNBTUNG >0)	(LNBTULP >0)	(GALLONFO >0)	(LNHHVMT >0)
IECC_6A6B	−1.096	0.558		
HHAGE	0.001	−0.007	−0.051	0.345
NHSLDMEM	−0.279	−0.041	−0.150	
PRICENG.SQ	0.014	−0.012	0.004	
White	0.205	−0.492		
SomeCollege	0.379	−0.436		0.508
IECC_3B4B	0.516	0.859	0.979	
HEAT_Propane	−1.492	0.065	−0.533	
IECC_4A	−1.344	0.045	0.138	
REG_South	−0.422	0.121	−0.813	
MADE_age	0.011	−0.005	−0.002	
PRICEKWH:HHAGE	−0.020			
HDD65.SQ		0.000	0.000	
PRICEKWH:NHSLDMEM	1.027	0.171		
NHSLDMEM:PRICENG.SQ	0.001			
HDD65:PRICENG.SQ	−0.00000			
TOTROOMS:LNMADE_age	−0.039			
LNNHSLD:HDD65	−0.00002			
CDD65:HDD65	−0.00000			
DIV_Pacific:HEAT_NaturalGas	−0.137			
PRICEKWH:LNMADE_age		−0.026		
PRICENG:OCC_age		−0.001		
LNNHSLD:PRICEFO.SQ		−0.010		
OCC_age:PRICEFO.SQ		−0.0003		
LNCDD65:BEDROOMS		0.057		
HDD65:TOTROOMS.SQ		0.00000		
LNNHSLD:LNHDD65		−0.024		
LNCDD65:MADE_age		0.001		
LNMADE_age:HDD65.SQ		−0.000		
HSLDINC:OCC_age		−0.00000		
LNCDD65:OCC_age		0.010		
REG_South:TYP_Mobile		0.004		
REG_South:HEAT_Electricity		0.839		
REG_South:HS		−0.688		
REG_West:TYP_SingleDetached		−0.155		
REG_West:White		−0.228		
DIV_MiddleAtlantic:HEAT_Propane		0.002		
Observations	31,407	31,407	31,407	269,128
Deg. Freedom	85	128	43	38

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.4: Probit Model Coefficients (4)

	(LNBTUNG >0)	(LNBTULP >0)	(GALLONFO >0)	(LNHHVMT >0)
TYP_Mobile:HEAT_Propane		0.013		
TYP_Mobile:IECC_3A		−0.669		
TYP_Mobile:IECC_4A		−0.821		
TYP_SingleDetached:HEAT_NaturalGas		−0.650		
TYP_SingleDetached:HEAT_FuelOil		−0.935		
TYP_SingleDetached:IECC_4A		0.119		
TYP_Apartment2to4:HEAT_Propane		0.003		
Rented:HEAT_NaturalGas	0.267	1.116		
HEAT_NaturalGas:Hispanic	0.605			
HEAT_NaturalGas:White	0.341			
HEAT_NaturalGas:SomeCollege	0.083			
HEAT_NaturalGas:IECC_3B4B	−0.298			
HEAT_NaturalGas:IECC_3C	−0.091			
HEAT_Propane:IECC_4A	0.056			
HS:IECC_1A2A	0.302			
PRICEKWH:REG_South	−3.537			
PRICEKWH:HEAT_NaturalGas	0.078			
PRICEKWH:IECC_1A2A	−2.080			
BEDROOMS:BA	0.197			
TOTROOMS:HEAT_NaturalGas	0.325			
REG_West:MADE_age	−0.006			
HEAT_NaturalGas:MADE_age	0.045			
IECC_3B4B:MADE_age	−0.014			
LNOCC_age:REG_South	0.169			
Rented:White		−0.051		
Rented:TwoRaces		0.645		
HEAT_Propane:Hispanic		0.062		
HEAT_Propane:IECC_3B4B		0.001		
HEAT_Propane:IECC_5A		0.005		
HEAT_Propane:IECC_5B5C		0.004		
HEAT_Propane:IECC_6A6B		0.011		
HEAT_Electricity:IECC_4C		0.746		
IECC_4A:HS		−0.321		
SomeCollege:IECC_1A2A		−0.600		
Observations	31,407	31,407	31,407	269,128
Deg. Freedom	85	128	43	38

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.5: Probit Model Coefficients (5)

	(LNBTUNG >0)	(LNBTULP >0)	(GALLONFO >0)	(LNHHVMT >0)
BA:IECC_1A2A		−0.278		
PRICEKWH:SomeCollege		−0.263		
PRICENG:HEAT_NaturalGas		−0.020		
HEAT_Electricity:PRICENG		−0.019		
White:PRICEFO		0.074		
PRICEFO.SQ:HS		0.007		
TYP_SingleDetached:BEDROOMS		−0.077		
BEDROOMS:HEAT_NaturalGas		0.214		
SomeCollege:BEDROOMS		0.065		
IECC_3A:BEDROOMS		0.194		
TOTROOMS.SQ:Owned		0.025		
TOTROOMS.SQ:HEAT_NaturalGas		0.001		
HEAT_Propane:TOTROOMS.SQ		0.237		
White:TOTROOMS.SQ		−0.0001		
HHAGE:REG_South		0.005		
HHAGE:HEAT_FuelOil		0.008		
NHSLDMEM:TYP_SingleDetached		−0.104		
NHSLDMEM:HEAT_NaturalGas		−0.002		
IECC_3A:MADE_age		−0.018		
REG_South:LNMADE_age		−0.202		
REG_West:LNMADE_age		−0.090		
HEAT_Electricity:LNMADE_age		0.022		
SomeCollege:LNMADE_age		0.101		
LNOCC_age:HEAT_FuelOil		0.381		
HSLDINC:HEAT_NaturalGas		−0.00001		
HSLDINC:HEAT_Electricity	0.00001	−0.00000		
TYP_SingleDetached:CDD65	0.0001			
DIV_SouthAtlantic:HDD65	0.0004			
HDD65:HEAT_NaturalGas	0.007			
LNHSLDINC:IECC_1A2A		0.005		
LNCDD65:Owned		−0.109		
LNCDD65:HEAT_Propane		0.464		
LNCDD65:SomeCollege		0.027		
HEAT_Electricity:CDD65.SQ		0.00000		
TYP_SingleDetached:CDD65.SQ		−0.000		
Rented:LNHDD65		−0.072		
HDD65.SQ:HEAT_NaturalGas		−0.00000		
Constant	1.135	0.007	−13.758	5.199
Observations	31,407	31,407	31,407	269,128
Deg. Freedom	85	128	43	38

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

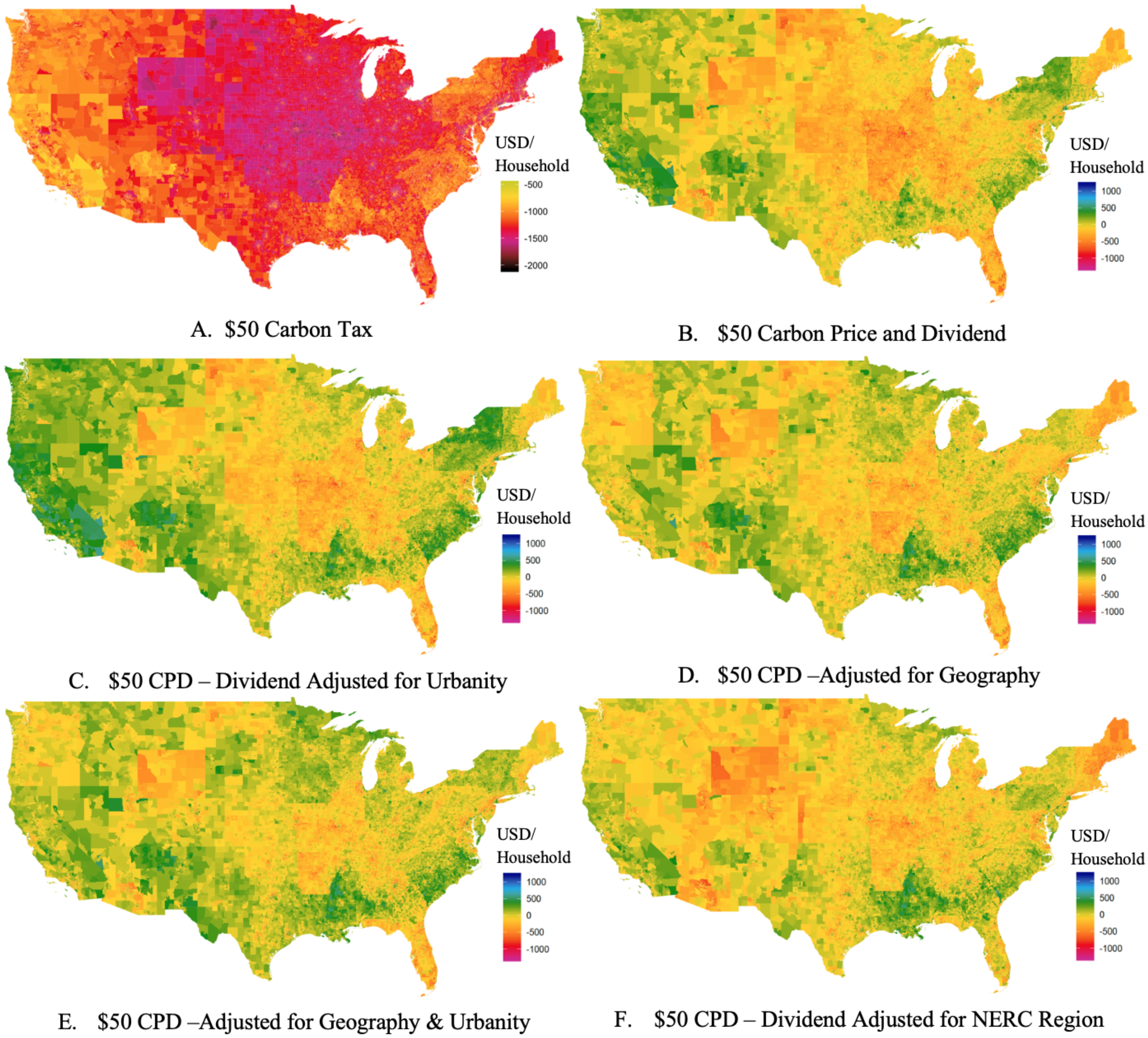


Figure B-1: Policy Scenarios 1 - 6

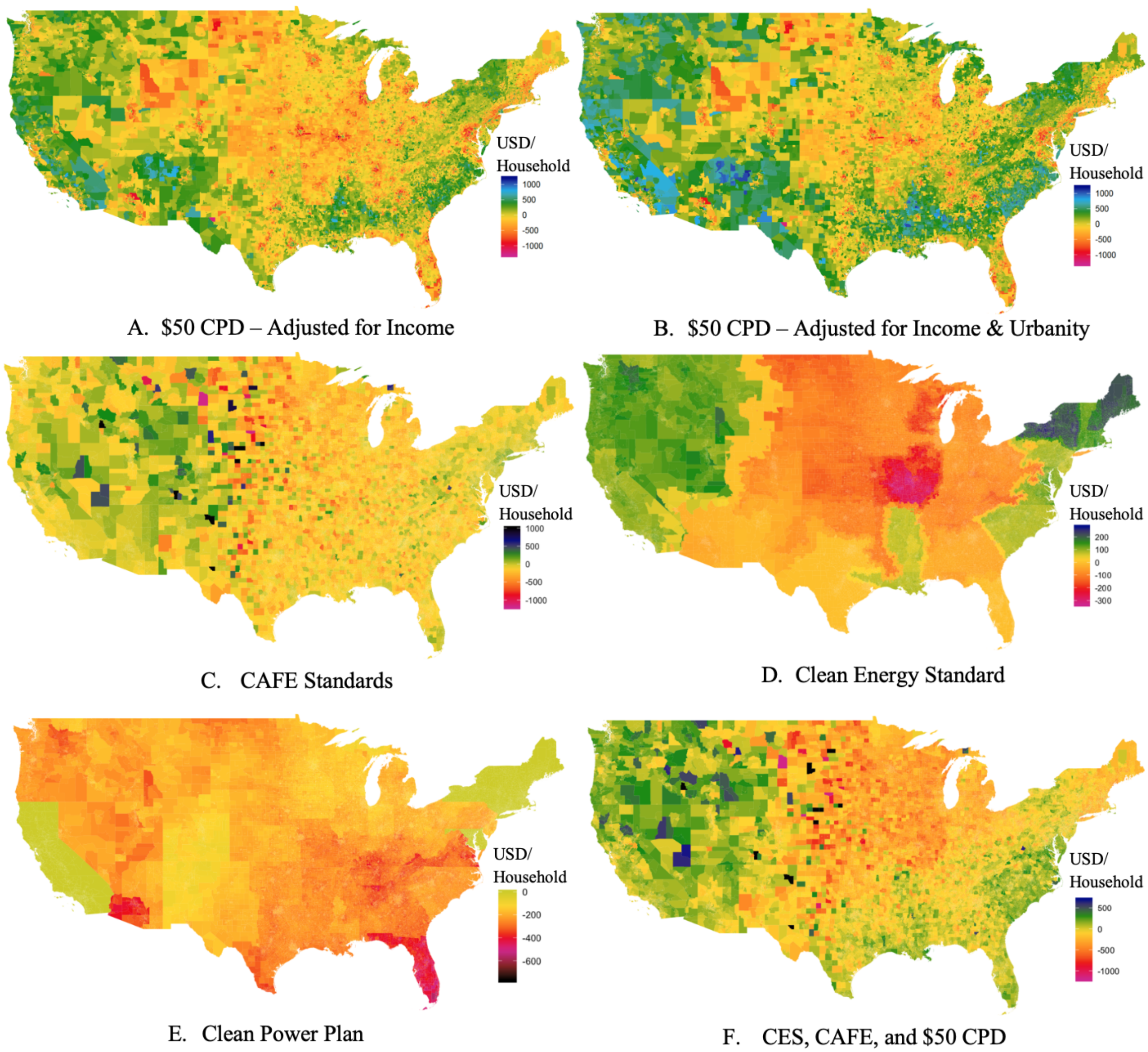
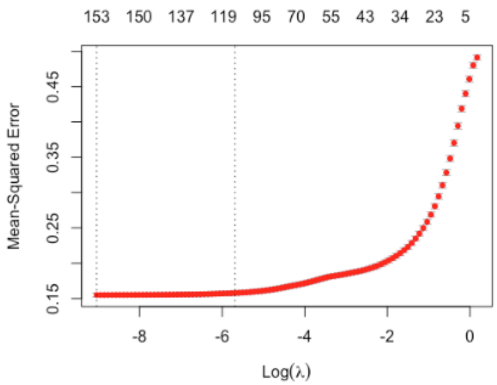
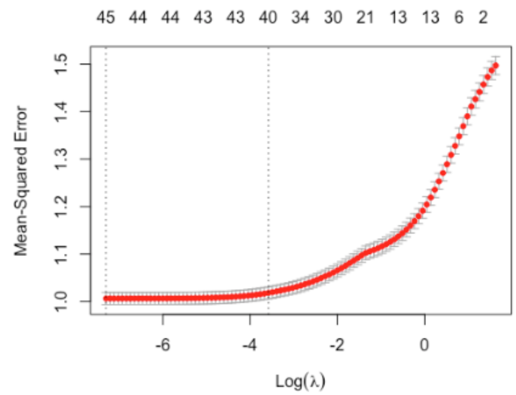


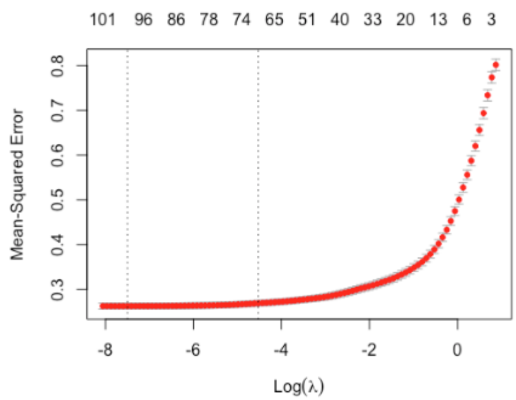
Figure B-2: Policy Scenarios 7 - 12



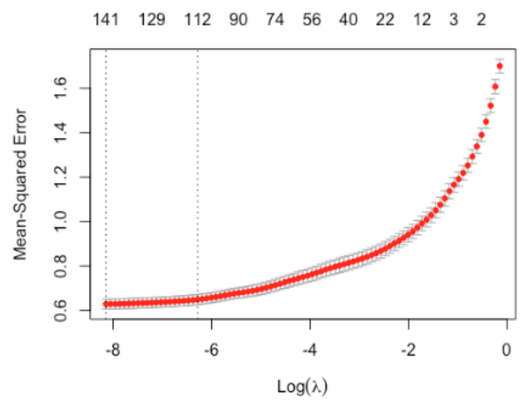
A. Log-KWHs



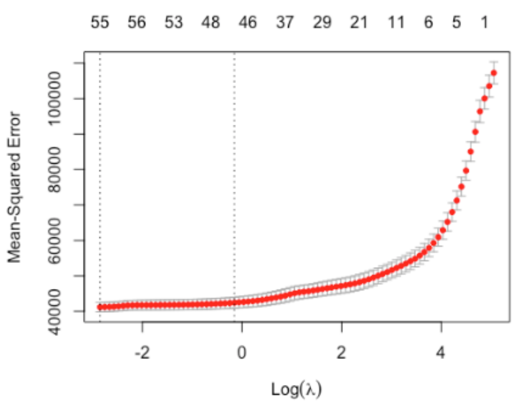
B. Log-VMTs



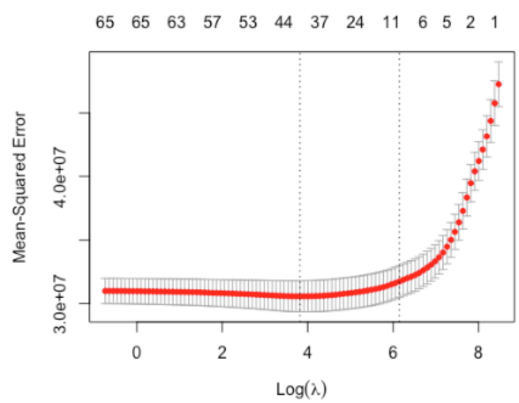
C. Log-BTUs of Methane



D. Log-BTUs of Propane

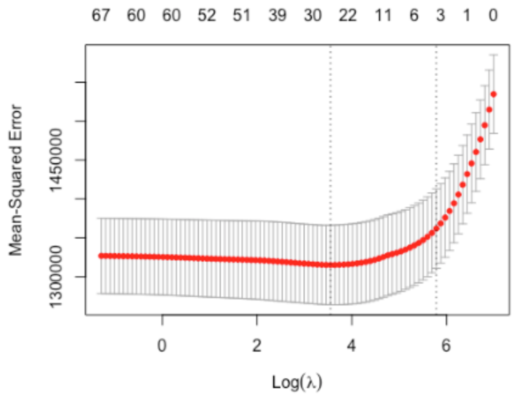


E. Gallons of Fuel Oil

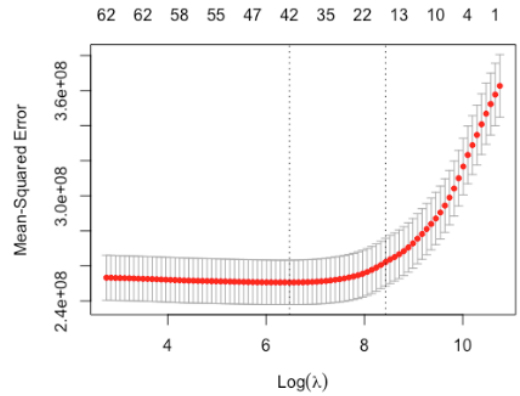


F. Spending on Food Consumption

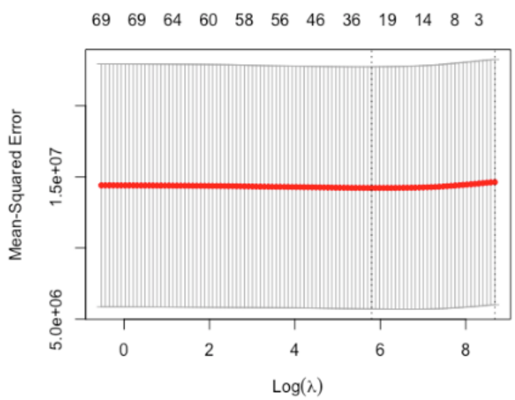
Figure B-3: Cross-Validation Error and Lambda Values for Models 1 - 6



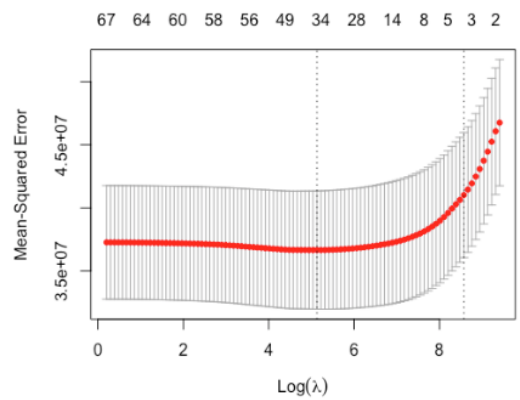
G. Spending on Alcoholic Bevs.



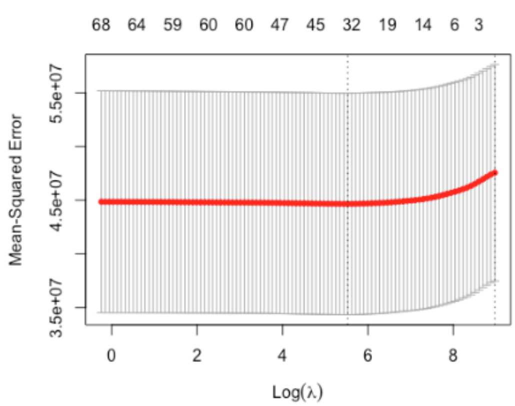
H. Spending on Housing



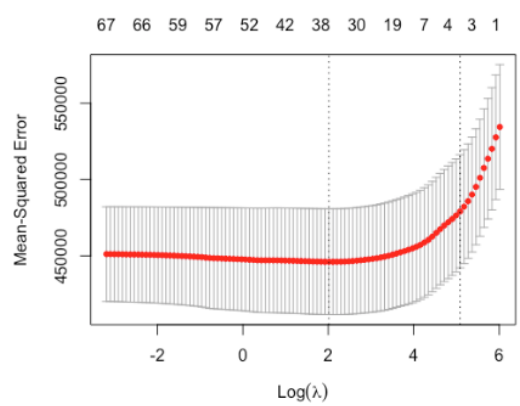
I. Spending on Apparel



J. Spending on Healthcare

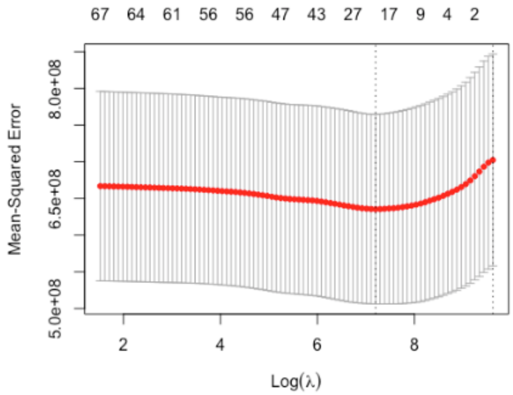


K. Spending on Entertainment

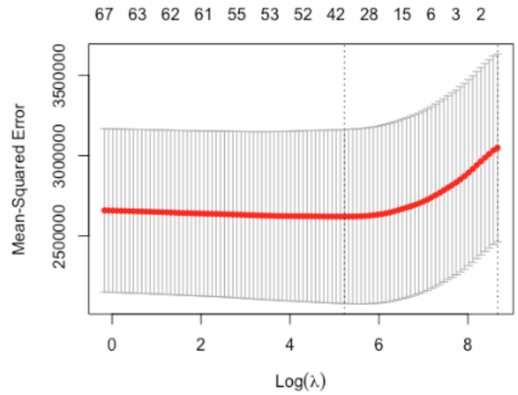


L. Spending on Personal Care

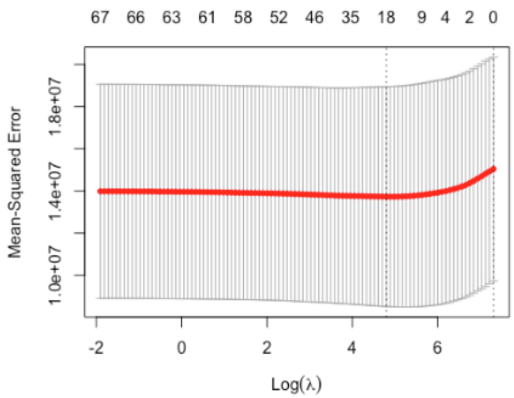
Figure B-4: Cross-Validation Error and Lambda Values for Models 7 -12



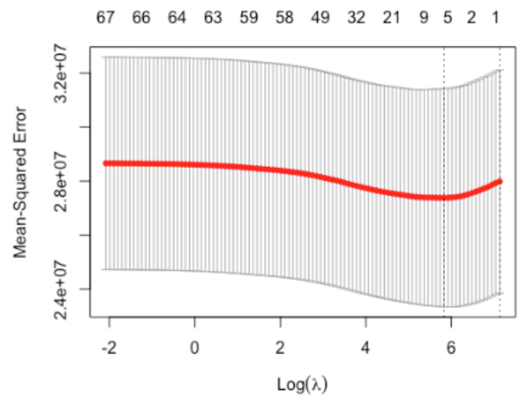
M. Spending on Education



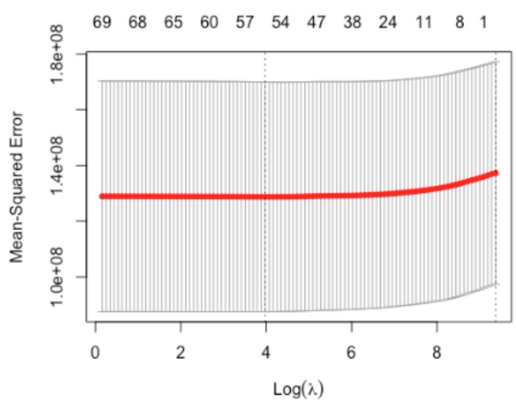
N. Spending on Tobacco Products



O. Spending on Life Insurance



P. Miscellaneous Spending



Q. Cash Contributions

Figure B-5: Cross-Validation Error and Lambda Values for Models 13 -17

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