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TAX CREDITS FOR CLEAN ELECTRICITY:
THE DISTRIBUTIONAL IMPACTS OF SUPPLY-PUSH POLICIES IN THE POWER SECTOR

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Tax Credits for Clean Electricity: The Distributional Impacts of Supply-Push Policies in the Power Sector
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ABSTRACT

We evaluate distributional and efficiency consequences of the bulk power clean electricity tax credits authorized by the 2022 Inflation Reduction Act. To do so, we link detailed electricity capacity expansion, computable general equilibrium, data-rich microsimulation, and air pollution models to estimate the policy incidence in terms of economic welfare and health impacts across a wide range of demographic groups. We evaluate the tradeoff between policy efficiency and income progressivity by comparing the tax credits to cap-and-trade policies that vary revenue recycling approaches. Under the scenarios analyzed the bulk power tax credits lead to increased clean electricity technology deployment resulting in a reallocation of capital from elsewhere in the economy, higher prices for capital and other goods, lower power prices, and lower emissions. The tax credits yield progressive outcomes for both economic welfare and health impacts. The health benefits exceed total policy costs and provide greater benefits for low-income and historically-marginalized households given the coincidence of household and emission source locations.

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1 Introduction

The Inflation Reduction Act (IRA) was signed into law by President Biden on August 16, 2022. Among several provisions, the law authorizes the renewal, expansion, and creation of a broad range of energy and climate programs and incentives with the majority of the associated support dedicated to clean electricity and energy tax credits (CBO, 2022). A number of studies have demonstrated the potential for these tax credits to have a dramatic impact on clean electricity deployment and associated emissions reductions (Larsen et al., 2022; Jenkins et al., 2022; Mahajan et al., 2022; Zhao et al., 2022) but few have evaluated the broader economic and distributional impacts. Therefore, we seek to answer the following question: What are the distributional and efficiency impacts of the IRA bulk power clean electricity tax credit provisions? The bulk power clean electricity tax credits evaluated here, explained in greater detail below, are the production and investment tax credits for generation and storage capacity as well as the CO_2 carbon capture and storage tax credit, commonly referred to as 45Q.

Analyses of the efficiency and distributional impacts of electricity emissions abatement policies have generally centered on the design of carbon taxes and cap-and-trade programs - typically referred to as first-best policies given their minimal efficiency detriment relative to other, second- or third-best policies such as rate-based standards (Pigou, 1920; Baumol and Oates, 1988; Aldy et al., 2022). With the passing of the IRA, there is a need to understand and compare the impacts of incentive-based policies for pollution reduction given the unprecedented magnitude and approach of the legislation and in an era of competitive renewable electricity and storage technologies. Therefore, we simulate the IRA bulk power clean electricity tax credits' impact on the US electricity grid, economy, and human health across a wide range of demographics using a suite of detailed, publicly-available models and across a wide range of scenarios. We then benchmark the incentive-based policy's efficiency and progressivity relative to first-best policies that meet the same emissions reductions through cap-and-trade programs that vary in carbon permit revenue recycling mechanisms; this comparison is intended to both gauge the relative impacts of incentive-based and emissions-pricing policies as well as put this study in the context of previous work.

The simulations present significant emissions reductions from a rapid buildout of clean electricity generation capacity, similar to previous studies (Jenkins et al., 2022; Steinberg et al., 2023; Larsen et al., 2022; Zhao et al., 2022; Mahajan et al., 2022; Bistline et al., 2023a,b). The reallocation of capital from non-electricity sectors and the assumed funding mechanisms for the tax credits simultaneously drive up the effective cost of capital, leading to increased labor demand and thus increased wages relative to the pre-tax rental rate as well as reduced electricity prices. Given labor is the primary source of lower-income households' factor income and lower-income households spend a greater portion of their income on electricity relative to other income groups, we find the bulk power clean electricity tax credits to be progressive. Reinforcing the findings from other studies (Fullerton and Heutel, 2011; Rausch et al., 2011; Fullerton et al., 2012; Caron et al., 2018a,b; Goulder et al., 2019; Williams et al., 2015), we demonstrate the trade-off of policy efficiency with progressivity while contributing findings that the tax credits present greater progressivity at a loss of efficiency relative to an equivalent cap-and-trade policy, regardless of carbon permit revenue recycling mechanism.

Air quality improvement from all modeled electricity decarbonization policies is demonstrated to be progressive given the reductions of particulate matter-emitting electricity generation that impacts low-income and/or historically-marginalized communities at a higher rate given location coincidence. Agnostic to approaches for converting human lives into financial terms, reduced deaths per capita from electricity decarbonization are demonstrated to be monotonically decreasing with respect to household income. At a national level, all modeled policies result in a net benefit when combining estimates of equivalent variation with health benefits using a static value of statistical life (VSL) and/or when considering climate benefits, while demographic- and region-specific results vary in net impact.

For important caveats, this analysis focuses only on the bulk power clean electricity tax credits of the IRA and does not encompass the entirety of the law's provisions. As such, results and conclusions should only be viewed through this limited scope. Specifically, we do not include in our analysis other changes to the US tax code, distributed electricity generation, health care and infrastructure spending, manufacturing tax credits, vehicle tax credits, efficiency tax credits, or any other provisions not explicitly stated in Section 3.2 below. In addition, how the tax credits are funded in the model through broad capital taxes is a simplification of the more-specific tax mechanisms in the IRA. Related, the necessity to raise additional taxes to cover transfer losses is a result of the modeling assumption towards constant government expenditures. In reality, the transfer loss haircut could be funded through a wide range of government responses and we choose to model a subset of those options to provide a range of potential impacts. To summarize, this exercise should be viewed as an evaluation of the potential implications of the bulk power clean electricity tax credits, with the understanding that there are several other portions of the IRA not considered which could have a substantive effect on the US economy and the well-being of the US population.

The rest of the paper proceeds as follows. Section 2 puts our contribution in the context of the existing literature. Section 3 describes our modeling methods and data sources. Section 4 discusses our main findings and sensitivity analysis. Section 5 concludes.

2 Literature

The distributional impacts of emissions reduction policy designs have been evaluated in several past studies; in a literature review, Wang et al. (2016) find that a primary determinant of the progressivity or regressivity of market-based policies is the revenue recycling mechanisms, a finding reinforced in similar efforts (Burtraw et al., 2009; Fullerton and Heutel, 2011; Rausch et al., 2011; Fullerton et al., 2012; Caron et al., 2018a; Goulder et al., 2019; Hafstead and Williams, 2019). Unique findings from each study are summarized below, but the conclusion is generally the same: there is a tradeoff between overall economic efficiency and progressivity which varies based on the carbon revenue recycling mechanisms. However, the paradigm of tax credits and clean energy subsidies introduced by the IRA warrants a new evaluation of the distributional impacts of such policies.

Computable General Equilbrium (CGE) models have been used in several analyses to assess the distributional impacts of Pigouvian taxes as well as cap-and-trade pollution reduction policies, with few studies focused on subsidy-based policies such as clean energy tax credits and especially those of this magnitude. Caron et al. (2018b) explore distributional effects across income groups and regions in a multi-model comparison of different national carbon pricing and revenue recycling mechanisms. Rausch et al. (2010) compare different allowance allocation and transfer payment assumptions under a national CO_2 emissions cap and trade system. Studies assessing revenue recycling mechanisms (Fullerton and Heutel, 2011; Rausch et al., 2011; Fullerton et al., 2012; Caron et al., 2018a,b; Goulder et al., 2019) generally find that returning carbon tax revenue to households is progressive but reduces overall efficiency while leveraging carbon tax revenue to reduce capital taxes is regressive but more efficient. Aside from situations that find double-dividend returns, typically from capital tax reductions and assumptions of inter-period capital accumulation in recursive dynamic setups, it is important to note that CGE models typically demonstrate a loss in economic output resulting from emissions abatement policy, regardless of policy choice. While theoretically consistent and sound, the calibrated share production functions and standard CGE model structure typically imply a loss in economic output when intervention causes a deviation from reference points (with proper tax revenue and expenditure accounting); studies that have evaluated the net impacts of emissions policies such as Caron et al. (2018a), Woollacott (2018), and Roy et al. (2022) consistently find positive net benefits when considering climate and/or health benefits.

Other work also explores how model inputs impact whether a GHG mitigation policy is found to be progressive. Grainger and Kolstad (2010), Hassett et al. (2009), and Rausch et al. (2011) compare outcomes when using measures of annual or lifetime income to measure welfare. Lifetime measures of income are generally found to be more progressive. Fullerton et al. (2012) explore the effect of government indexing of transfers to inflation on policy regressivity. Using annual income, Fullerton et al. (2012) find that a carbon tax is generally regressive, but including partial or full indexing is progressive. Residential and household-level clean energy tax credits have been explored by Borenstein and Davis (2016); using household tax return data they find tax credits to be highly regressive and much less attractive on distributional grounds compared to market-based mechanisms.

Several studies consider the region- and demographic-specific effects of GHG mitigation policies. Fullerton and Heutel (2011) find the regions that spend more on carbon-intensive goods are more negatively affected by the policy. Similarly, Rausch et al. (2011) find that the North and South Central regions of the country are more impacted because of their dependency on coal for electricity generation and that households with minority heads of household bear a larger burden. Hassett et al. (2009), on the other hand, finds only small differences in outcomes between regions. Other work employs household microdata in combination with national policies to explore household agents in more detail (García-Muros et al., 2022; Rausch et al., 2011). Williams et al. (2015) link a dynamic overlapping-generations model with a micro-simulation model to explore distributional effects across households in a US national model. Caron et al. (2018a) explore revenue recycling mechanisms using a linked model similar to our approach and find that the coupled model meaningfully changes the results. In a meta-analysis of 53 different studies of distributional impacts of carbon pricing, Ohlendorf et al. (2020) find that the likelihood of a progressive outcome is increased in lower-income regions and when indirect effects and/or lifetime incomes are considered.

Roy et al. (2022) and Bistline et al. (2023b) are the most similar in scope to our analysis.

Roy et al. (2022) utilize three models to perform their analysis: a bottom-up representation of the electricity sector, a detailed microsimulation model, and an atmospheric transport model. Bistline et al. (2023b) leverage a neoclassical macroeconomic framework to evaluate the potential economic impacts and then quantify economic impacts through the Federal Reserve's US (FRBUS) general equilibrium model but do not present quantitative estimates of distributional impacts. Results from Roy et al. (2022) indicate that the income losses are outweighed by electricity expenditure reductions and thus most income classes face a net benefit. Additionally, Roy et al. (2022) indicate that the health benefits dominate the economic impacts but are regionally concentrated, a finding reinforced by Woollacott (2018). Similarly, Bistline et al. (2023b) find that the clean electricity tax credits could imply progressive outcomes given their reduction in retail electricity rates and lower-income households' greater energy burden. Our results generally support these findings but differ from Roy et al. (2022) in that we do not find a net economic benefit across income groups, potentially given differences in model architectures and assumptions, yet health benefits still dominate and are generally progressive. Further research is warranted to explore the cause of these differences.

Analyses focusing on grid impacts of recently-passed clean electricity tax credits in IRA (Larson et al., 2020; Goldman School of Public Policy, 2020) have not considered the distributional consequences across income groups, though they have examined *gross*, not *net*, employment impacts. Importantly, neither of these studies considers changes in household consumption, income, or broader general equilibrium impacts. Therefore, we contribute to the literature by assessing recently-passed clean electricity tax credits' net economic impacts with a focus on distributional analysis. The CGE representation is important as distributional impacts are likely to operate both through sources (wages/income) and uses (cost of living), and thus a major advantage of CGE analysis is the ability to consider both in a theoretically coherent framework.

Other analyses have focused on market-based alternatives to carbon pricing such as clean energy standards or tradable emissions performance standards. Among these, Goulder et al. (2016) uses a dynamic general equilibrium model to show how a clean energy standard can dominate an emissions cap on cost-effectiveness grounds when pre-existing tax distortions are present. Using a linked version of ReEDS-USREP, Rausch and Mowers (2014) show how clean energy and renewable portfolio standards are regressive compared to carbon pricing.

3 Methods

In this section, we present an overview of the models used in the study, the methodology for linking the models, the policy designs, the assumptions around counterfactual scenarios, as well as caveats and considerations for improvement.

3.1 Models and Linkage

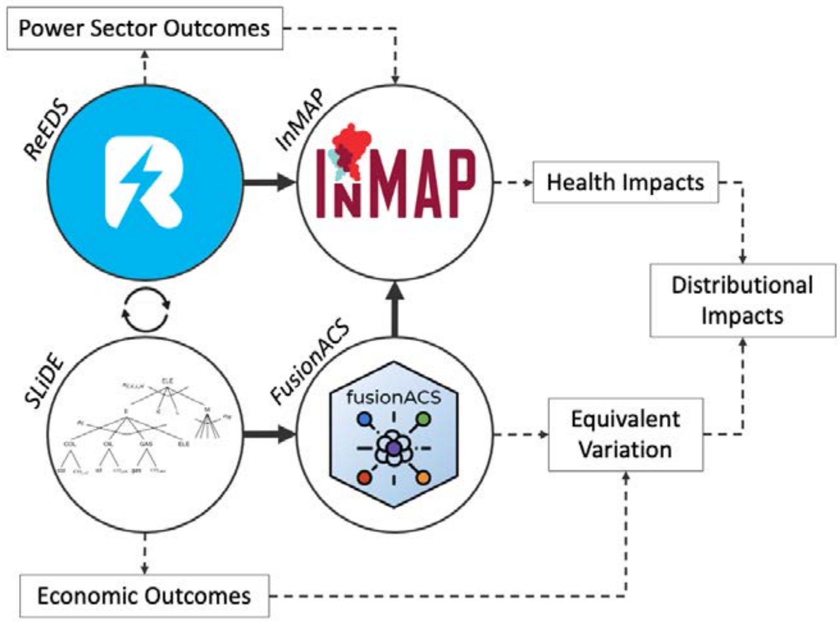

Figure 1: Model connections and outputs

Figure 1 presents the connections across models, each explained in more detail below, and the primary outputs. The Regional Energy Deployment System (ReEDS), an electricity capacity expansion model, iterates with the Scalable Linked Dynamic Equilibrium (SLiDE) model, a CGE model of the US economy. ReEDS communicates the power sector emissions to the Intervention Model for Air Pollution (InMAP) model to assess the health impacts of air pollution, specifically particulate matter[1] 2.5 (PM2.5). FusionACS-CE[2], a detailed dataset of US household characteristics and expenditure information, is used both to inform the demographics of InMAP as well as to down-scale the equivalent variation results from SLiDE to further disaggregated demographic breakdowns. The final output of distributional impacts includes both the health impacts from InMAP/fusionACS-CE as well as the equivalent variation from SLiDE/fusionACS-CE. Descriptions, linkage setup, and key assumptions are presented next for each of these models.

ReEDS is the National Renewable Energy Laboratory's flagship electricity capacity expansion model (Ho et al., 2021). ReEDS has been used in over 100 journal article publications as well as several policy analyses, including an evaluation of IRA's impacts on the electric power sector (Steinberg et al., 2023). The ReEDS model is a linear program that solves for the cost-minimizing combination of investment and operation of the US bulk power system. The model code and data are publicly available[3], including the version used in the Steinberg et al. (2023) analysis[4] which serves as the foundation for this study, and the linked version of the model will be made publicly available upon release of this work. The primary differences from the version of ReEDS

[1]InMAP represents health impacts from both primary and secondary PM2.5 emissions
[2]Note that '-CE' designation indicates consumer expenditure data, explained further below
[3]See: https://www.nrel.gov/analysis/reeds/
[4]See: https://github.com/NREL/ReEDS-2.0/tree/MB_IRA

used in Steinberg et al. (2023) and the version here is that load growth is endogenous to the linked model while based off AEO 2022 *Reference Case* trajectories (EIA, 2022a), fuel prices are computed endogenously within SLiDE, and there are no exogenously-assumed changes to distributed photovoltaic deployment.

The primary constraints in ReEDS are to provide enough electricity generation plus net transmission to meet load and to maintain reliability through both operating reserves provision and meeting the planning reserve margin. The ReEDS model meets these constraints at the 134 balancing areas presented in the left map in Figure 2 while having more resolved resolution for certain renewable energy technology specifications (costs and performance) at 356 resource supply regions. ReEDS portrays over 300 different electricity generation technologies while also maintaining an up-to-date representation of state and federal policies.

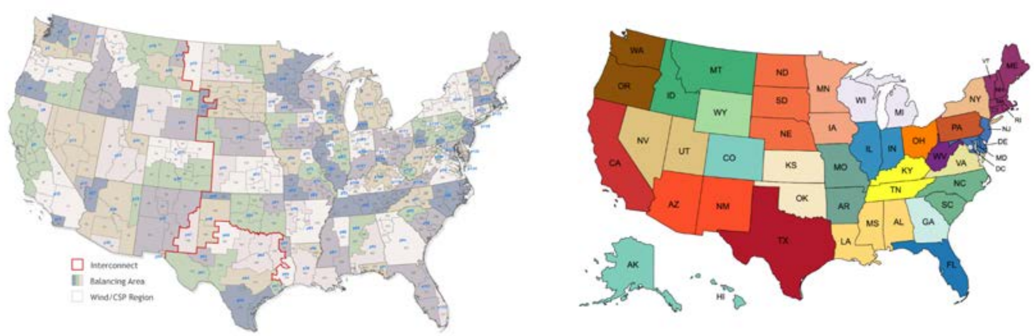

Figure 2: Map of ReEDS (left) and SLiDE (right) modeled regions

The SLiDE model is a recursive-dynamic, multi-regional, multi-commodity CGE model of the US based on the Wisconsin National Data Consortium's (WiNDC) benchmark dataset and blueNOTE energy-economy model (WiNDC, 2020; Marten et al., 2021). The WiNDC-based benchmark calibration point is aggregated to 26 regions (right map in Figure 2), 5 household income groups, and 11 sectors. Existing taxes on capital, labor, output, intermediate inputs, and imports are included in the benchmark economy.

The US is modeled as a small open economy with pooled national-domestic commodity trade represented by Armington composites of foreign, national, and local varieties (Armington, 1969). Production and consumption are modeled as nested constant elasticity of substitution (CES) production functions in the calibrated-share form (Rutherford, 1999, 2002). Each sector consumes intermediate inputs along with capital, labor, and natural resources. Putty-putty capital is perfectly mobile across sectors and regions whereas labor is perfectly mobile across sectors but restricted to a region. Primary fuel production sectors employ a fixed-resource factor that is calibrated to ensure upward-sloping supply schedules (Rutherford, 2002; Marten et al., 2021).

Each household, broken out by income quintile as presented in Table 1 (HH1 being lowest income and HH5 being highest) consumes a nested CES welfare composite consisting of investment and a full consumption composite. Full consumption consists of leisure and final consumption (Bovenberg and de Mooij, 1994; Ballard et al., 1985). Households earn income primarily from their capital and resource endowments, government transfer payments, and time endowment which consists of labor and leisure. The US government collects tax revenues, disburses subsidies and tax credits, demands a fixed quantity of commodities, and adjusts transfer payments to balance its budget. Growth in the recursive-dynamic model is forced through Harrod-neutral (labor-augmenting) technical change. To allow for distortionary capital taxation, we mimic the behavior of forward-looking elastic capital stock by allowing substitution between full consumption and investment (Ballard et al., 1985).

To link ReEDS and SLiDE, we adopt the methodology presented by Böhringer and Rutherford (2008) and similar to Rausch et al. (2010) and Caron et al. (2018a). Under this setup, the electricity sector capital and labor demand as well as fuel consumption are sent from ReEDS to SLiDE which then returns capital and labor price indices and fuel prices to ReEDS. The ReEDS model is converted to a quadratically constrained program (QCP) to maximize the area under the demand curve whose parameters (quantity, price, and local elasticity) are estimated in SLiDE. The models iterate until convergence is achieved when electricity and fuel price and quantity deviations are within a 3% tolerance across models and remain stable across iterations. For regional disaggregation from SLiDE to ReEDS, electricity load is allocated to the reference proportion by region and timeslice within each parent SLiDE region while price parameters and indices are broadcast from SLiDE to ReEDS balancing areas. For regional aggregation from ReEDS to SLiDE, the quantities are summed across corresponding balancing areas to their respective SLiDE regions.

Table 1: Income group statistics used in the SLiDE model

Label	Income Range	Number (Millions)	Percent of Total Income
HH1	< $25,000	22.2	2.60%
HH2	$25,000 - $49,999	24.9	8.10%
HH3	$50,000 - $74,999	21.3	11.60%
HH4	$75,000 - $149,999	34.7	32.30%
HH5	$150,000+	19.5	45.30%

The demographic analysis leverages data from the fusionACS project, which links the American Community Survey (ACS) with other surveys using variable-k, conditional expectation matching. The ACS contains person and household level information, including economic, demographic, and social characteristics (Ummel et al., 2023). We utilize the ACS 2019 linked with the Consumer Expenditure Survey (CE) with data from 2015 - 2019, which contains estimates of household expenditures and is referred to as the fusionACS-CE database herein. The fused CE estimates are modified using iterative proportional fitting so that overall expenditure amounts match totals from other data sources. The CE data set includes 30 implicates (copies) of the imputed data per household, where each implicate corresponds with one potential expenditure outcome for that household. We calculate average expenditures across the 30 implicates, which results in one set of expenditures for each household. We then map the CE expenditure categories to relevant sectors within SLiDE. CE estimates that are values rather than expenditures, such as the value of household vehicles, are omitted from the analysis. Using the ACS data, we link the household income to demographic information for a representative person within the household, where the member with the highest educational attainment is selected as the representative. In cases where education levels are equal among multiple household members, the representative person is chosen randomly.

We apply the methodology used in Williams et al. (2015) to calculate the welfare effects of each policy across demographic groups. We group[5] expenditures (x) for households by state (st), income (h), age (a), race/ethnicity (r), education (e), and sex (s) to find the share of total expenditures by group. Approximately 1.3 M households surveyed are grouped across 50 states, 5 income quintiles, 8 age groups, 7 race/ethnicity groups, 7 education groups, and two sexes. ACS Sample weights are applied to scale households to be representative of the total US population. The categorization of demographic groups and total population counts are shown in Table 5 in the Appendix. To calculate the change in case (k)- and demographic group-specific welfare ($V^k_{st,h,a,r,e,s}$), we start by disaggregating the case-specific aggregate welfare amount (W^k) to each demographic group by applying the following equation:

$$V^k_{st,h,a,r,e,s} = W^k \frac{x_{st,h,a,r,e,s}}{X}$$

Then, V^k is calculated as the percent change from the reference case outcome (V^{REF}):

$$\Delta V^k_{st,h,a,r,e,s} = \frac{V^k_{st,h,a,r,e,s} - V^{REF}_{st,h,a,r,e,s}}{V^{REF}_{st,h,a,r,e,s}}$$

The household-level health impacts are simulated via the InMAP model, a reduced complexity air pollution model (Tessum et al., 2017). More specifically, we leverage the InMAP model version capable of estimating human health impacts as was done by Thind et al. (2019) and broken out by further demographics in Goforth and Nock (2022). Representation of health damages from the linked models' endogenous emissions are thus at the local level[6] and then broken out by each regions' proportion of demographic groups. For example, an urban grid area of 4x4km consists of 25% low-income households and experiences a loss of eight statistical lives with an emissions change, then 2 lives will be attributed to the low-income demographic group. To compute final damages, we use a VSL of \$9.47 million dollars per life (EPA, 2023). Acknowledging the potential for variable VSL across income classes and greater self-reported values in correlation with income (Masterman and Viscusi, 2018), we opt for simplicity in translation and maintain a static VSL across all demographic categories.

3.2 Policy Design and Sensitivity Scenarios

Table 2 presents a summary of the modeled policies. To elaborate, the reference (**REF**[7]) case only includes the tax credits that were in effect before the passing of the IRA; that is, the policy

[5]The designation of groupings and the within-group labels are taken directly from the American Community Survey.

[6]InMAP grid sizes range from 500km horizontal grid cell width in remote locations to 4km horizontal grid cell width in urban areas. However, it is important to recognize the general uncertainty associated with pollution dispersion given variability in weather, climate, and other external factors.

[7]Throughout the text, policies are indicated in **bold** while scenario names are indicated in *italics*.

includes the incentives as they existed before August 16th, 2022. The tax credit (**TC**) cases include the clean electricity production tax credit (PTC), the clean electricity investment tax credits (ITC), extension/increase to 45Q, and the existing nuclear PTC included in the IRA. An explanation of the assumptions and implementations concerning these credits is detailed below. The carbon cap (**CAP**) policies match the emissions pathway from the TC-equivalent case; for example, the **CAP TK** *Constrained* case matches the emissions trajectory from the **TC LS** *Constrained* case. As is demonstrated in the results section, the emissions trajectory for the tax credit cases does not vary significantly across the various revenue assumptions ($< 1\%$), and thus we have chosen to match the emissions trajectories from the **TC LS** policy for all carbon cap cases.

The assumptions regarding how revenue is raised/recycled are key to this analysis. In all tax credit cases, the tax credit expenditures are covered by an endogenous increase in the capital tax rate, similar to Bistline et al. (2023b) and intended to reflect a portion of the capital-focused, revenue raising mechanisms included in the IRA: an increase in the minimum corporate income tax, increases to IRS tax enforcement, taxes on stock buybacks, as well as limitations on excess business losses used for tax deductions (CBO, 2022). However, the overall government budget is not fixed and thus is responsive to other macroeconomic forces. Under the **TC NT** policy, erosion of the tax base leads to reduced household transfers. Under the **TC LS** and **TC TK** policies, government transfer losses are compensated through either lump-sum redistribution based on each household's share of total income or covered by an additional increase in the capital tax rate, respectively. Under the **CAP LS** and **CAP TK** policies, an emissions cap is imposed on the power sector. Revenues from the cap are distributed lump sum back to households based on population or to offset total payments of capital taxes, respectively.

Table 2: Policy acronyms and descriptions

Acronym	Description
REF	Only pre-IRA electricity generation or carbon capture tax credits
TC NT	Capital tax increase to cover the tax credit expenditures - Reduction in transfer payments to households
TC LS	Capital tax increase to cover the tax credit expenditures - Lump sum redistribution to compensate for loss in transfers
TC TK	Capital tax increase to cover the tax credit expenditures - Increase in capital tax to compensate for loss in transfers
CAP LS	Carbon cap meeting same emissions reduction as TC-equivalent case with revenue recycled lump sum back to households
CAP TK	Carbon cap meeting same emissions reduction as TC-equivalent case with revenue recycled to reduce capital taxes

The assumptions surrounding the tax credits are an important component to understanding the representation of IRA's clean energy incentives; here we offer a summary of the incentives while more detail is available in Gagnon et al. (2022) and Steinberg et al. (2023). In short, we mimic the implementation with ReEDS in Steinberg et al. (2023) with the addition of the model linkages. The PTC is \$27.5 per MWh for 10-years of operations from when the unit begins generating which also includes a bonus credit starting at 5% in 2023 that increases to 10% by

2028. The ITC is a tax credit valued at 30% of the cost basis—effectively the installed cost—of a facility plus a bonus credit that is assumed to start at 5% in 2023 and increases to 10% by 2028. Both the PTC and ITC[8] include the technology-neutral and emissions basis as well as the associated technology eligibility limitations. The captured CO_2 incentive (45Q) consists of an $85 per tonne incentive for CO_2 that is captured and stored in geologic formations. This credit is available to plants for 12 years from when they begin generating or when retrofitted carbon capture and storage (CCS) equipment comes online. The representation of nuclear provisions is simplified in that we do not allow endogenous retirements of existing facilities until after 2032. Finally, and in contrast to Steinberg et al. (2023), we do not vary the exogenously-defined distributed photovoltaic capacity across scenarios in order to isolate the impacts from bulk power clean electricity tax credits.

The sensitivity scenario assumptions are presented in Table 4 in Appendix I. In total, there are nine scenarios including the *Mid Case* set of assumptions. The *Mid Case* does not reflect the most likely or probable outcome but instead represents the central assumptions relative to other cases from the Annual Technology Baseline (NREL, 2022) and Annual Energy Outlook (EIA, 2022a). For this reason, it is highlighted in several of the figures for comparison purposes. The remaining cases vary the technology and fuel cost assumptions, the availability (or lack thereof) of siting available for renewable energy deployment, as well as the monetization and bonus crediting for incentives. The implementation of the low and high natural gas price scenarios differs from Steinberg et al. (2023) in that they are reflected through increasing or decreasing the oil and gas fixed resource availability in SLiDE as opposed to shifting the supply curve in ReEDS; the price reduction or increase in SLiDE is calibrated to the values from the Energy Information Administration (EIA) in EIA (2022a), similarly to ReEDS.

4 Results

In this section, we begin by presenting a brief overview of the power sector implications of the bulk power clean electricity tax credits with a focus on capacity, generation, and emissions. Then, we review the economic welfare implications of each policy along with the factors that determine welfare changes by income class. Finally, we present results across demographic groups and regions. Note, all monetary values expressed throughout this section are in $2020 USD unless otherwise mentioned.

[8]The decision of whether a technology elects to receive the PTC or ITC is done a priori; generally, all zero-carbon generation technologies elect the PTC except for hydro, offshore wind, nuclear, and storage. The ITC is neither overnight nor fully annualized but we do not represent any annualized ITC payments in the exchange with SLiDE given a better alignment with the structure of ReEDS investment representation.

4.1 Power Sector Results

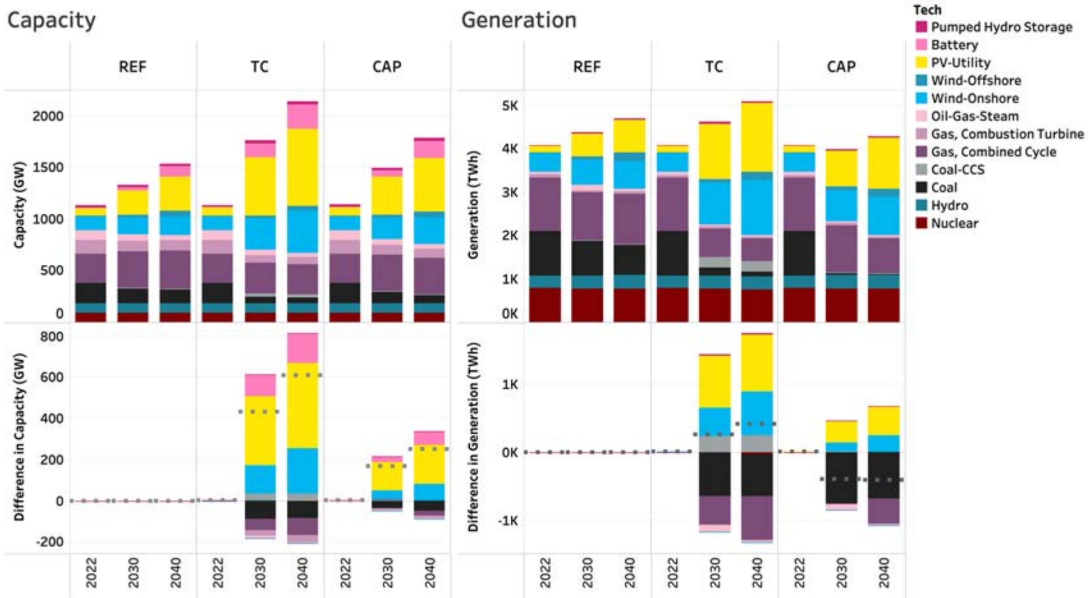

Figure 3: *Mid Case* power sector capacity (left) and generation (right) by policy (column) in total (top row) and difference from **REF** (bottom row)

Power sector capacity and generation by policy under *Mid Case* assumptions are presented in Figure 3. Total capacity increases under both the tax credit and carbon cap policies, while generation (given elastic demand) increases under the tax credit policy but decreases under the carbon cap policy. In 2040 and from the policies' inherit price impacts, the tax credit policy leads to an increase of 380 TWh of generation, while the carbon cap policy leads to a decrease of 418 TWh of generation relative to the reference, no-policy case. Total capacity additions are significantly greater relative to **REF** under the tax credit and to a lesser extent the carbon cap policies, with net changes of 607 GW and 280 GW, respectively. This result highlights one of the key differences between policies that create output subsidies for clean production and those that price emissions: the incentives they create for consumption. In short, tax credits reduce electricity prices and in turn increase demand, while the cap and the resulting price on emissions leads to increased prices for electricity and reduced demand. The depressionary effect on electricity prices and reduced fossil fuel demand have broader, economy-wide implications explored below. As a caveat, this analysis does not explore electrification in detail which could be encouraged through reduced electricity prices under the tax credits and has been demonstrated as a key component of economy-wide decarbonization (Murphy et al., 2021), this is discussed further in Section 5.

Important for regional results, the technology mix varies across policy designs. Under all cases, PV and wind generation increase but the magnitude of the increase differs by policy. PV and wind generation increase more under the tax credit policies relative to the carbon cap policy. Wind makes up a greater share of low-carbon generation under the tax credit policy than under the carbon cap. For coal with CCS, we estimate 35GW of capacity as retrofits from existing plants and 248TWh of generation under the tax credit cases but no capacity and generation for the equivalent carbon cap cases. Aside from retrofitting, responses of non-CCS coal are similar under both policies while natural gas capacity and generation declines more under the tax credit than carbon cap cases. As is discussed further below, the responses of the fossil fuel-fired generators play an important role when considering regional impacts for fossil fuel supply regions.

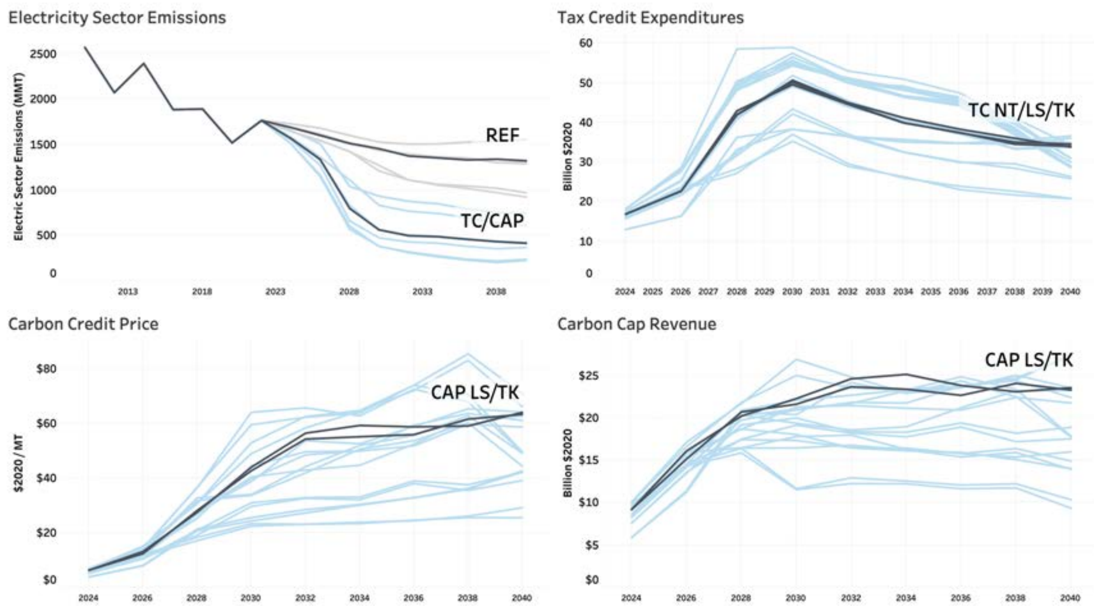

Figure 4: Power sector CO_2 emissions, tax credit expenditures, carbon credit prices, and carbon cap revenues - Darker lines represent the *Mid Case* while lighter lines represent alternative assumptions

Power sector emissions, tax credit expenditures, the carbon credit price, and total carbon cap revenues are presented in Figure 4. In this figure, the darker lines represent the *Mid Case(s)* while the lighter lines reflect sensitivity scenarios detailed in Table 4. Grey lines in the electricity sector emissions plot represent **REF** scenarios while blue lines represent **TC** and equivalent-cap cases; the two dark lines represent the **REF** *Mid Case* (top) and the **TC/CAP** *Mid Case* (bottom). The darker lines in the tax credit expenditures plot represent the **TC NT/LS/TK** *Mid Case* while the darker lines in the carbon credit price and carbon cap revenue plots represent the **CAP LS/TK** *Mid Case*. To reiterate, the carbon cap policies for each reference-equivalent are set to match their tax credit counterpart exactly. For example the *Constrained* case carbon cap is set to match the emissions resulting from the *Constrained* tax credit policy. Thus the variations in the electricity sector emissions chart are overlapping.

Annual power sector emissions in the *Mid Case* decline to 415 million MT by 2040, which is a 76% reduction in annual emissions from 2022 and a 68% reduction from the **REF** *Mid Case* in 2040. Importantly, the reduction in emissions as estimated by ReEDS is relatively more than some models performing similar simulations such as Roy et al. (2022); for a comparison of these emissions levels and to place ReEDS in this context, see Bistline et al. (2023a). A steep decline in emissions occurs in 2028 under the *Mid Case*, because this is assumed to be the first year power plants are permitted to retrofit using CCS equipment. Following the initial reduction, emissions continue to decline but at a lower year-over-year rate. Emissions are lowest in the *Low All Clean Cost* case and the *Low RE Cost* case, reaching 228 and 235 million MT per year in 2040, respectively. Conversely, the *High All Clean Cost* and *Constrained* cases have the lowest emissions reductions when tax credits are available with 747 and 611 million MT per year in 2040, respectively.

Tax credit expenditures peak in 2030 in all but the *Low RE Cost* case, which peaks in 2028. This result is primarily driven by the tax credit phaseout often being met after the first year CCS retrofits become available. In the *Low RE Cost* case, more rapid buildouts of wind and solar decrease electricity prices and out-compete other technologies, particularly CCS retrofits; implying an earlier peak and subsequent phaseout of tax credit expenditures. Overall, undiscounted tax credit expenditures total $752 billion[9] over the 2024-2040 timeframe in the *Mid Case*. Given the path of the power sector emissions under the tax credits, carbon credit prices rise at a steady rate until they plateau in 2032. Undiscounted tax credit revenues total $324 billion[10] over the 2024-2040 timeframe.

4.2 Aggregate Welfare and Distributional Impacts by Income Class

The change in the net present value[11] (NPV) of equivalent variation by the relative change in the Gini coefficient for the NPV of each household's income is shown in Figure 5. This provides a straightforward method to evaluate the tradeoff of the policy cost (as gauged by the vertical axis) by the resulting income equality (horizontal axis) with the origin being the highest cost and highest income equality output. Additionally, regressive policies can be identified by positive Gini coefficient changes. For reference, the darker colored symbols represent the *Mid Case* while the lighter colored symbols represent alternative scenarios.

Focusing on Figure 5, we are able to gauge the relative economic efficiency of the **TC** and **CAP** policies in NPV terms. Specifically, we estimate a range of the NPV of equivalent variation changes between -0.093% to -0.022% for the **CAP** policies and a relatively wider range of -0.216% to -0.121% for the **TC** policies. Additionally, the plot demonstrates a general tradeoff of overall policy costs and the resulting progressivity or regressivity of the policy. However, there are several cases with similar overall policy costs but substantially different progressivity outcomes. The variations from the *Mid Case* also play an important role in any policy outcome; for example, the point nearest the origin represents the **TC TK** policy, *Low RE Cost* scenario which, as mentioned prior, has the highest tax credit expenditures but also leads to the greatest reduction in electricity price given the highest level of renewable energy deployment.

Our results align with previous literature in demonstrating that reducing (increasing) capital taxes increases (decreases) overall output more than lump sum recycling. However, the differ-

[9] Min: $541 billion, Max: $977 billion, StdDev: $112 billion

[10] Min: $217 billion, Max: $376 billion, StdDev: $51 billion

[11] All net present value calculations in this paper use a discount rate of 5% unless otherwise mentioned

ences in revenue-acquisition and revenue-recycling methods we explore within each of these cases are relatively modest in comparison with the differences produced by the tax credits versus the carbon cap. As a result, the main effect of changing the revenue rules is to influence the inherent progressivity or regressivity of the policy. The inclusion of the tax credits in this study allows for a new policy for comparison and results indicate that the tax credits are more progressive than the most-progressive carbon cap with lump sum revenue recycling but less efficient than all carbon-cap counterparts.

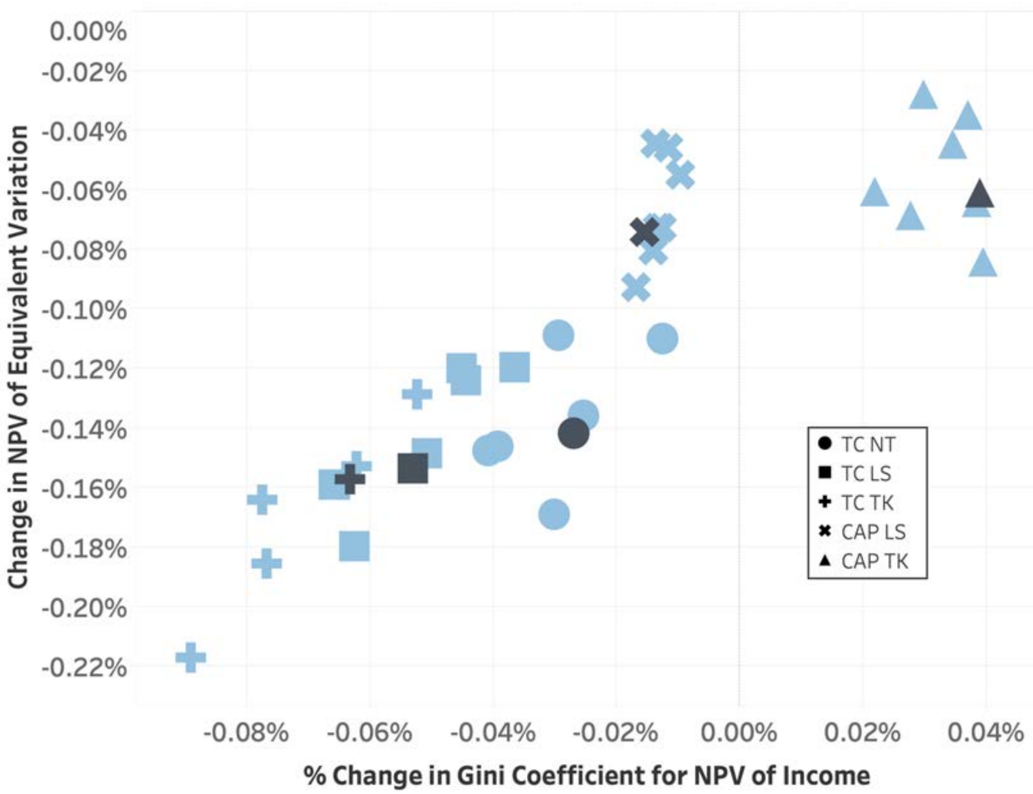

Figure 5: Change in NPV of equivalent variation by change in Gini coefficient from **REF** - Darker colors represent *Mid Case* and lighter colors represent sensitivities

Figure 6 presents a summary of the net present value of equivalent variation (left plot), average reduced deaths per 1,000 people from 2023-2040 (center plot), and the net present value of the combined health impacts and equivalent variation (right plot) relative to the **REF** case by policy (columns) and household income (shapes). The same data but across modeled years is presented in Figure 11 in Appendix II.

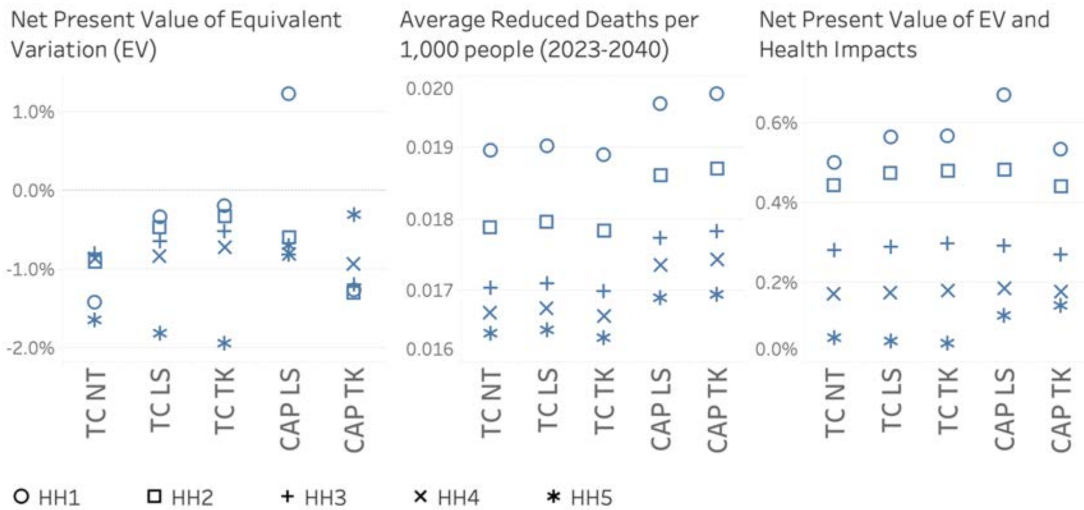

Figure 6: Net present value of equivalent variation (left), average reduced deaths from 2023-2040 (center), and net present value of equivalent variation and health impacts (right) relative to **REF** by income class (symbol) under *Mid Case* assumptions

Under **TC NT**, total government revenue declines without repayment from a revenue-raising tax mechanism. In this case, the lowest income class experiences the largest decline when tax credit expenditures are at their peak (2028 - 2030) since a greater share of their income originates from government transfers but eventually recovers after expenditures decline. When government transfers are accounted for through either the lump-sum or capital tax mechanisms in the **TC LS** and **TC TK** policies, respectively, the distributional impacts are strictly progressive, i.e. the relative welfare impacts follow the same ordering as the income classes. Under the **CAP LS** policy design, HH1 (and briefly HH2) sees a relative improvement to welfare as the additional income received from carbon credit revenue outweighs the detriment from other income sources. Finally, the **CAP TK** policy is the only regressive policy design as the capital tax reductions benefit the primary capital owners, higher income households, most.

Reduced deaths by household, featured in the center plot by policy in Figure 6, are similar across policies but consistently greater under the **CAP** policies. The primary driver to these differences is that a portion of the reductions in emissions under the tax credit cases is from the investment and roll-out of coal with CCS which does not capture all emissions (in this analysis it is assumed at a 90% capture rate) while coal has the highest PM2.5 emissions rate of all techs. However, under the **CAP** cases, the general removal of almost all coal generation implies all coal emissions are reduced. Said differently, under the assumptions here, only 90% of coal emissions are captured using coal with CCS technologies which are deployed under the **TC** case while all coal is removed under the **CAP** case; the difference in the technology deployment under the two scenarios (removal of coal versus capturing most, but not all, coal emissions) results in a difference in total reduced deaths. The equivalent variation estimates are dominated by the health impacts when applying the static VSL to reduced deaths. In total and on average across policies, we estimate total reduced deaths to be approximately 17,600 people in 2040 and total deaths reduced from 2023-2040 to be approximately 208,000 under *Mid Case* assumptions.

To help unpack the key drivers and impacts on household income, Figure 7 decomposes the changes in income sources relative to **REF** in the *Mid Case* by household and policy design. Note that the vertical axis ranges for each household type differ. Under the **TC** policy designs, the lowest income class is negatively impacted most by the reduction in transfer payments while the middle three income classes face a mix of negative impacts from the transfer payment reductions as well as their time (wage) earnings. In contrast, the highest-income households face the largest detriment from a reduction in their capital income, primarily through the funding of the tax credit expenditures by increasing the capital tax rate. For the **TC TK** policy, the transfer losses and compensation in the latter are significantly greater than the **TC LS** policy as the capital tax further reduces overall output and thus further erodes the tax base.

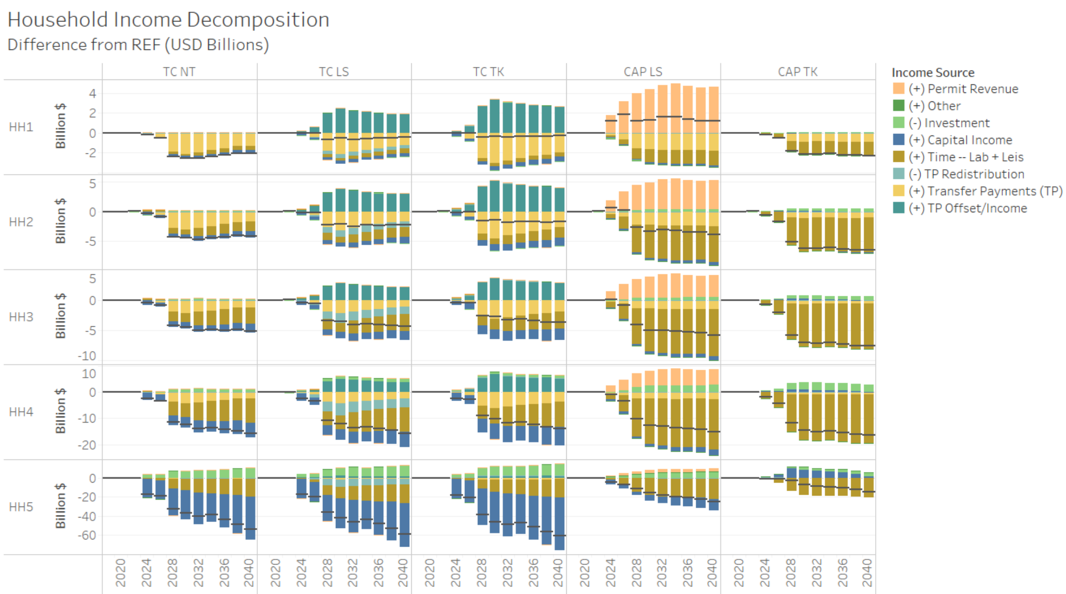

Figure 7: Decomposition of welfare by income class, policy, and income source

Under the **CAP** policies, the lump sum recycling in **CAP LS** has a relatively higher impact on the lower income households, leading to positive impacts for HH1 and, briefly, for HH2. In contrast, the **CAP TK** policy increases the capital income gains for the highest income household, but the lack of revenue combined with reduced time and transfer income to the lower income households leads to their greater relative detriment.

The relative magnitude of the absolute change by household is important to recognize. For example, acquiring the revenue to ensure transfers are held constant reduces HH5 income by 0.01-0.04% but increases the relative welfare of HH1 by 0.3-0.35% and the middle three households by smaller but still substantial relative magnitudes. To summarize, the transfers required to compensate the lower-income households and ensure progressivity are fairly small portions of overall income and do not lead to a decline in overall output. This general finding of relatively inexpensive compensation schemes to ensure progressivity has been demonstrated by Caron et al.

(2018a) but, in this setup, it does not require the implementation of an explicit progressivity constraint.

4.3 Regional and Demographic Breakdown

Figure 8 presents a map of the combined equivalent variation and health impacts in the US for each policy (columns) and income group (rows) under *Mid Case* assumptions; maps featuring only equivalent variation as well as combined health and equivalent variation by race/ethnicity are included in Appendix II as Figures 12 and 13, respectively. The benefits of the policies are isolated throughout the east-central US (the 'rust belt') as well as the south east where, historically, PM2.5 exposure has been more heavily concentrated. The location of fossil fuel fired electricity generation facilities coincides with higher concentrations of lower-income populations and thus we estimate a largely progressive outcome, the extent of which varies across regions and policies (see Appendix II, Figure 10 for the Gini coefficient change by state and policy).

When considering equivalent variation, the **TC** policies are less economically detrimental to fossil fuel producing regions than the **CAP** policies. In certain regions, the Gini coefficient increases under the **CAP LS** policy, implying regressivity - notable since the **CAP LS** policy is seen as progressive from the national perspective. The reduction in fossil fuel supply primarily drives these states' outcomes, leading to suppressed labor demand and wages which impact lower income classes more heavily than upper income classes. However, if overall economic output declines, the Gini coefficient will still decrease if the upper-income classes face a larger relative detriment than the lower-income classes.

States in the west are estimated to have a lower degree of health benefits from the reduced air pollution relative to states with greater populations and generally more fossil fuel fired electricity generators. Some states, and especially those in the northwest US, always face a net detriment even when considering health impacts given both (a) the lacking presence of air pollution from electricity generation under the **REF** scenario and (b) their hydropower-intensive electricity generation. On the latter, they also face reduce rents from their electricity generation capital given lower regional prices under the **TC** scenarios and typically less investment of incentivized, clean generation capacity relative to other regions.

Several of the higher income households face a detriment when still considering health impacts given the detriment in equivalent variation; this is primarily centered in the western US where population is less dense and PM2.5 exposure is lower. The largest number of states seeing a positive benefit for the highest income class is under the **CAP TK** policy in which 39 of the 49 modeled states (and DC) face a net benefit. This raises the point that who benefits from decarbonization varies widely across policies, demographics, sectors, and regions. For example, historically-marginalized racial groups face a larger benefit than their counterparts under any of the modeled policies.

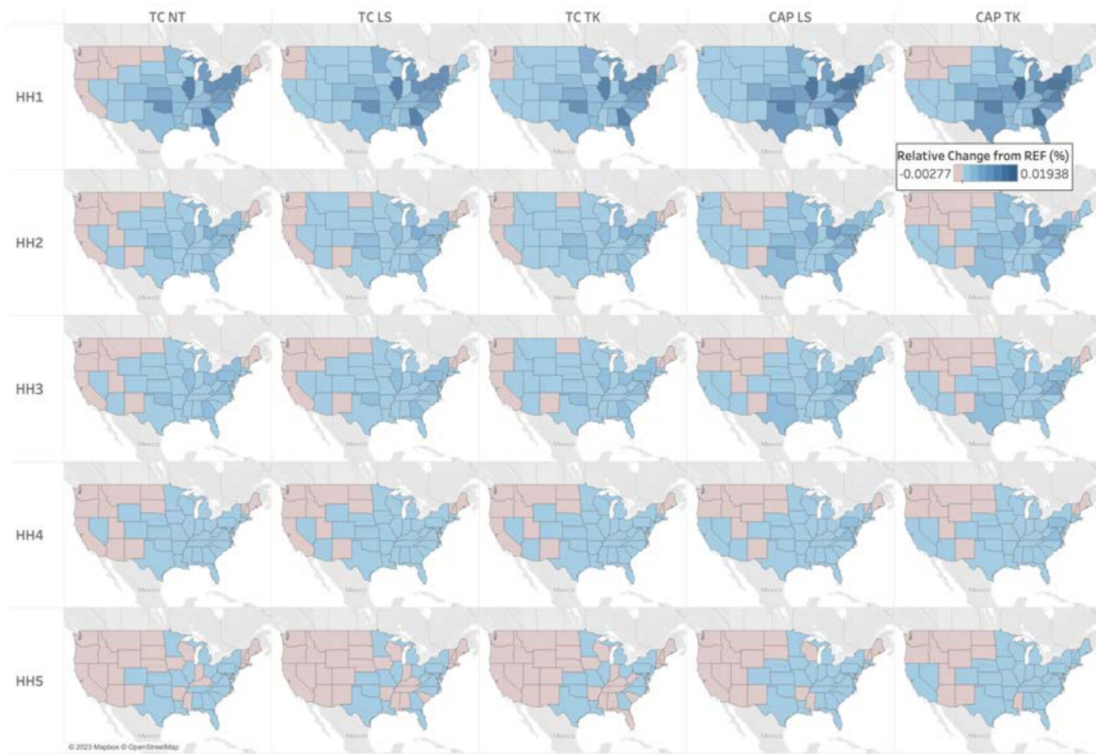

Figure 8: Change in NPV of equivalent variation and health impacts by demographic groups from **REF** in the *Mid Case*

Across policies, the difference in equivalent variation from **REF** is the most distinct in coal-producing regions and especially those with relatively less total economic output. All else equal, several of the coal-producing regions are less impacted by the **TC** policies than the **CAP** policies as coal-fired generation is retrofitted with CCS equipment under the former as opposed to being retired under the latter. Regions with higher natural gas production generally have a greater relative decline in equivalent variation under the **TC** cases than the **CAP** cases as the decline in gas-fired generation is greater under the former than the latter.

Figure 9 presents the NPV of equivalent variation over a subset of demographic characteristics available in the fusionACS-CE data: state, income, age, race/ethnicity, educational attainment, and sex. For brevity, the individual states are presented without labels to show the range of outcomes, and are discussed in more detail below. Aside from location, a policy's impact on demographic groups can be traced to income levels and sources, as well as the percentage of income a group spends on electricity. Refer to Table 5 in Appendix III for supplemental information by demographic group.

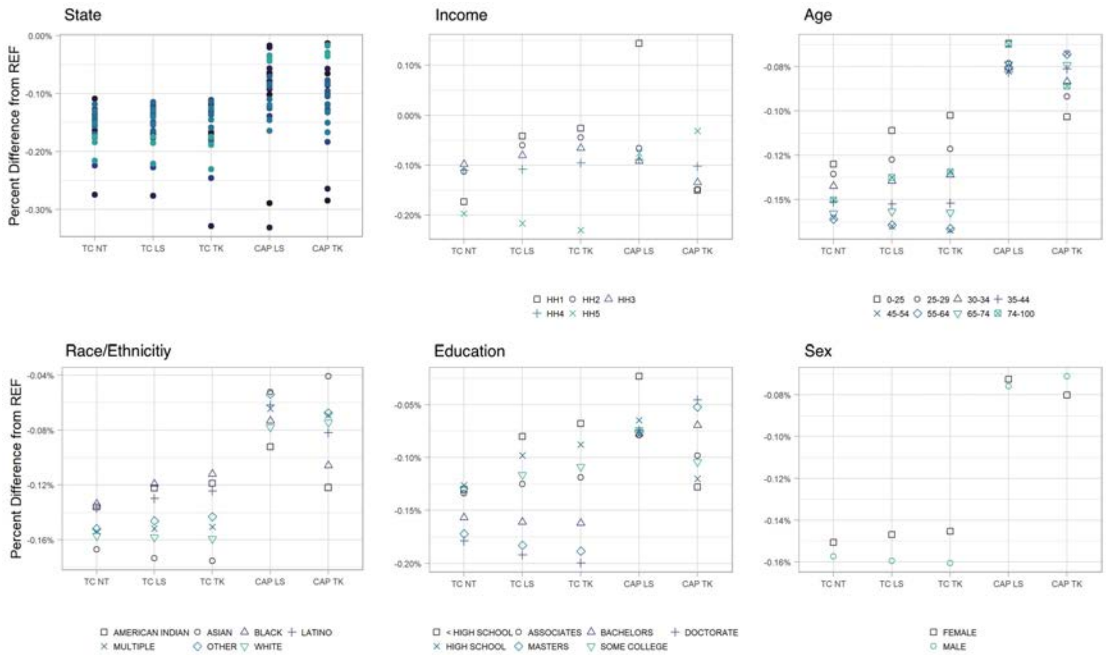

Figure 9: Change in NPV of equivalent variation, absent health impacts, by demographic groups from **REF** in the *Mid Case*

Results across income groups in Figure 6 and 9 are consistent, but Figure 9 presents a more concise and time-agnostic illustration of welfare changes. The lowest income class experiences the highest detriment under the **TC NT** policy, due to the decrease in government transfers. A higher discount rate amplifies this effect because tax credit expenditures peak earlier. Additionally, outcomes for the middle-income classes, and particularly HH4, differ only slightly across the policies. This is most evident relative to HH5 which experiences the lowest detriment from policies that limit reductions in or provide an increase to overall capital income.

The relative impacts across age, race/ethnicity, education, and sex tie back to a groups' relative income and expenditure profile – particularly the percentage of income spent on electricity. Examining effects across age groups, the youngest age groups experience less of an NPV loss than older groups under the **TC** policies. We see the reverse occur under the more regressive **CAP TK** policy, which is also the policy that results in the smallest loss in total welfare. The middle segments (ages 35 - 74) are the most negatively impacted by the **TC** policies, and the least under the **CAP TK** policy. This is related to their higher share of total income but also the smaller share of their income spent on electricity. Thus, these groups are not as positively impacted by reduced electricity prices. The oldest age group's outcomes fall in between the youngest and middle segments.

Outcomes by race/ethnicity differ across policies. Examining the **TC** policies, American Indian, Black, Latino, multiple races/ethnicities, and other race/ethnicity groups are least impacted under the **TC TK** policy followed by **TC LS** and **TC NT** policies. Asian and, to a lesser extent, White populations have the opposite experience. Comparing the two **CAP** policies, Asian and White race/ethnicity groups experience a smaller negative impact under the

CAP TK policy. All other groups have the opposite experience, with more benefit under the **CAP LS** policy. Again, these results primarily reflect the share and sources of income as well as the percentage of income a group spends on electricity.

Earned income can help explain differences seen in outcomes by education group. For those with a bachelor's degree and above, the most beneficial of the **TC** policies is **TC TK**, followed by **TC LS** and **TC NT**. Those with less than a bachelor's degree, and especially those with no high school diploma, have greater benefit under policies in the opposite order. Under the **CAP** policies, individuals who have a bachelor's degree or more have more benefit in the **CAP TK** over **CAP LS** and those with less education have more benefit from policies in the opposite order.

Finally, males face less equivalent variation detriment under policies that have less of an impact on capital and overall income while females incur greater benefit under the opposite. However, given the smaller disparity in income and the more aggregated nature of the grouping, the differences are not as stark as with the other demographics.

4.4 Climate Benefits

Table 3 contains the NPV of policy impacts computed as the change in equivalent variation and the value of emissions avoided using the social cost of carbon (SCC) estimates from EPA (2022) and Rennert et al. (2022). Specifically, we linearly interpolate the decadal, certainty equivalent SCC estimates applied to the annual, economy-wide emissions reductions. To arrive at the NPV, we discount policy costs and emissions abatement benefits with a 2% discount rate - the same value used to compute the chosen SCCs.

All policies result in a positive NPV (benefit) when including the SCC. The NPV of impacts by policy and the ranges across sensitivities are presented in Table 3. The **TC** cases provide approximately $1.71-2.73 trillion dollars in net benefits across all scenarios while the **CAP** cases provide approximately $1.83-2.79 trillion in net benefits across all scenarios. The standard deviations across all policy setups are very similar, implying consistent relative impacts of scenario assumptions. The **TC NT**, **TC LS**, and **TC TK** policies result in a loss of 4.5%-5.4% of benefits relative to the most-efficient **CAP TK** policy under the *Mid Case* scenario and 4.2%-5.3% on average across all possible scenarios.

Table 3: NPV of impacts including avoided climate damages (billion $2020, 2% discount rate)

SCC estimates from EPA (2022)

	TC NT	TC LS	TC TK	CAP LS	CAP TK
Mid Case	$ 2,505	$ 2,483	$ 2,496	$ 2,608	$ 2,623
Average	$ 2,267	$ 2,241	$ 2,450	$ 2,355	$ 2,367
Maximum	$ 2,733	$ 2,730	$ 2,728	$ 2,841	$ 2,850
Minimum	$ 1,770	$ 1,756	$ 2,169	$ 1,870	$ 1,879
StdDev	$ 354	$ 345	$ 187	$ 347	$ 349

SCC estimates from Rennert et al. (2022)

	TC NT	TC LS	TC TK	CAP LS	CAP TK
Mid Case	$ 2,453	$ 2,432	$ 2,445	$ 2,554	$ 2,569
Average	$ 2,220	$ 2,195	$ 2,399	$ 2,306	$ 2,318
Maximum	$ 2,677	$ 2,673	$ 2,672	$ 2,783	$ 2,792
Minimum	$ 1,733	$ 1,720	$ 2,124	$ 1,831	$ 1,840
StdDev	$ 347	$ 337	$ 183	340	341

5 Conclusions

We evaluate distributional impacts of the clean electricity tax credits provisions included in the 2022 Inflation Reduction Act and compare those to cap-and-trade policies reaching equivalent emissions reductions through the lens of combined economic and health impacts. To do so we link a bottom-up, detailed power sector capacity expansion model with a top-down, CGE representation of the US economy, with the outputs sent to a microsimulation framework based on the fusionACS-CE dataset as well as a reduced-complexity air pollution health impacts model. In doing so, we arrive at several conclusions for policy design through the perspectives of both economic efficiency and public health considerations.

First, we see a large and rapid buildout of clean generation and storage technologies as a result of the incentives that were introduced, modified, or expanded under the IRA. The tax credits also yield a reduction in electricity price and thus an increase in the amount of electricity consumed while the opposite is true under the equivalent emissions-pricing policy. The tax credits induce a substantial reduction in power sector emissions relative to the no-policy base case and across the scenarios modeled.

As gauged by the Gini coefficient, the tax credit and carbon cap with lump sum recycling policies are all progressive. However, without any redistribution in place, whether it be through lump sum transfers or further raising capital tax rates, the lowest income class suffers the most in relative, NPV terms. When redistribution and compensation for the eroded tax base occur, the tax credits become strictly progressive. As is evidenced in previous work and reinforced here, the re-distribution to compensate lower-income classes leads to a small loss in overall economic output and a relatively small loss to the upper-income classes. An important caveat here is that we are imposing additional taxes to cover the reduced government transfers given the assumption of constant government expenditures when the government expenditures for other programs could also be reallocated.

The distributional equivalent variation and health impacts across demographic groups can be traced to each group's income levels, capital ownership rates, proximity to pollution sources, as well as expenditure profiles. Generally, demographic groups with higher rates of government transfers as a source of income and lower capital ownership rates have less of a negative impact from clean electricity tax credits (when government transfers are held constant) while the opposite is true for higher-income groups that prefer less capital taxation. On aggregate, we see a tradeoff between reducing overall economic impact and the resulting progressivity of the policies with the tax credits typically being more costly than first-best but leading to greater income equality. All policies have nearly-equal health impacts across income classes given the existing locations of fossil fuel fired generation facilities.

The resulting electricity generation mix is important in understanding the regional impacts on the economy, as fossil fuels play an important role in several regions. Regions with higher shares of economic output from fossil fuel supply are more negatively impacted by the carbon pricing policies than the tax credit policies. The opposite is true for regions that have a high concentration of capital assets (such as New England) and face greater detriment from higher capital tax rates under the tax credits. Additionally, the interaction of existing electricity generation assets and investment in new generation capacity is demonstrated to be an important factor for the northwest US.

Due the computational challenges associated with linking two, high-dimensional models, we elected to model capital accumulation in the CGE model using a recursive-dynamic approach, and to model elastic capital supply through the design of the household utility structure. It would be instructive to compare the outcomes produced by this approach with those produced by a model based on the assumption of perfect foresight, as in the standard neoclassical growth models. We recognize that there are several other policy options and combinations of both revenue raising and re-distribution mechanisms such as labor tax reductions, optimal policy specifications such as Caron et al. (2018a), and an extensive range of policies in-between. Finally, this work represents only an evaluation of the bulk power clean electricity tax credits included in the Inflation Reduction Act and further research is needed to evaluate the full extent of the law's potential impacts. Given the limit in scope as well as ongoing, net-zero discussions, which policy lends itself better to a fully-decarbonized economy remains as an extension to this research. We leave these topics to future research.

References

Aldy, Joseph E., Dallas Burtraw, Carolyn Fischer, Meredith Fowlie, Roberton C. Williams, and Maureen L. Cropper. 2022. How is the u.s. pricing carbon? how could we price carbon? *Journal of Benefit-Cost Analysis* 13 (3): 310–334.

Armington, Paul S. 1969. A theory of demand for products distinguished by place of production (une théorie de la demande de produits différenciés d'après leur origine) (una teoría de la demanda de productos distinguiéndolos según el lugar de producción). *Staff Papers (International Monetary Fund)* 16 (1): 159–178.

Ballard, Charles, Don Fullerton, John B. Shoven, and John Whalley. 1985. *A General Equilibrium Model for Tax Policy Evaluation.* National Bureau of Economic Research, Inc.

Baumol, William J., and Wallace E. Oates. 1988. *The Theory of Environmental Policy.* 2 edition. Cambridge University Press.

Bistline, John, Geoffrey Blanford, Maxwell Brown, Dallas Burtraw, Maya Domeshek, Jamil Farbes, Allen Fawcett, et al. 2023a. Emissions and energy impacts of the inflation reduction act. *Science* 380 (6652): 1324–1327.

Bistline, John, Neil Mehrotra, and Catherine Wolfram. 2023b. Economic implications of the climate provisions of the inflation reduction act. conference draft, Brookings.

Böhringer, Christoph, and Thomas F. Rutherford. 2008. Combining bottom-up and top-down. *Energy Econ* 30 (2): 574–596.

Borenstein, Severin, and Lucas W. Davis. 2016. The distributional effects of us clean energy tax credits. *Tax Policy and the Economy* 30 (1): 191–234.

Bovenberg, A. Lans, and Ruud A. de Mooij. 1994. Environmental levies and distortionary taxation. *The American Economic Review* 84 (4): 1085–1089.

Burtraw, Dallas, Margaret Walls, and Joshua Blonz. 2009. Distributional impacts of carbon pricing policies in the electricity sector. *US Energy Tax Policy* .

Caron, Justin, Stuart M Cohen, Maxwell Brown, and John M Reilly. 2018a. Exploring the impacts of a national U.S. CO2 tax and revenue recycling options with a coupled electricity-economy model. *Clim Chang Econ* 9 (1): 1840015.

Caron, Justin, Jefferson Cole, Richard Goettle, Chikara Onda, James McFarland, and Jared Woollacott. 2018b. Distributional implications of a national co2 tax in the us across income classes and regions: A multi-model overview. *Climate Change Economics* 09 (01): 1840004.

CBO. 2022. Estimated budgetary effects of h.r. 5376, the inflation reduction act of 2022. Technical report, Congressional Budget Office (CBO).

EIA. 2022a. Annual energy outlook. Technical report, Energy Information Administration (EIA).

———. 2022b. Electricity market module. Technical report, U.S. Energy Information Administration, Washington, D.C.

EPA. 2022. Supplementary material for the regulatory impact analysis for the supplemental proposed rulemaking, "standards of performance for new, reconstructed, and modified sources and emissions guidelines for existing sources: Oil and natural gas sector climate review".

———. 2023. Mortality risk valuation.

Fullerton, Don, and Garth Heutel. 2011. Analytical General Equilibrium Effects of Energy Policy on Output and Factor Prices. *The B.E. Journal of Economic Analysis & Policy* 10 (2): 1–26.

Fullerton, Don, Garth Heutel, and Gilbert Metcalf. 2012. Does the indexing of government transfers make carbon pricing progressive? *American Journal of Agricultural Economics* 94 (2): 347–353.

Gagnon, Pieter, Maxwell Brown, Dan Steinberg, Patrick Brown, Sarah Awara, Vincent Carag, Stuart Cohen, et al. 2022. 2022 standard scenarios report: A u.s. electricity sector outlook. Technical report, National Renewable Energy Laboratory.

García-Muros, Xaquín, Jennifer Morris, and Sergey Paltsev. 2022. Toward a just energy transition: A distributional analysis of low-carbon policies in the usa. *Energy Economics* 105: 105769.

Goforth, Teagan, and Destenie Nock. 2022. Air pollution disparities and equality assessment of us national decarbonization strategies. *Nature Communications* 13: 7488.

Goldman School of Public Policy. 2020. The 2035 Report.

Goulder, Lawrence H., Marc A. C. Hafstead, and III Williams, Roberton C. 2016. General equilibrium impacts of a federal clean energy standard. *American Economic Journal: Economic Policy* 8 (2): 186–218.

Goulder, Lawrence H., Marc A.C. Hafstead, GyuRim Kim, and Xianling Long. 2019. Impacts of a carbon tax across us household income groups: What are the equity-efficiency trade-offs? *Journal of Public Economics* 175: 44–64.

Grainger, Corbett A., and Charles D. Kolstad. 2010. Who pays a price on carbon? *Environmental and Resource Economics* 46 (3): 359–376.

Hafstead, Marc, and Roberton Williams. 2019. Distributional effects of environmental policy across workers: A general-equilibrium analysis. *National Tax Association* .

Hassett, Kevin A., Aparna Mathur, and Gilbert E. Metcalf. 2009. The incidence of a u.s. carbon tax: A lifetime and regional analysis. *The Energy Journal* 30 (2): 155–177.

Ho, Jonathan, Jonathon Becker, Maxwell Brown, Patrick Brown, Ilya Chernyakhovskiy, Stuart Cohen, and Wesley Cole. 2021. Regional energy deployment system (reeds) model documentation: Version 2020. Technical report, National Renewable Energy Laboratory.

Jenkins, Jesse, Erin Mayfield, Jamil Farbes, Ryan Jones, Neha Patankar, Qingyu Xu, and Greg Schivley. 2022. Preliminary report: The climate and energy impacts of the inflation reduction act of 2022. Technical report, REPEAT Project, Princeton, NJ.

Larsen, John, Ben King, Hannah Kolus, Naveen Dasari, Galen Hiltbrand, and Whitney Herndon. 2022. A turning point for u.s. climate progress: Assessing the climate and clean energy provisions in the inflation reduction act. Technical report, Rhodium Group.

Larson, Eric, C. Greig, Jesse Jenkins, Erin Mayfield, A. Pascale, C. Zhang, J. Drossman, et al. 2020. Net-Zero America: Potential Pathways, Infrastructure, and Impacts, interim report.

Mahajan, Megan, Olivia Ashmoore, Jeffrey Rissman, Robbie Orvis, and Anand Gopal. 2022. Updated inflation reduction act modeling using the energy policy simulator. Technical report, Energy Innovation, San Francisco, CA 94111.

Marten, Alex, Andrew Schreiber, and Ann Wolverton. 2021. SAGE Model Documentation.

Masterman, Clayton J., and W. Kip Viscusi. 2018. The income elasticity of global values of a statistical life: Stated preference evidence. *Journal of Benefit-Cost Analysis* 9 (3): 407–434.

Murphy, Caitlin, Trieu Mai, Yinong Sun, Paige Jadun, and Matteo Muratori. 2021. Electrification futures study: Scenarios of power system evolution and infrastructure development for the united states.

NREL. 2022. 2022 annual technology baseline. Technical report, National Renewable Energy Laboratory, Golden, CO.

Ohlendorf, Nils, Michael Jakob, Jan Christoph Minx, Carsten Schröder, and Jan Christoph Steckel. 2020. Distributional impacts of carbon pricing: A meta-analysis. *Environmental and Resource Economics* 78: 1–42.

Pigou, A. C. 1920. *The economics of welfare / by A. C. Pigou.* Macmillan London.

Rausch, Sebastian, Gilbert E. Metcalf, and John M. Reilly. 2011. Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households. *Energy Economics* 33: S20–S33. Supplemental Issue: Fourth Atlantic Workshop in Energy and Environmental Economics.

Rausch, Sebastian, Gilbert E Metcalf, John M Reilly, and Sergey Paltsev. 2010. Distributional implications of alternative u.s. greenhouse gas control measures. Working Paper 16053, National Bureau of Economic Research.

Rausch, Sebastian, and Matthew Mowers. 2014. Distributional and efficiency impacts of clean and renewable energy standards for electricity. *Resource and Energy Economics* 36 (2): 556–585.

Rennert, Kevin, Frank Errickson, Brian C. Prest, Lisa Rennels, Richard G. Newell, William Pizer, Cora Kingdon, et al. 2022. Comprehensive evidence implies a higher social cost of CO_2. *Nature* 610 (Y): 687–692.

Roy, Nicholas, Maya Domeshek, Dallas Burtraw, Karen Palmer, Kevin Rennert, JhihShyang Shih, and Seth Villanueva. 2022. Beyond clean energy: The financial incidence and health effects of the ira. Technical Report Report 22-11, Resources for the Future, https://media.rff.org/documents/Report$_2 2 - 11_v 5.pdf$.

Rutherford, Thomas F. 1999. Applied General Equilibrium Modeling with MPSGE as a GAMS Subsystem: An Overview of the Modeling Framework and Syntax. *Comput Econ* 14 (1): 1–46.

———. 2002. Lecture notes on constant elasticity functions.

Steinberg, Daniel, Maxwell Brown, Ryan Wiser, Paul Donohoo-Vallett, Pieter Gagnon, Anne Hamilton, Matthew Mowers, et al. 2023. Evaluating impacts of the inflation reduction act and bipartisan infrastructure law on the u.s. power system. Technical Report NREL/TP-6A20-85242, US Department of Energy National Renewable Energy Laboratory.

Tessum, Christopher W., Jason D. Hill, and Julian D. Marshall. 2017. Inmap: A model for air pollution interventions. *PLOS ONE* 12 (4): 1–26.

Thind, Maninder P. S., Christopher W. Tessum, Inês L. Azevedo, and Julian D. Marshall. 2019. Fine particulate air pollution from electricity generation in the us: Health impacts by race, income, and geography. *Environmental Science & Technology* 53 (23): 14010–14019. PMID: 31746196.

Ummel, Kevin, Narasimha Rao, Daniel Aldana-Cohen, Nicholas Graetz, Miguel Poblete Cazenave, Karthik Akkiraju, Hero Ashman, et al. 2023. fusionacs guidebook.

Wang, Qian, Klaus Hubacek, Kuishuang Feng, Yi-Ming Wei, and Qiao-Mei. 2016. Distributional effects of carbon taxation. *Applied Energy* 184: 1123–1131.

Williams, Roberton C., Hal Gordon, Dallas Burtraw, Jared C. Carbone, and Richard D. Morgenstern. 2015. The initial incidence of a carbon tax across income groups. *National Tax Journal* 68 (1): 195–213.

WiNDC. 2020. Getting Started: WiNDC Data Stream.

Woollacott, Jared. 2018. The economic costs and co-benefits of carbon taxation: A general equilibrium assessment. *Climate Change Economics* 09 (01): 1840006.

Zhao, Alicia, Shannon Kennedy, Kowan O'Keefe, Maria Borrero, Kyle Clark-Sutton, Ryna Cui, Camryn Dahl, et al. 2022. An all-in pathway to 2030: The beyond 50 scenario. Technical report, Center for Global Sustainability, University of Maryland and America is All In.

Appendix I: Scenario Definitions

Table 4: Scenario structure and definitions of scenario assumptions (Steinberg et al., 2023)

Sensitivity Type	Sensitivity	Abbrev.	Description
Mid Case	Moderate cost and performance for all technologies, Reference natural gas price	Mid	• Cost and performance assumptions for all technologies except CCS-retrofits are from the 2022 Annual Technology Baseline (ATB) *Moderate* case; plant-level CCS-retrofit costs and performance impacts are from the EIA-NEMS model (EIA, 2022b). • Power sector delivered fuel prices are from the AEO2022 *Reference* case (EIA, 2022a)
Technology cost and performance (C&P)	Advanced renewable and battery technologies	AdvBRE	• Cost and performance assumptions for battery storage and renewable technologies are from the 2022 ATB *Advanced* case.
	Conservative Renewable and Battery Technologies	ConsBRE	• Cost and performance assumptions for battery storage and renewable technologies are from the 2022 ATB *Conservative* case.
	Advanced All Clean Technologies	AdvClean	• Cost and performance assumptions for battery storage, renewable, nuclear, and greenfield CCS technologies are from the 2022 ATB *Advanced* case; plant-level CCS-retrofit costs (from EIA-NEMS) assumed to decline from 2023 to 2030 at the same rates as the greenfield CCS technologies in the 2022 ATB.
Natural gas price	High natural gas price	HGP	• Power sector delivered natural gas prices are from the AEO2022 *Low Oil and Gas Resource* case
	Low natural gas price	LGP	• Power sector delivered natural gas prices are from the AEO2022 *High Oil and Gas Resource* case
Constrained deployment	Constrained	Constr.	• Reduced land area/resources available for renewable development (applies to wind, solar, geothermal, and bio) • New long-distance transmission builds restricted to the historical national average build rate (1.4 TW-mi per year) and to builds within transmission planning regions • Increased (2x) cost of CO_2 pipeline, injection, and storage infrastructure
Policy impacts	Low IRA impact	LII	• Increased cost of monetization of tax credits: 10% to 15% for non-CCS techs and 7.5% to 11.25% for CCS techs • Eligible techs earn, on average, one-half of a bonus or 5% (decreased from 10%).
	High IRA impact	HII	• Decreased cost of monetization of tax credits: 10% to 5% for non-CCS techs and 7.5% to 3.75% for CCS techs • Eligible techs earn, on average, one and one-half of a bonus or 15% (increased from 10%)

Notes: Both the **REF**, **TC**, and **CAP** scenarios are simulated with all sensitivity assumptions listed here, with exception of the 'policy impacts' sensitivities which are only applied to the **TC** and **CAP** cases. For each sensitivity, with exception to the differences noted in the "Description," assumptions are identical to the Mid case assumptions. Cost and performance projections for generation and storage technologies are from the National Renewable Energy Laboratory's Annual Technology Baseline (ATB) (NREL, 2022), with exception to costs and performance impacts of plant-level CCS-retrofits which are from the EIA-NEMS model (EIA, 2022b) and further modified for the *Advanced All Clean* scenario; fuel price projections are from EIA's 2022 Annual Energy Outlook (EIA, 2022a). Consistent with the 2022 Standard Scenarios report (Gagnon et al., 2022) all scenarios include a near-term technology-neutral capital cost adjustment to reflect recent increases in costs associated with supply-chain constraints.

Appendix II: Further Results

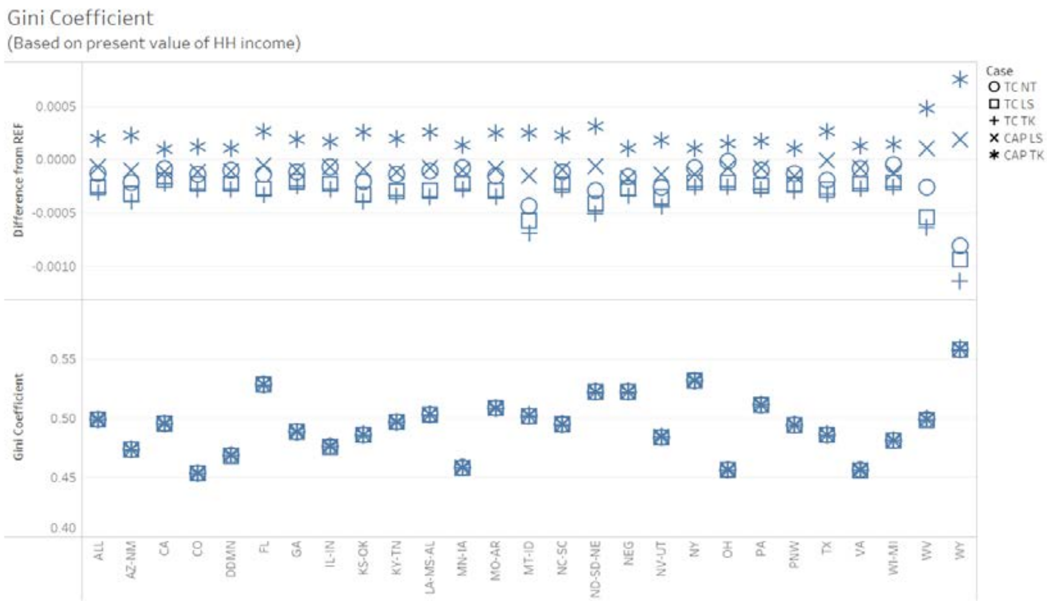

Figure 10: Change in Gini coefficient by SLiDE region and policy in the *Mid Case*

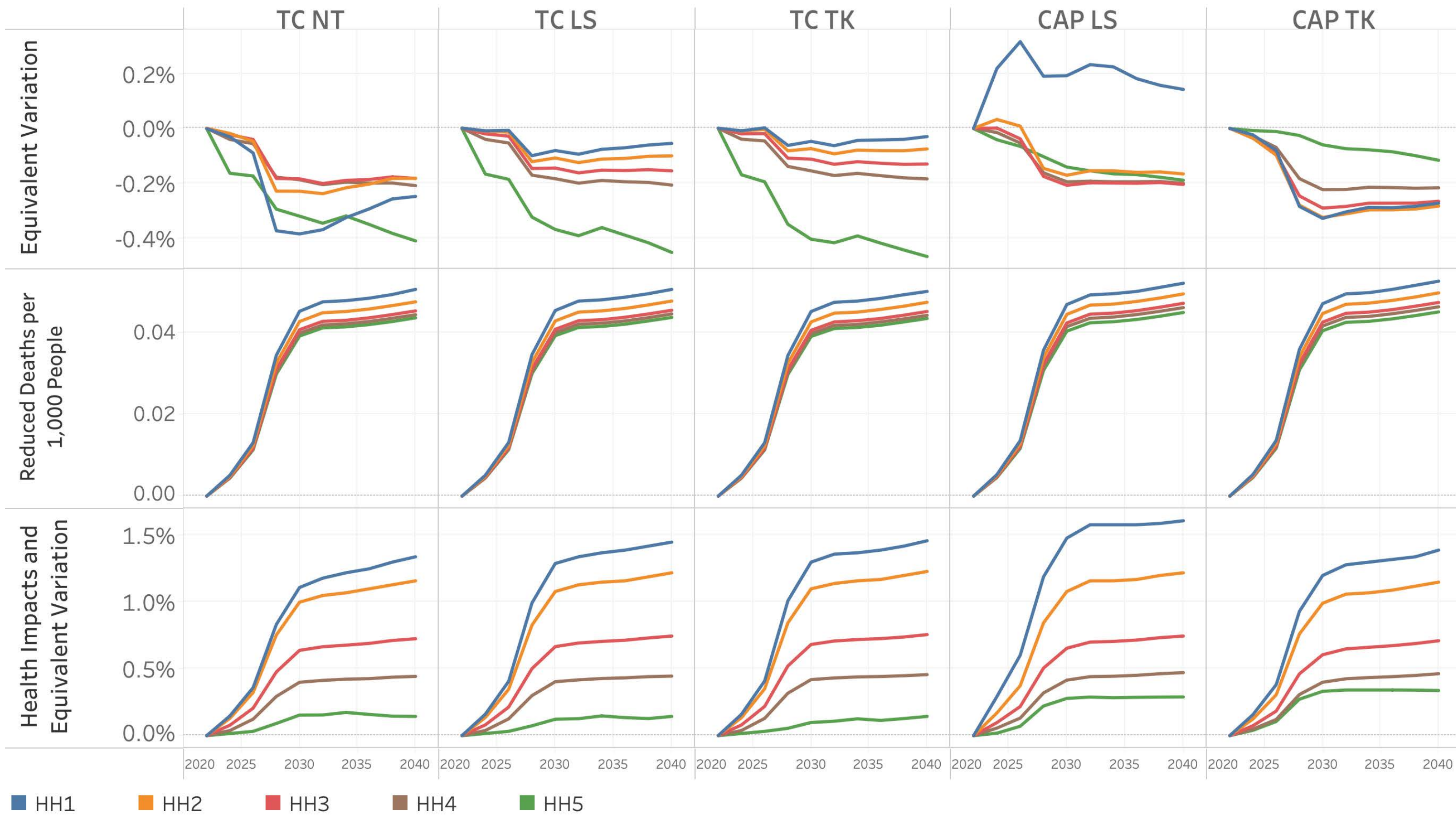

Figure 11: Equivalent variation (top), reduced deaths (middle), and combined health impacts and equivalent variation (bottom) relative to **REF** by income class in the *Mid Case*

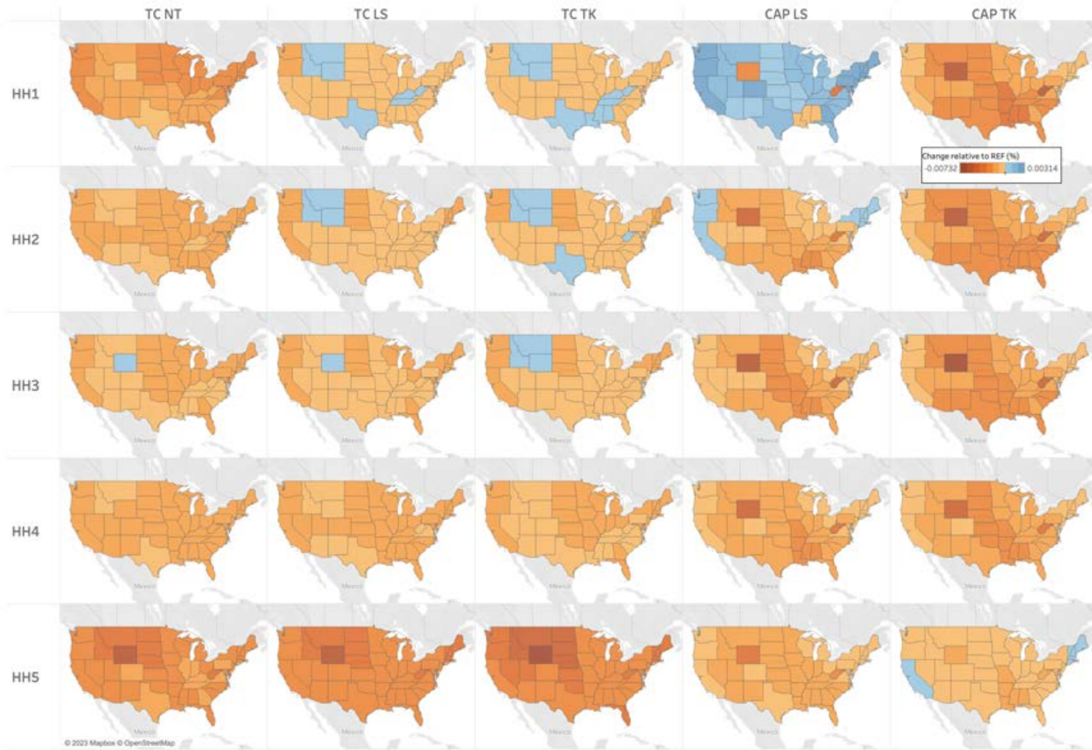

Figure 12: Change in NPV of equivalent variation by household from **REF** in the *Mid Case*

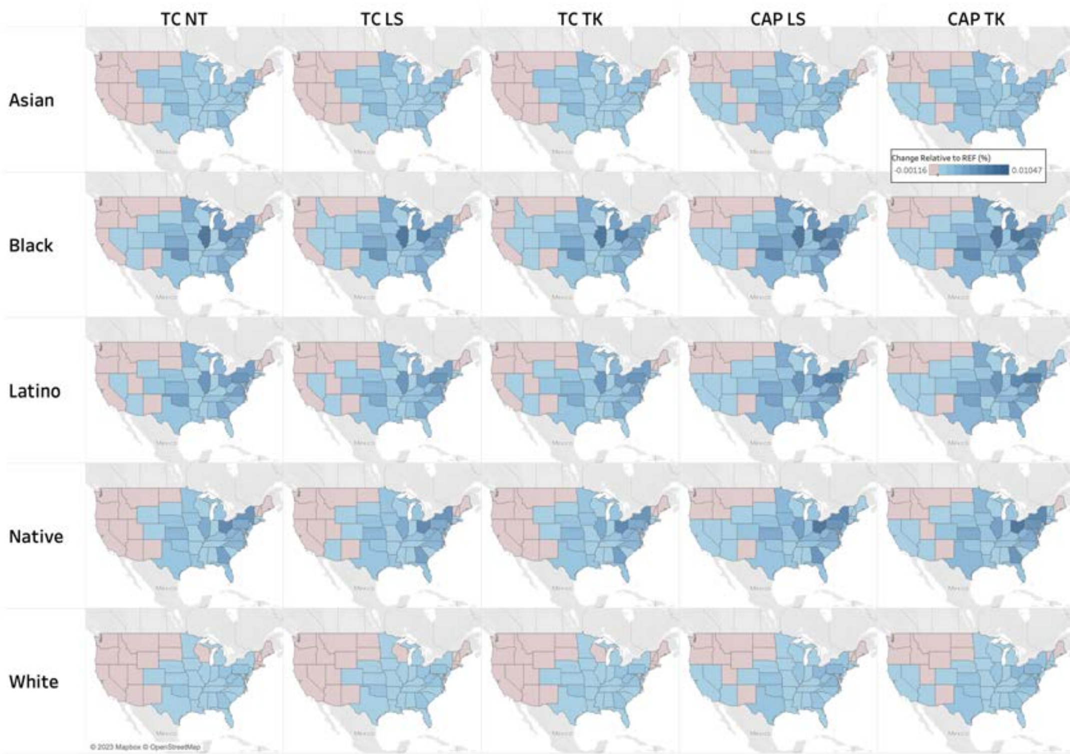

Figure 13: Change in NPV of equivalent variation and health impacts by race/ethnicity from **REF** in the *Mid Case*

Appendix III: Further Demographic Information

Table 5: Characteristics of demographic groups

	Group	Observations	Percent of Total Income	Energy Expenditures	Electricity Expenditures
Income	HH1: <\$25,000	22.2	2.60%	4.90%	2.00%
	HH2: $25,000-49,999$	25.0	8.10%	4.90%	1.80%
	HH3: $50,000-74,999$	21.3	11.60%	4.50%	1.60%
	HH4: $75,000-149,999$	34.7	32.30%	3.70%	1.20%
	HH5: \$150,000+	19.6	45.30%	2.10%	0.60%
Age	0-25	7.2	3.60%	4.60%	1.50%
	25-29	9.8	6.60%	4.00%	1.30%
	30-34	10.8	8.70%	3.70%	1.20%
	35-44	20.8	20.00%	3.50%	1.10%
	45-54	20.2	20.70%	3.30%	1.10%
	55-64	22.2	19.80%	3.20%	1.10%
	65-74	18.3	13.10%	3.10%	1.20%
	74-100	13.5	7.40%	3.20%	1.20%
Race	American Indian	0.6	0.30%	4.60%	1.60%
	Asian alone	6.2	7.10%	2.60%	0.90%
	Black	15.0	8.10%	4.40%	1.70%
	Other	0.6	0.40%	3.70%	1.30%
	Hispanic	16.6	10.80%	4.10%	1.40%
	Two or More Races	2.1	1.60%	3.40%	1.20%
	White alone	81.6	71.60%	3.30%	1.10%
Education	Some high school or below	6.7	1.80%	5.10%	2.00%
	High School or equivalent	24.3	10.80%	4.80%	1.70%
	Some college	26.0	15.20%	4.30%	1.50%
	Associate's degree	12.7	8.90%	4.10%	1.40%
	Bachelor's degree	29.8	30.00%	3.10%	1.00%
	Master's	20.3	28.50%	2.50%	0.80%
	Doctorate degree	3.0	4.90%	2.20%	0.70%
Sex	Female	65.1	48.30%	3.60%	1.30%
	Male	57.7	51.70%	3.20%	1.10%