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

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Abstract

We evaluate the distributional and efficiency consequences of the bulk power clean electricity tax provisions authorized by the Inflation Reduction Act (IRA) . To do so, we link and apply a detailed, power system optimization model, a computable general equilibrium model, and a spatially and demographically rich microsimulation model. This coupling allows us to simultaneously evaluate the impact of the power sector tax provisions on the evolution of the US power system, the reallocation of factors of production, and the incidence of the resulting price changes on different demographic groups. We find that the bulk power tax credits lead to a substantial increase in clean electricity technology deployment with a net welfare benefit to society when considering reduced climate and health damages. These effects are primarily mediated through a reallocation of capital from elsewhere in the economy, leading to lower power prices, higher prices for other goods, and lower greenhouse gas and criteria pollutant emissions. The distortionary effects of the tax credits and the increase in taxes to finance them discourage capital accumulation and reduce economic output. However, these negative impacts on total welfare are balanced by large national welfare benefits associated with the reduction in harmful pollution. We find that the direct impacts of clean energy tax credits are progressive, but the government's response to compensating for reduced household transfers could be decisive in shaping the full distributional consequences of the policy. Comparing with various first-best policies that meet the same emissions reductions, we find a tradeoff between economic efficiency versus general income equality as gauged by the Gini coefficient.

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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 allocates $391 billion[1] towards energy and climate [CBO, 2021]. The majority of that spending allotment is allocated towards clean electricity and energy tax credits, ushering in a new era in US climate change policy [Larsen et al., 2022, Jenkins et al., 2022, Mahajan et al., 2022, Zhao et al., 2022]. The tax credits focused specifically on the electric power sector, 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. The primary mechanisms for funding the IRA expenditures as well as other provisions are 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].

This design departs from that of first-best policies [Pigou, 1920, Baumol and Oates, 1988, Aldy et al., 2022] targeting greenhouse gas reductions in the power sector, namely carbon pricing mechanisms such as CO_2 emissions taxes or cap and trade policies, which generate revenue that can be used to offset other distortionary taxes. However, while one clear objective of the IRA climate and energy provisions is to decrease harmful emissions, improving equity and increasing equality, creating new clean energy jobs, developing nascent industries, and domesticating of clean energy manufacturing have also been cited as core objectives [White House, 2022]. In addition, given the potential political advantages of policy designs like clean electricity tax credits, it is conceivable that other jurisdictions will follow the lead of the US in its attempts to address climate change. Thus there is a need to understand the general performance of this class of policy instruments relative to the first-best based on aggregate measures of efficiency as well as to understand the differences in distributional outcomes, particularly given past findings that equity impacts of energy policies are often negatively associated with efficiency outcomes [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].

Here, we answer the following question: What are the distributional and efficiency impacts of the IRA bulk power clean electricity tax provisions? To do so, we construct a new, coupled simulation model with three main components. To model the direct impacts of the tax credits on the power sector, we use the Regional Energy Deployment System (ReEDS), a highly spatially and temporally detailed model of the evolution of the US power system. Although the US power sector represents approximately X% of the US economy, given that electricity is a central input to many sectors of the US economy the IRA clean electricity tax credits could represent a major change in productivity in those sectors with economy-wide impacts cascading. To understand these effects, we link ReEDS to the Scalable Linked Dynamic Equilibrium (SLiDE) model, a dynamic, multi-sector, multi-region, computable general equilibrium (CGE) model of the US economy. Finally, we use the price changes generated by our simulations as inputs to a new microsimulation model based on the fusionACS database, allowing us to measure the use and source incidence of the policy on various demographic groups.

Consistent with past studies [Jenkins et al., 2022, Steinberg et al., 2023, Larsen et al.,

[1] All monetary values expressed throughout this paper are in $2020 USD unless otherwise mentioned

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2022, Zhao et al., 2022, Mahajan et al., 2022], we find that the power-sector provisions result in a substantial increase in deployment of clean electricity technologies, a higher share of clean energy generation, and reduced emissions. While the tax credits have the effect of stimulating demand for capital in the power sector, the increase in tax rates discourages capital accumulation across the economy as a whole. As a result, the power sector expansion is achieved primarily through a reallocation of capital from other sectors, leading to lower electricity prices and higher prices for other non-energy goods. Wages rise relative to the pre-tax capital rental rate. Collectively, these effects lead to our finding that the IRA bulk power clean electricity tax credits are progressive.

The distortionary effects of the tax credits and the increase in the capital-focused taxes slow economic growth. This leads to an erosion of the tax base and an increase in the cost of delivering government services. As a result, our simulations in which the tax increase is used only to finance the outlays directly associated with the tax credits indicate that the government would experience an annual budget shortfall. This suggests that additional measures would be required to balance the government's budget. If the government responds to the shortfall by reducing transfers to households proportionately, for example, the net effect of the policy becomes generally less progressive. Thus, the character of the government's response could be decisive in shaping the full distributional consequences of the policy.

As an important caveat, this analysis focuses only on the bulk power clean electricity tax credits of the IRA and does not encompass the entirety of the bill'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 discussed in Section 3.2 below. To summarize, this exercise should be viewed as an evaluation of the potential economic 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.

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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. This finding has been reinforced in similar efforts such as Burtraw et al. [2009], Fullerton and Heutel [2011], Rausch et al. [2011], Fullerton et al. [2012], Caron et al. [2018a], Goulder et al. [2019], and 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 by the carbon revenue recycling mechanisms. However, the current paradigm of tax credits and clean energy subsidies 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, although few studies have focused on subsidy-based policies such as clean energy tax credits. 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 CO2 emissions cap and trade system. 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 U.S. 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. The 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 economic output while leveraging carbon tax revenue to reduce capital taxes is regressive but more efficient.

Other work also explores how model inputs impact whether a greenhouse gas 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, authors 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 tax 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 regional effects of greenhouse gas 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. 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.

To date, Bistline et al. [2023] is the most similar in scope to our analysis. The authors leverage a neoclassical macroeconomic framework to evaluate the potential economic impacts and then quantify certain impacts through the Federal Reserve's US (FRBUS) general equilibrium model but do not present quantitative estimates of distributional impacts. Bistline et al. [2023] 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. We support these findings with the caveat that the overall progressivity depends on how the government balances its budget with a particular focus on transfers to households; additionally, we evaluate the impacts across a wide range of demographics and compare with first-best policies that meet equivalent emissions reductions.

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Recent 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 consider 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 exist. 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.

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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

The Regional Energy Deployment System (ReEDS) is the US Department of Energy 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[2], including the version used in the Steinberg et al. [2023] analysis, and the linked version of the model will be made publicly available upon release of this work.

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 1 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.

[2]See: https://www.nrel.gov/analysis/reeds/

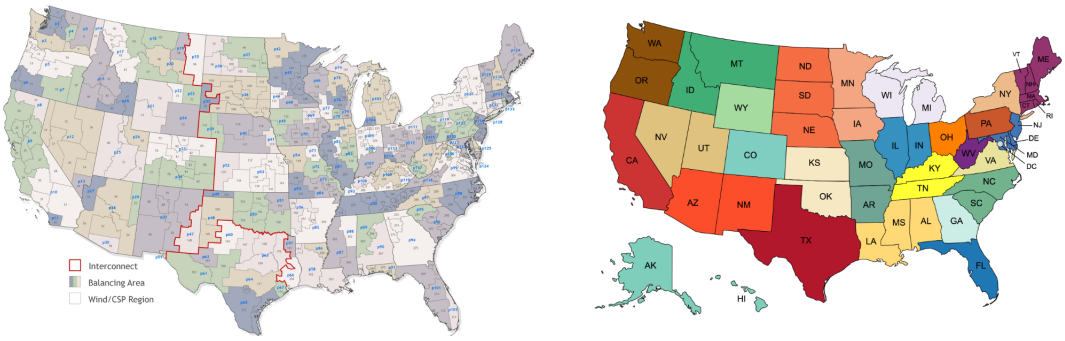


Figure 1: Map of ReEDS (left) and SLiDE (right) Modeled Regions

The Scalable Linked Dynamic Equilibrium (SLiDE) model is a recursive-dynamic, multi-regional, multi-commodity CGE model of the U.S. based on the Wisconsin National Data Consortium's (WiNDC) benchmark dataset and blueNOTE energy-economy model [WiNDC, 2020]. The WiNDC-based benchmark calibration point is aggregated to 26 regions (right map in Figure 1), 5 household income groups, and 11 sectors containing important energy and emissions characteristics. Existing taxes on capital, labor, output, intermediate inputs, and imports are included in the benchmark economy.

The U.S. 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].

Each household 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 U.S. 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

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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.

Table 1: Income Group Statistics Used in the SLiDE Model

Label	Income Range	Population (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%

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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 characteristicsUmmel 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 expenditures (x) for households by state (st), income (h), age (a), race (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 groups, 7 education groups, and two genders. 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}):

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

3.2 Policy Design and Sensitivity Scenarios

Table 2 presents a summary of the modeled policies. To elaborate, the reference (**REF**) case only includes the tax credits that were in effect before the passing of the IRA; that is, the policy includes the incentives as they existed before August 16th, 2022. The tax credit (**TC**) cases include the production tax credit, the investment tax credit, extension/increase to 45Q, and the existing nuclear production tax credit included in the IRA legislation. 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, intended to reflect a portion of the capital-focused, revenue raising mechanisms included in the IRA legislation. 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 either refunded via a 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.

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Table 2: Policy Acronyms and Descriptions

Acronym	Description
REF	No recently-passed 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 in Steinberg et al. [2023] with the addition of the linkage with SLiDE and further demographics disaggregation using the fusionACS-CE data. The production tax credit (PTC) is $26 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 investment tax credit (ITC) encompasses 30% of capacity costs plus a bonus credit that is assumed to start at 5% in 2023 and increases to 10% by 2028. Both the PTC and ITC[3] 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 / 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 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 3. 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. 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) 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 differ from Steinberg et al. [2023] in that they are reflected through increasing or decreasing the oil and gas resource availability in SLiDE as opposed to shifting the supply curve in ReEDS; the reduction in SLiDE is calibrated to the values in EIA [2022a], similarly to ReEDS.

[3]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.

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Table 3: 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
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%)

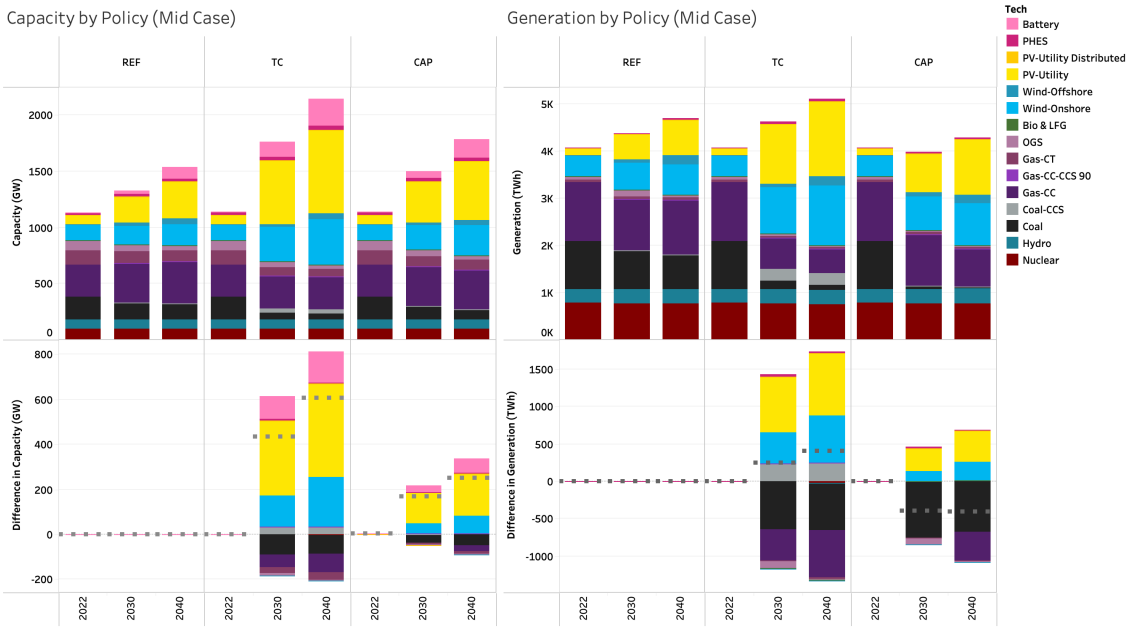
Notes: Both the *No New Policy* and *IRA-BIL* scenarios are simulated with all sensitivity assumptions listed here, with exception of the 'policy impacts' sensitivities which are only applied to the *IRA-BIL* cases. For each sensitivity, with exception to the differences noted in the "Description," assumptions 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.

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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, focusing 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. Next, we consider the tradeoff between increasing income equality and policy cost in terms of aggregate welfare, and compare these outcomes with first-best policies. Finally, we present results across demographic groups and regions and explain the underlying mechanisms.

4.1 Power Sector Results



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Figure 2: Power sector capacity (left) and generation (right) by policy - *Mid Case*

Power sector capacity and generation by policy under *Mid Case* assumptions are presented in Figure 2. Total capacity increases under both the tax credit and carbon cap policies, while generation increases under the tax credit policy, but decreases under the carbon cap policy. In 2040, 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 less relative to **REF** under the carbon cap policy than the tax credit policy, with net changes of 340 GW and 607 GW, respectively. This result highlights the inherent inefficiency of subsidy policies: they lead to an over-production of the subsidized goods, illustrated in this case by clean electricity generation.

Importantly, the technology mix varies across policy designs. Without exception PV and wind generation increase, but the magnitude of the increase differs by policy. In 2040, under

the tax credit policy, PV increases by 834 TWh and wind by 636 TWh, while under the carbon cap policy, PV increases by 419 TWh and wind by 242 TWh. Under the tax credit policy, we estimate Coal-CCS will have 35 GW of capacity and 248 TWh of generation. Meanwhile, under the carbon cap policy, we observe larger declines in non-CCS coal-fired generation and less of a decline in natural gas-fired generation, relative to the tax credit policy.

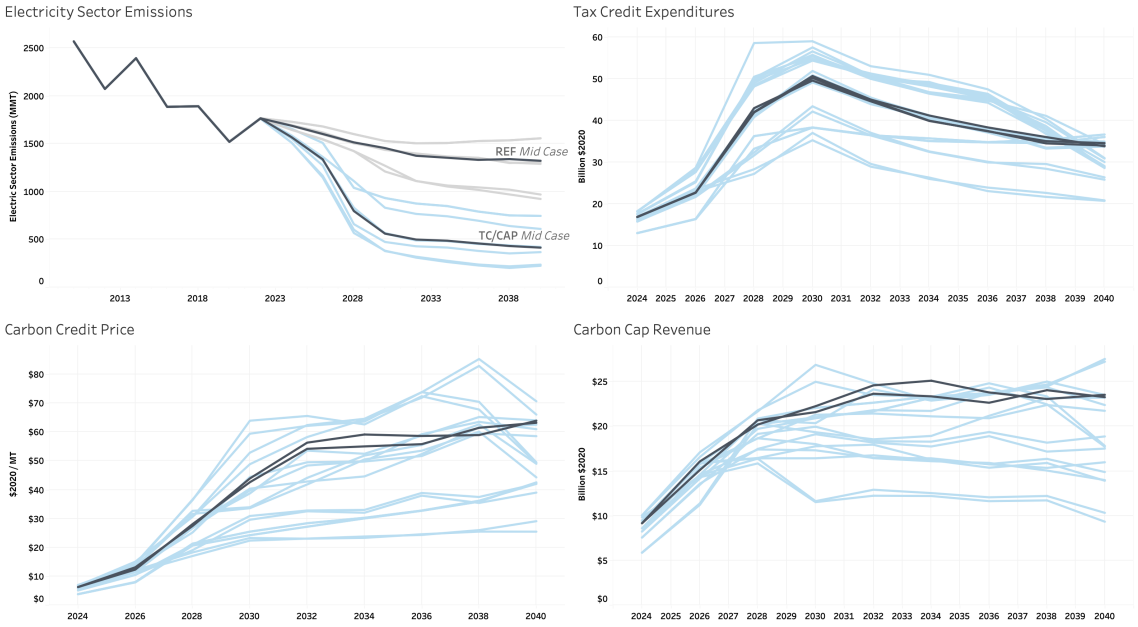


Figure 3: Power sector emissions, tax credit expenditures, carbon credit prices, and carbon cap revenues - Darker lines represent the *Mid Case* while lighter lines represent alternative assumptions

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Power sector emissions, tax credit expenditures, the carbon credit price, and total carbon cap revenues are presented in Figure 3. In this figure, the darker lines represent the *Mid Case(s)* while the lighter lines reflect sensitivity scenarios detailed in Table 3. 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. A large portion of the decrease in emissions occurs in 2028, because this is 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. Adversely, 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[4] 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[5] over the 2024-2040 timeframe.

4.2 Aggregate Welfare and Distributional Impacts by Income Class

Table 4 presents information on the net present value (NPV) of policy impacts computed as the change in aggregate welfare and the value of emissions avoided using the social cost of carbon (SCC) estimates from 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 emissions abatement benefits with a 2% discount rate - the same value used to compute the chosen SCC.

All policies result in a positive NPV (benefit). The NPV of impacts by policy and the ranges across sensitivities are presented in Table 4. The **TC** cases provide approximately $1.71-2.67 trillion dollars in net benefits across all scenarios while the **CAP** cases provide approximately $1.83-2.79 trilion 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.

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Table 4: NPV of impacts including avoided climate damages by policy (billion $2020)

	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	$ 1,717	$ 1,831	$ 1,840
StdDev	$ 347	$ 337	$ 333	$ 340	$ 341

Aggregate welfare and distributional impacts by income class across policy designs in the

[4]Min: $541 billion, Max: $977 billion, StdDev: $112 billion
[5]Min: $217 billion, Max: $376 billion, StdDev: $51 billion

Mid Case are presented in Figure 4. The income-class definitions are described in Table 1. These welfare measures do not include the environmental benefits of the modeled policies, so they reflect only social costs. A net cost is reported as a negative number. These values could potentially be skewed towards being less progressive than when including environmental benefits as the emissions from power plants cause greater harm to lower-income and marginalized groups [Goforth and Nock, 2022]. An assessment of how the benefits of emissions reduction would be spread across the income groups and demographics is outside the scope of this study.

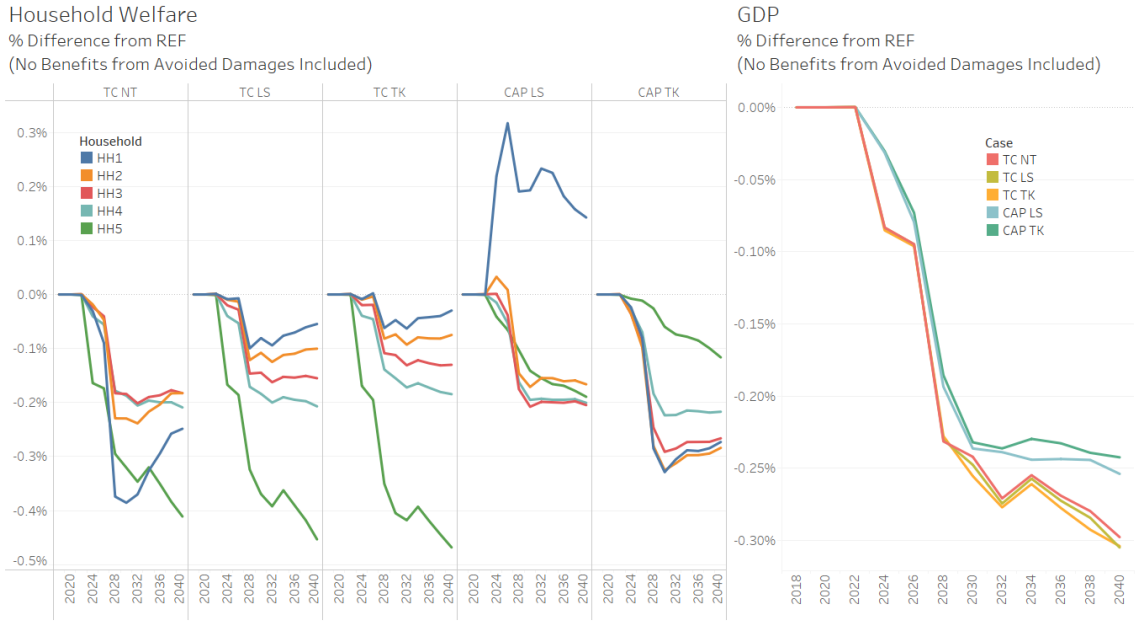


Figure 4: Change in welfare relative to **REF** by income class (left) and economic output (right) by policy design in the *Mid Case*

Overall, the relative change in welfare by household ranges from -0.47% (HH5 under the **TC TK** policy design) to 0.32% (HH1 in the **CAP LS** policy design). Focusing on the right-most panel in the figure, the **TC** cases are more costly than the first-best **CAP** cases, as expected. Our results also align with previous literature in demonstrating that reducing (increasing) capital taxes increases (decreases) overall output more than lump sum recycling. However, the differences 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 changes in the Gini coefficient generated by the different policies are shown on the x-axis of figure 5, demonstrating that all of the policies considered are progressive by this metric with the exception of the carbon cap with capital tax recycling (**CAP TK**). To help unpack the key drivers and impacts on individual household types, Figure 6 decomposes the changes in income sources relative to **REF** in the *Mid Case* by household and policy design. Note that the y-axis ranges for each household type differ.

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Under **TC NT**, total government revenue declines without repayment from a 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. When government transfers are accounted for through either the lump-sum or capital tax mechanisms in the **TC LS** and **TC TK** policies, 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.

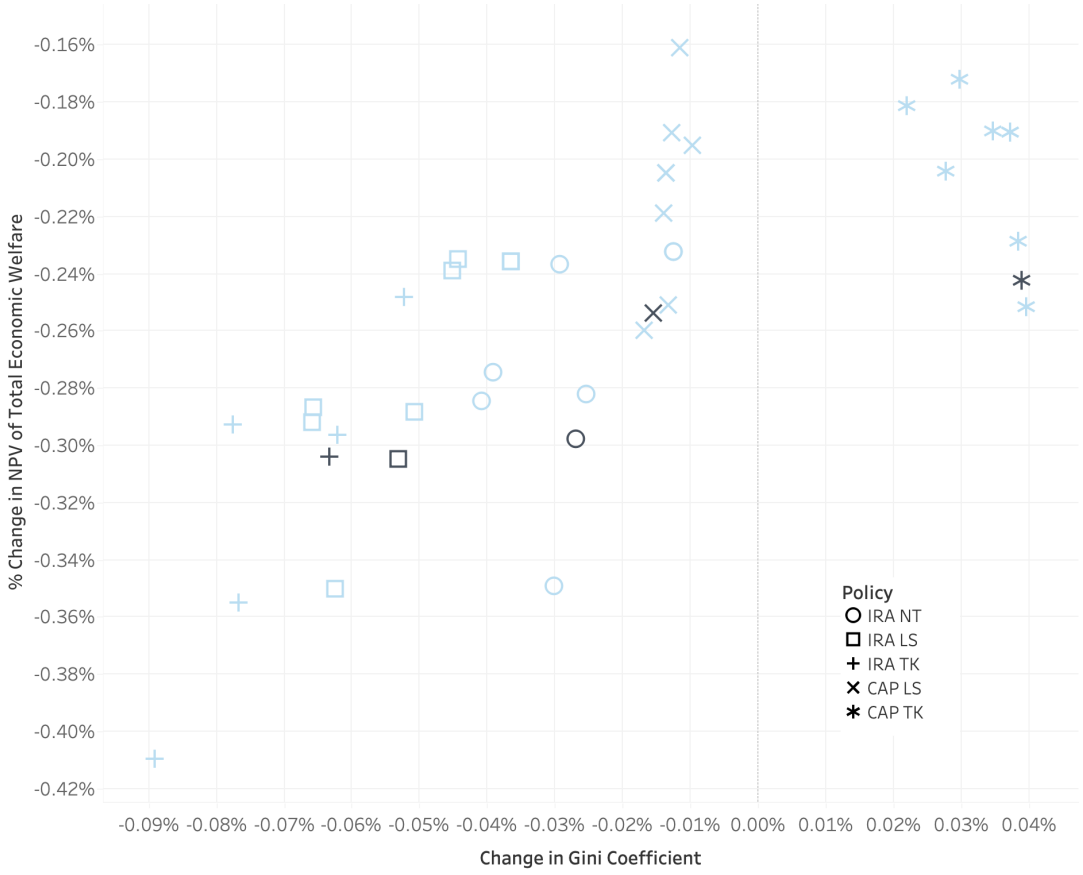


Figure 5: Change in NPV of welfare by change in Gini coefficient from **REF** - Darker colors represent *Mid Case* and lighter colors represent sensitivities

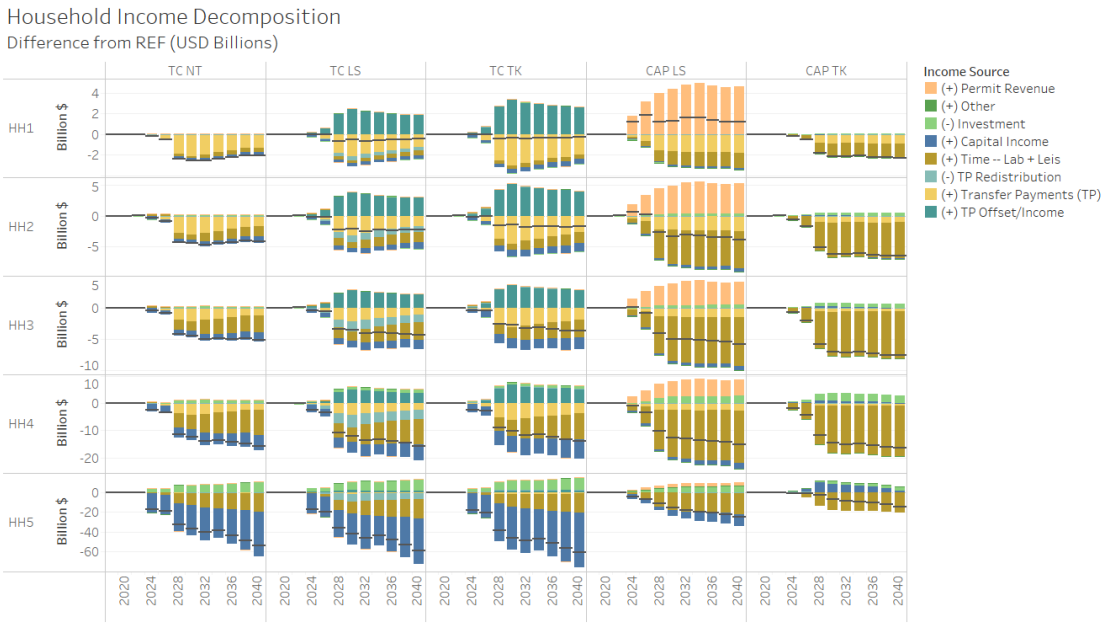


Figure 6: Decomposition of welfare by income class, policy, and income source

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.

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 explicit progressivity constraint.

Figure 5 presents the change in the NPV of welfare by the relative change in the Gini coefficient for the NPV of each household's income. This provides a straightforward method to evaluate the tradeoff of the policy cost (as gauged by the vertical axis) by the resulting

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income equality (horizontal axis) with the origin being the highest cost and highest income equality output. Additionally, regressive policies can be identified by positive values on the horizontal axis. For reference, the darker colored symbols represent the *Mid Case* while the lighter colored symbols represent alternative scenarios.

Focusing on Figure 5, there is 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 with substantially different progressivity outcomes. The variations from the *Mid Case* also play an important role in both the policy outcomes; 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.

4.3 Demographic Breakdown

Figure 7 presents the NPV of welfare change over a subset of demographic characteristics available in the fusionACS-CE data: state, income, age, race, 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 the Appendix for supplemental information by demographic group.

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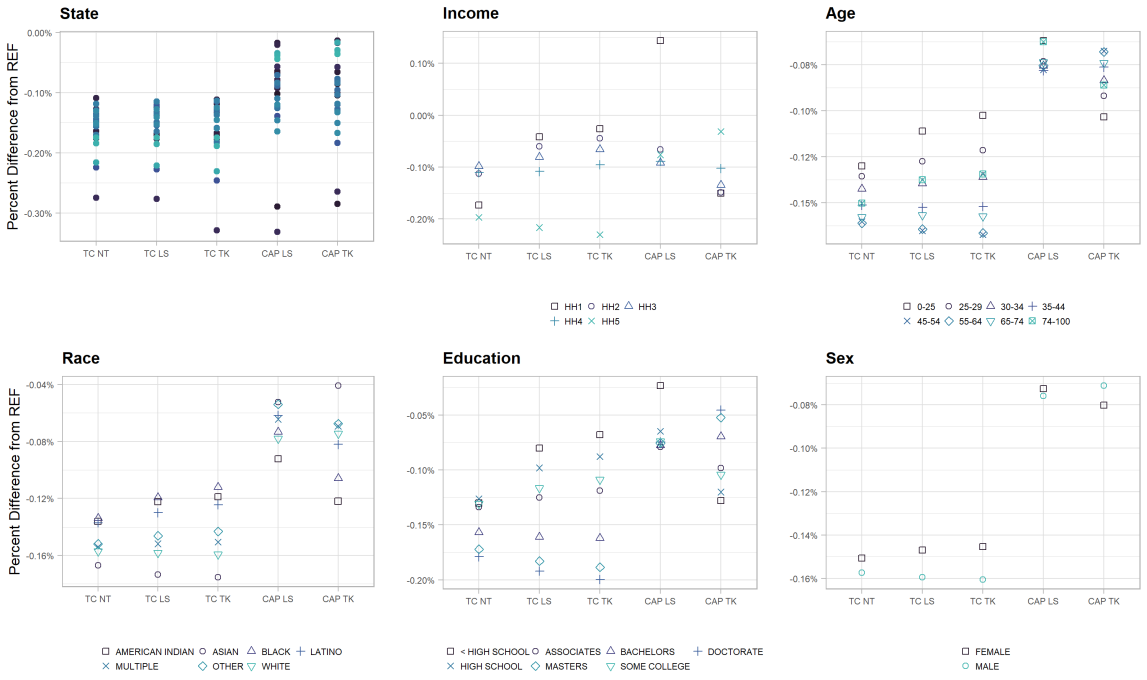


Figure 7: Change in NPV of welfare by various demographic groups from **REF** in the *Mid Case*

Results across income groups in Figure 4 and 7 are consistent, but Figure 7 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, 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 differ across policies. Examining the **TC** policies, American Indian, Black, Latino, multiple races, and other race groups are least impacted under the **TC TK** policy followed by **TC LS** and **TC NT** policies. Asian and, to a lesser extent, White groups have the opposite experience. Comparing the two **CAP** policies, Asian and White groups experience a smaller negative impact under the **CAP TK** policy. All other groups have the opposite experience, with a preference for 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 preferred 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, prefer policies in the opposite order. Under the **CAP** policies, individuals who have a bachelor's degree or more prefer the **CAP TK** over **CAP LS** and those with less education prefer the opposite order.

Finally, males prefer policies that have less of an impact on capital and overall income while females prefer 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.

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4.4 Regional Breakdown

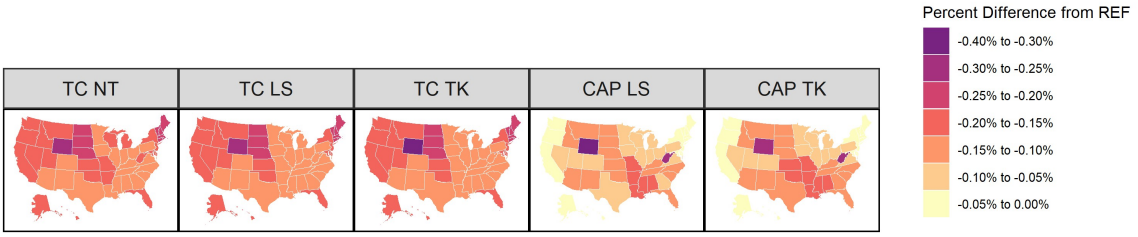


Figure 8: Map of NPV of welfare change from **REF** by policy in the *Mid Case*

The NPV of welfare change by region and policy is presented in Figure 8. Across policies, the difference from **REF** is the most distinct in Wyoming given its role as the highest coal-producing state as well as its relatively less total economic output. West Virginia is less affected by the **TC** policies than the **CAP** policies. This can be explained by the role and geographic locations of Coal-CCS electricity generation under the **TC** policies. Additionally, under **CAP** policies, coal generation phases out quickly and is not retrofitted with CCS equipment. The ND-SD-NE region is estimated to incur the third largest relative detriment under the **TC** policies. The region reduces their fossil fuel output through coal and/or gas supply reductions (particularly relevant for ND), and also has a relatively less total economic output.

To provide more detail on regional outcomes, we present the Gini coefficient and the difference from REF by SLiDE region in Figure 9. In addition, Figures 10 - 13 in the appendix delineate the demographic outcomes by income, age, education, and race, respectively. Referring to Figure 9 and 10, it is apparent which income groups are driving the regional changes and distributional impacts within each state.

Regions with higher fossil fuel output (TX, WV, WY, ND-SD-NE) and initially higher degrees of inequality have larger ranges of Gini coefficient changes than others. In TX, WV, and WY the Gini coefficient increases under the **CAP LS** policy, implying regressivity. This is 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, it is important to note that if overall economic output declines, the Gini coefficient will still become more negative if the upper-income classes face a larger relative detriment than the lower-income classes.

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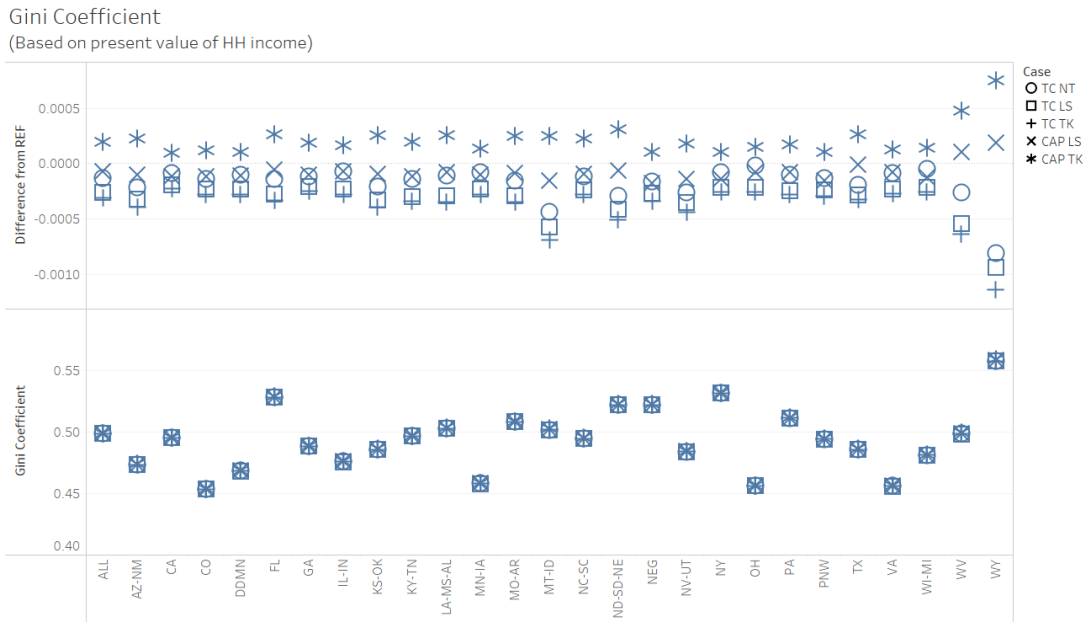


Figure 9: Change in Gini coefficient by SLiDE region and policy in the *Mid Case*

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5 Conclusions

We evaluate the broader distributional impacts of the clean electricity tax credits provisions included in the 2022 Inflation Reduction Act and compare those to first-best policies (equivalent emission limits) that vary revenue recycling schemes. To do so we combine a bottom-up, detailed power sector capacity expansion model with a top-down, CGE representation of the US economy with the output sent to a microsimulation framework based on the fusionACS-CE dataset. In doing so, we arrive at several conclusions for policy design through the lenses of both economic efficiency as well as economic equality.

First, we see a large and rapid buildout of clean generation technologies when incentives are available. The tax credits also lead to a reduction in electricity price and thus an increase in the amount of electricity consumed while the opposite is true under the first-best emissions-equivalent policy. The tax credits imply a substantial reduction in power sector emissions, averaging 60-80% reductions in 2040 relative to the no-policy base case and across the scenarios modeled.

However, these tax credits increase the capital tax rates and erode the tax base through reduced overall output. 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.

The distributional impacts across demographic groups can be traced to each group's income levels, capital ownership rates, locations, 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 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.

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. States with higher shares of economic output from fossil fuel supply (such as ND, TX, WV, WY) are more negatively impacted by the first-best policies than the tax credit policies which do not directly penalize emissions and increase total electricity output. The opposite is true for regions that have a high concentration of capital assets (such as New England) and suffer at the hands of the higher capital tax rates under the tax credits. Overall, this work represents an isolated representation of the entire Inflation Reduction Act and further research is needed to evaluate the potential impacts of the bill in its entirety.

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. Additionally, we present aggregate net benefits from pollution abatement but not the impacts that emissions reductions would have on specific populations which is important from environmental equity perspective. We leave this to future research.

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6 Appendix: Further results and information

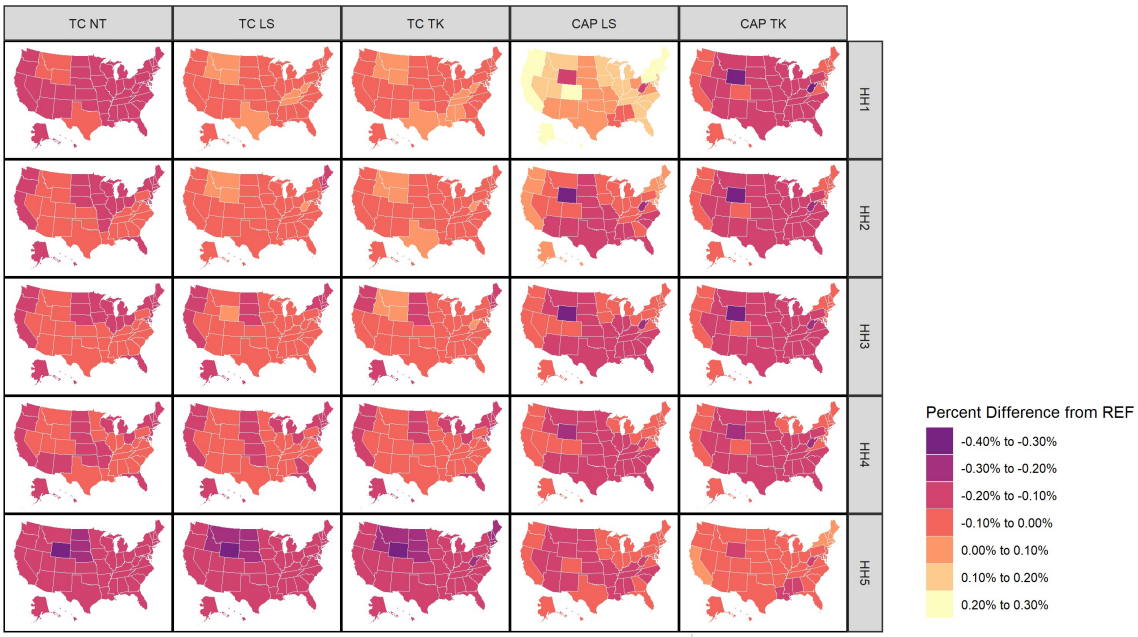


Figure 10: Map of NPV of welfare change by income group and policy in the *Mid Case*

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Figure 11: Map of NPV change by age group and policy in the *Mid Case*

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Figure 12: Map of NPV change by educational attainment and policy in the *Mid Case*

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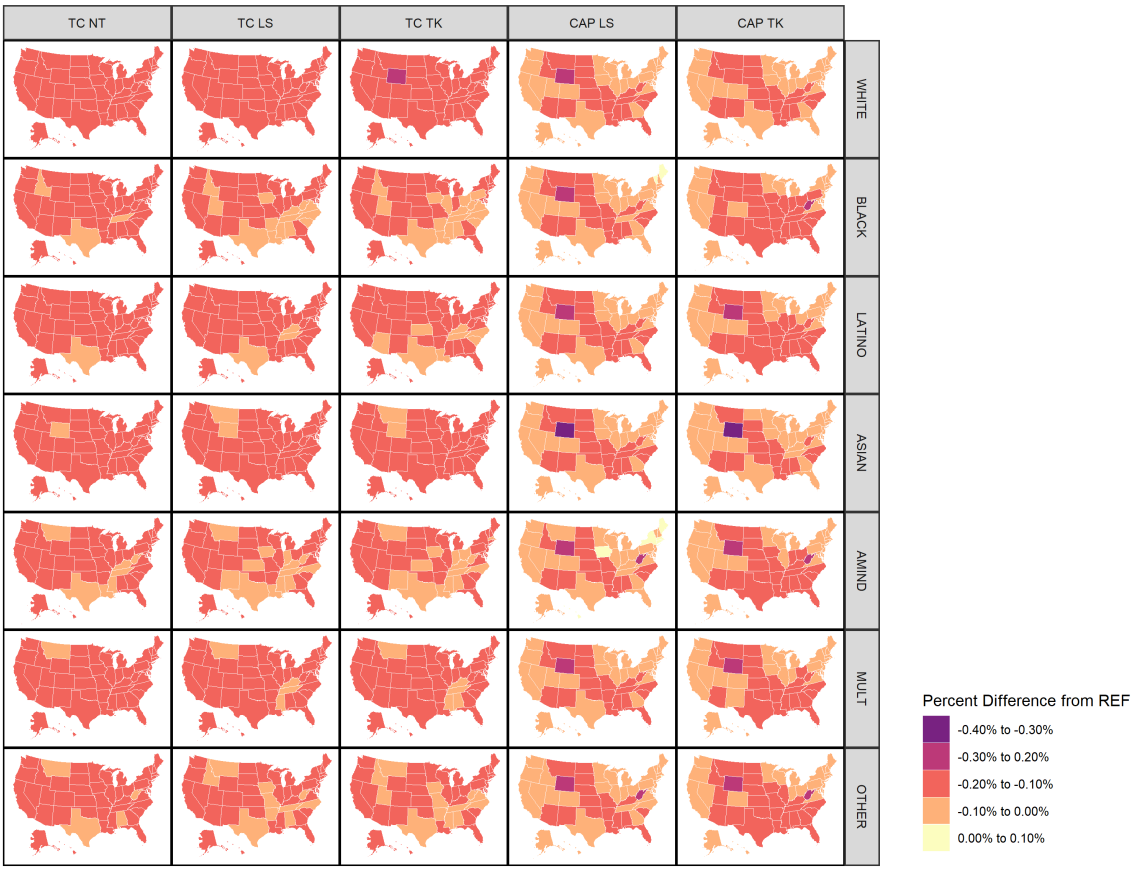


Figure 13: Map of NPV change by race and policy in the *Mid Case*

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Table 5: Characteristics of demographic groups

	Group	Population	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%

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