ABSTRACT

Title of Dissertation:	THE DECARBONIZATION TRANSFORMATION: ESSAYS ON THE ROLE OF CONSTITUENT ENTITIES IN THE U.S. ELECTRICITY SECTOR TRANSITION TO A LOW-CARBON FUTURE
Dissertation directed by:	Associate Professor Nathan E. Hultman School of Public Policy

The threat of climate change requires significant transitions across all U.S. economic sectors should a substantial reduction in greenhouse gas (GHG) emissions be achieved by 2050. The U.S. electricity sector is the second-largest contributor to total emissions in the United States. This dissertation looks at entities that are the most likely to contribute towards the electricity grid transitions and the reasons why. The first essay finds that states with more aggressive electricity grid decarbonization policies require less adjustments to their electricity generation strategy on the event of federal intervention. Nationally, more aggressive policies ensure that the Federal government can impose less carbon taxes to obtain greater reduction of emissions from the electricity sector. The second essay finds that while most households own energy efficient appliances, they do not effectively control the temperatures of their equipment. The households that do use thermostats tend to be educated wealthy homeowners. The third essay finds that for several prosumers and utility combinations, there exists a valuation of distributed solar power generation that is

amenable to both parties in terms of their economic benefits. These combinations are typically characterized by affordable systems, low leftover demand, and higher tariffs. Analyzing all three sets of actors, it is important to recognize that certain characteristics make some of them more suited to provide leadership in the U.S. electricity grid transition. While encouraging these actors to continue providing leadership in their relative segments, policymaking should also be concerned about incentivizing other actors to step up and play an important role in the transition process.

THE DECARBONIZATION TRANSFORMATION

ESSAYS ON THE ROLE OF CONSTITUENT ENTITIES IN THE U.S. ELECTRICITY SECTOR TRANSITION TO A LOW-CARBON FUTURE

by

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Chapter 1

Introduction: Identifying the Players and their Roles in U.S. Electricity Sector Decarbonization

Anthropogenic climate change has been considered as one of the greatest threats to mankind in the recent history with the increasing global trajectory of greenhouse gas (GHG) emissions considered a threat to human health, water and food security, economy, infrastructure, and national security(Mora et al. 2018). The United States is the second largest emitter of greenhouse gas (GHG) in the world, behind China(Boden, Marland, and Andres 2017). In the United States, the electricity sector is the second largest emitter of GHG, accounting for 28 per cent of the emissions in 2017, right behind transport, which overtook the electricity sector in emissions after 2016(US EPA 2015). Emissions from fossil fuels play a major role in GHG emissions(Janssens-Maenhout et al. 2017). More than 60 per cent of the U.S. electricity comes from burning fossil fuels – coal, natural gas, and oil("What Is U.S. Electricity Generation by Energy Source? - FAQ - U.S. Energy Information Administration (EIA)" n.d.). This share has declined slightly over the past decade("EIA - Electricity Data" n.d.), with renewables displacing some of the fossil fuel generation. Two other factors have contributed to the decline of electricity sector emissions. The first factor is the switching of fuels within the fossil fuel part of the mix, with coal being phased out in the favor of gas. In 2010, natural gas accounted for a third of the fossil fuel-based generation in the United States, and in 2019 it accounted for over 60 per cent("EIA - Electricity Data" n.d.). Natural gas also emits at a rate about 40-50 per cent lower than coal while being used for power generation in its life cycle(Weisser 2007). The second factor is the near flattening of the electricity consumption growth. In 2010, the utility scale facilities generated 4.125 TWh of electricity with no credible measurements of the small-scale generation. In 2019, the utility-scale generation dropped to 4,118 TWh, while the small-scale generators approximated to around 0.35 TWh of generation, bringing the total to around 4,138 TWh, or a mere 0.68 per cent growth over a ten year period("EIA - Electricity Data" n.d.). Generation between 2001 and 2010 meanwhile increased by over 10 per cent("Electricity Data Browser - Net Generation for All Sectors (Filtered between 2001 and 2010 - Comparing All Fuel Values under United States)" n.d.). This can be partially attributed to the increasing energy efficiency standards, especially in the residential and commercial segments of the electricity sector which dominate retail sales (Saundry 2019).

In order to mitigate the impacts of global climate change however, the United States and its electricity sector however must become more ambitious in reducing GHG emissions. While the country was one of the front-runners in developing the Paris Agreement(Schreurs 2016) to reduce global GHG emissions in order to curb the rise in global temperature, the recent administration has decided to withdraw from the agreement(Zhang et al. 2017) bringing into question the long-term motivations of the federal government. The Paris Agreement targets of the United States, reducing GHG emissions by 26 to 28 per cent from 2005 levels by 2025 were not considered particularly ambitious to begin with (Peters et al. 2015), and by most estimates – the country is not on track to meet these targets without federal government intervention or substantial changes in state policies or economic circumstances(Greenblatt and Wei 2016) (Hultman 2020). While the present administration has seemingly abandoned the Obama Administration's U.S. Mid Century Strategy (MCS) which called for 80 per cent GHG reduction from 2005 levels by 2050("United States Mid-Century Strategy for Deep Decarbonization" 2016), several lawmakers have tabled a bill to move the U.S. economy to a net zero carbon scenario by 2050 which is an even more stringent target(Carper et al., n.d.). Given that without significant federal help, the actions of the remainder of the actors participating in the U.S. electricity sector will struggle to meet even the Paris targets, it is highly implausible that a business-as-usual scenario will enable the country to meet a target like the MCS, let alone the net zero carbon one.

1.1 The Actors in the U.S. Electricity Sector

This brings us to the question of identification of the major actors in the U.S. electricity sector – i.e. entities who play a major role in generation, transmission, distribution and consumption of electricity directly or indirectly (See Fig 1.1 for a Sankey Diagram of electricity usage). The U.S. federal government has passed four major regulations related to the electricity sector - the most recent ones of significance being the Energy Policy Act of 2005(Act 2005) which in terms of decarbonization of the electricity grid – created provisions to incentivize shale gas production, promote technologies that avoid greenhouse gas emissions, increase energy efficiency standards, and require utilities to offer net metering. A more direct proposal to control GHG emissions in the economy, the American Clean Energy and Security Act, which would have created a nationwide cap and trade system and instruct utilities to meet certain percentage of generation from renewables as well as ancillary actions such as subsidizing clean energy technology development, and protection of consumers from increased prices, failed at the Senate in 2009(Waxman 2009).

At the institutional level, the U.S. Department of Energy is in charge of several federal organizations that are involved in making regulations at the interstate level, e.g. the Federal

Energy Regulatory Commission (FERC). However for electricity, FERC is mainly concerned with regulating the transmission and wholesale sale of electricity in interstate commerce (which it typically carries out through designated Independent System Operators and Regional Transmission Operators) and not overseeing the decarbonization of the grid("FERC: About FERC - What FERC Does" n.d.). The U.S. Environmental Protection Agency (EPA) can issue economywide regulations towards the abatement of pollutants that can be considered harmful to public health, but the one policy designed to target power sector emissions, the Clean Power Plan (CPP) met its end at the hand of the Trump Administration(U.S. Environmental Protection Agency, n.d.). An "Affordable Clean Energy Rule" has replaced the CPP(US EPA 2019), but this is likely to increase emissions compared to a no-policy scenario(Keyes et al. 2019).

As far as the electricity sector goes however, the states wield most of the power in directly regulating the utilities who are responsible for procuring, transmitting, and distributing electricity to the end-use consumers. Each state has a state electricity regulatory commission("Regulatory Commissions" n.d.) responsible for regulating the utilities (which are generally natural monopolies) by approving costs, tariff, service quality, energy efficiency standards, and renewable energy standards(Wang and Liu 2018). State governments typically dictate state energy policies through legislations and use regulators to enforce these, e.g. California's renewable portfolio standards (RPS)("RPS Program Overview" n.d.). Certain states or groups of states have legislations regarding greenhouse gas emission reduction, either a hard cap or a market mechanism designed to achieve the cap. Examples include California's Cap and Trade (Bang, Victor, and Andresen 2017), the Regional Greenhouse Gas Initiative (RGGI) which several northeastern states take part in

(Murray and Maniloff 2015), and caps from Washington("Chapter 173-442 WAC:" n.d.) and New York("NY State Senate Bill S6599" 2019). A coalition of State Governors formed the U.S. Climate Alliance ("Inslee, New York Governor Cuomo, and California Governor Brown Announce Formation of United States Climate Alliance | Governor Jay Inslee" n.d.) in the aftermath of the Trump Administration's withdrawal from the Paris Agreement, planning to meet the targets of the Agreement without federal support, which led to the America's Pledge(Hultman et al. 2018) initiative.

Utility-scale generation dominate the generation mix, accounting for more than 99 per cent of the generation mix("EIA - Electricity Data" n.d.). Utilities who do not generate power themselves (vertically integrated) will buy from several independent power producers in the wholesale market. Utility ownership is primarily public or cooperative based, but it is the investor-owned utilities that supply more than 70 per cent of the electricity to the end-users ("Investor-Owned Utilities Served 72% of U.S. Electricity Customers in 2017 - Today in Energy - U.S. Energy Information Administration (EIA)" n.d.). Among the end-use consumers, the most significant contributors are residential and commercial sectors, which account for three quarters of the total electricity consumption(Saundry 2019). With the falling price of rooftop solar modules("Solar Industry Research Data" n.d.) and the advent of favorable net metering regulations (DSIRE 2019), there has been a significant growth in generation from rooftop PV system installations across the United States ("EIA - Electricity Data" n.d.), effectively turning some residential and commercial consumers into prosumers – those who both produce and consumer electricity(Miller and Senadeera 2017). As far as actual end use goes, EIA estimates("Use of Electricity - U.S. Energy Information Administration (EIA)" n.d.) that the residential sector uses about 14-15 per cent energy for cooling and space heating each, the largest contributors to the mix. For commercial sector, the biggest use of electricity is in office and computer equipment, followed by refrigeration, space cooling, ventilation, and lighting. Motors (machined drivers) account for nearly half of the electricity use in the energy sector. Most energy efficiency initiatives, including the ENERGY STAR labeling program(Datta and Filippini 2016) and the adoption of programmable energy saving measures such as thermostats(Huchuk, O'Brien, and Sanner 2018) are targeted towards the residential and commercial sector.

1.2 Actors and Actions of Interest

This dissertation concentrates on three sets of actors, each with a chapter of this dissertation analyzing their issues, actions, and consequences (See Table 1.1 for summary) –

i. **States and Federal Government (Chapter 2)** who have the power to make overarching policies that affect GHG emissions, electricity prices, and consequently the electricity generation mix at the state and national level.

ii. **Households (Chapter 3)** who purchase and use energy efficient appliances in order to reduce their electricity expenditure

iii. **Prosumers (Chapter 4)** who deploy rooftop PV systems in order to reduce electricity expenditure by both reducing their retail usage and selling additional generation to the **Utilities** who must compensate the prosumers for the additional output in a way that leaves the utilities no worse off than a no-rooftop PV situation but still incentivizes the prosumers to deploy the rooftop PV systems. State utility regulatory commissions are not explicitly considered among the actors analyzed, but they play a significant role in setting a tariff that ensures certain financial returns for both parties.

For **States and Federal Government**, Chapter 2 of this dissertation looks at the impact of differently-oriented state electricity policies (States that are part of the Climate Alliance favoring more aggressive policies, while states that are outside it favoring more conservative policies) on the emission, electricity prices, and generation mix of the U.S. electricity grid regions. Grid regions are considered because states trade electricity within a particular grid region and most electricity policies are based on consumption which will at the very least include imports and exports within the grid region. It also helps in tracking the issues of leakage and re-shuffling(Bushnell and Chen 2009) that are generally considered prevalent in any type of greenhouse emission reduction process. The chapter also assumes that a future point, the Federal Government re-engages in GHG reduction policy by imposing an economy-wide carbon tax. The chapter then investigates whether or not aggressive state policies benefit the grid regions in terms of having to adjust less when the tax come in, and if aggressive state policies benefit the federal government in terms of having to impose a lesser amount of carbon tax or help achieve a higher national emission reduction in the electricity sector on a per dollar basis.

For **Households,** Chapter 3 of the dissertation[1] investigates the behavior of U.S. households from a nationally sampled survey of EIA(U.S. Energy Information Administration n.d.) regarding their approach on adopting energy efficient appliances and their strategies on using them. Many households tend to have at least one energy appliance

[1] Chapter 3 of the dissertation has been published on IEEE Transactions on Engineering Management as "Aggregate Household Behavior in Heating and Cooling Control Strategy and Energy-Efficient Appliance Adoption" with committee member Dr. Yueming "Lucy" Qiu(Sen and Qiu 2020).

but not all use their appliances in a manner that will lead to maximum energy savings. For space heating and cooling, the largest sources of electricity consumption in a residential setting, that means using programmable thermostats to control temperature rather than doing it manually (or not changing the temperature at all in response to weather conditions). This chapters classifies households on the joint behavior of appliance adoption and usage, and attempts to determine the demographic characteristics that are associated with each class of households.

For **Prosumers and Utilities**, Chapter 4 of the dissertation analyzes the economics of rooftop PV systems for several prosumer-utility combinations, selected from a national database of rooftop PV installations(Barbose et al. 2019) in the United States. The proper compensation of solar power that is generated by the prosumers in excess of their consumption requirements and then sold to the utilities in a given billing period has been a source of major controversy across the United States with utilities pushing back against existing compensation regulations(Davies and Carley 2017). However, it is also true that given the expensive nature of the rooftop PV system and the retail structure faced by the prosumer, an appropriate amount of compensation is required to incentivize the growth of distributed generation, which can be significantly contribute towards meeting state level goals of renewable energy policy targets(Carley 2009). This chapter attempts to determine a valid range of solar compensations that are compatible with motivations of both the prosumers (ensuring they are paid back for their investment) and the utilities (ensuring that they are no worse off in terms of their energy costs compared to a no-rooftop PV scenario). The analysis also determines financial benefits of the prosumers, utilities, and the society as a whole (which gains from avoiding pollution-related expenses when distributed solar generation displaces utility generation but loses out by partially subsidizing these statements through taxpayer expenses). Also analyzed are the major factors behind the ability to find a valid set of compatible tariffs for certain prosumer-utility combinations but not others.

1.3 Common Themes

In the analysis of the motivations and actions of these diverse sets of actors, the dissertation aims to find common themes across all the chapters. There are three common themes along which this dissertation tries to analyze the key research problems in each chapter.

i. Documenting the effort of every actor in making the electricity grid more sustainable by decarbonization and reduction of electricity consumption. The states enact policies to promote renewable energy which reduces GHG emissions and to institute energy efficiency measures. The federal government imposes a carbon tax to reduce GHG emissions which directly decarbonizes the grid. The households reduce electricity consumption by purchasing and using energy efficient appliances. The utilities also are also able to reduce electricity purchase/generation by purchasing the excess energy from the prosumers, which also has the side effect of at least partially displacing electricity purchases from high-emitting sources. The latter creates social benefit through avoided cost of pollution, not only from GHG emissions, but also from the emission of local pollutants.

ii. All three chapters are characterized by an analysis of joint actions within of between all groups of interest. In Chapter 2, the combined effort of states that are part of the Climate Alliance and those that are not determine how far can the states alone help in the reduction of GHG emissions; and the interaction of state efforts with federal taxes determine how much emission reduction can be nationally achieved with varying level of state efforts and the impact of federal cost from the interaction. In Chapter 3, joint analysis of adoption and usage of energy efficient appliances households is undertaken to determine the share of households that are lagging in one or both, and the share of households that are excelling in both. In Chapter 4, a range of tariffs are identified that would jointly benefit both the prosumers and utilities, and the interaction of these benefits with the larger societal benefits.

iii. In all three chapters, leaders and laggards are identified, that is the subset of actors that are the most effective in achieving their objectives and those that are the least effective. In addition, possible reasons why certain actors are leaders and others are discussed, with suggestions on improving the position of the laggards through policy. In Chapter 2, the analysis identifies grid regions that are effectively setting themselves up for a carbon tax imposition in the future, and those that have to significantly alter their emissions, pricing, and generation trajectory in response to a tax. The analysis also attempts to illustrate the reasons why the leader states are successful, and the laggards are less so. In Chapter 3, the analysis classifies households that are excelling in both adoption and usage of appliances, and those that are lagging. The chapter then identifies demographic characteristics that are associated with leaders and laggards. In Chapter 4, the analysis identifies prosumer-utility combinations that are able to find a range of mutually aggregable compensations that also improve social benefits, and the combinations that do not have the same outcomes. The chapter identifies characteristics of these combinations (e.g. cost, size of project, tariff structure) that are associated with leaders and laggards.

1.4 The Key Questions: Specific and Overarching

For the three chapters, we ask three specific research questions:

Chapter 2 asks Is it worthwhile for the states to pursue aggressive climate policies with a federal policy on the horizon in terms of minimizing their deviation from existing electricity sector outcomes once a federal policy is instituted? Will federal policymakers and the U.S. electricity grid benefit when every state pursues relatively more aggressive policies compared to existing ones?

Chapter 3 asks How can household behavior in terms of adoption of energy efficient appliances and temperature control strategy of space heating and cooling equipment be jointly categorized? What are the factors associated with households being categorized into different behavioral groups?

Chapter 4 asks for given prosumer-utility combinations, what are the valuations of distributed solar generation that make sense for both prosumers and utilities – such that utility cost of energy acquisition for the prosumer remain unaffected and the prosumers still receive enough compensation to ensure payback for the installed system within its lifetime? What explains the differences in these valuations between and within certain prosumer-utility combinations?

Based on these three questions, and the common themes identified in the previous section, the following overarching questions are relevant to the dissertation as a whole.

1. Which actors are best positioned to contribute towards meeting objectives that would assist the transition of the U.S. electricity grid towards a sustainable future?
2. What is the impact of joint actions by actors in accomplishing their objectives?
3. What are the factors that make these actors better positioned than others in the same segment?
4. What policy options can be used to assist actors that are lagging behind?

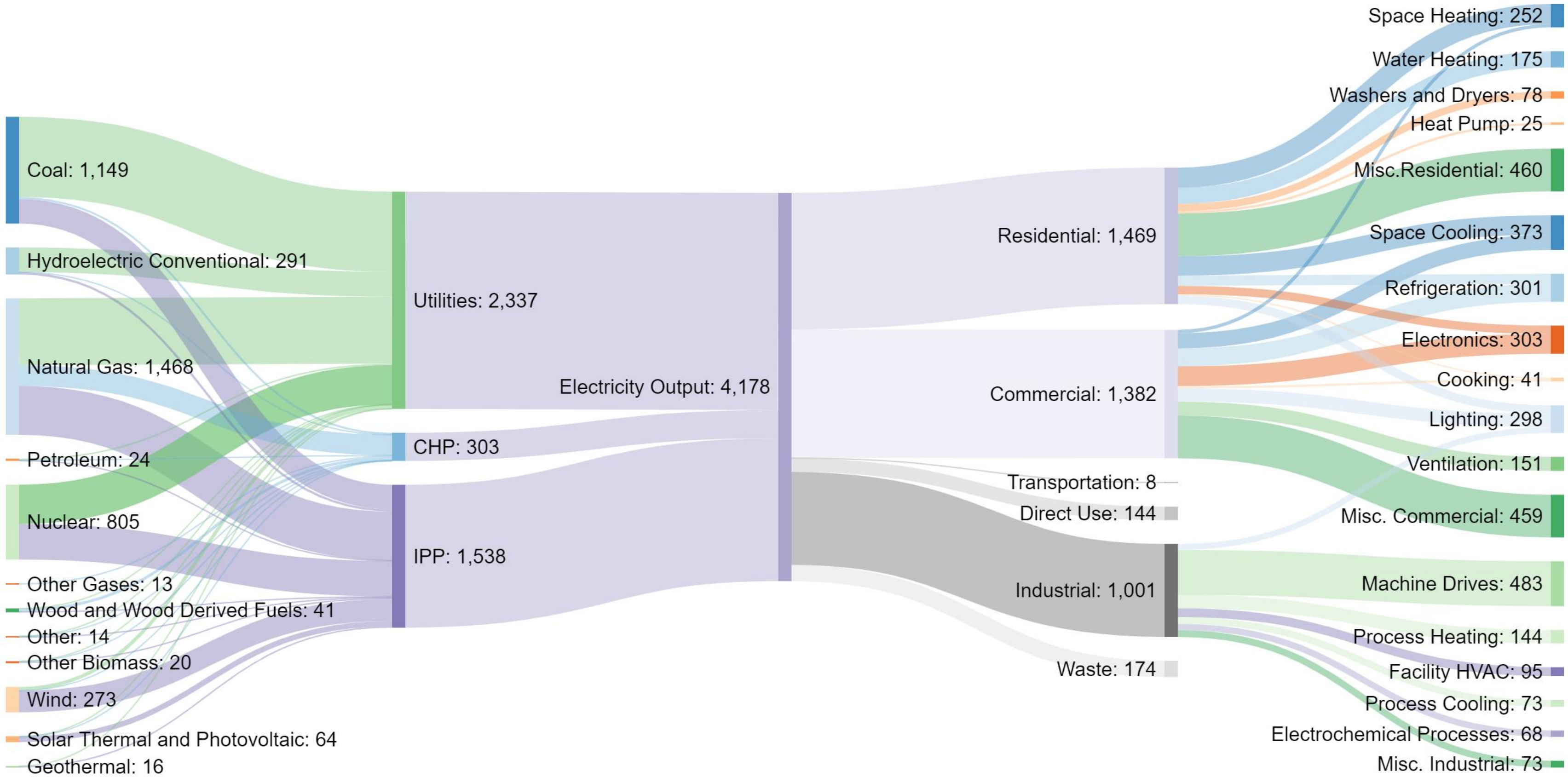
1.5 Organization of the Remainder of the Dissertation

The remainder of the dissertation is organized into three chapters analyzing the actions (analysis chapters) of the three different sets of actors and a concluding chapter that ties all the answers of the chapter-specific research questions to answer the overarching research questions. Each analysis chapter introduces the research topic, analyzes the existing literature, identifies potential gaps and demonstrates how the research question can address these gaps, provides methodological information and results that answers the research question, and closes with a discussion of the results, limitations, and avenues of future research. The dissertation also contains three separate Supplementary Materials sections each dedicated to one of the three analysis chapter which expands on the methods described in the relevant chapter and provides additional data and results that supplements the analysis of the chapters. References relevant to each chapter are self-contained.

Table 1.1: Summary of Actors, Objectives, and Actions

Actor	Objectives	Actions	Chapter
States and Federal Government	Meet long-term economy wide GHG emission goals	State policies and carbon taxes	2
Households	Improve energy efficiency of appliance usage	Purchase and usage of energy efficient appliances	3
Prosumers and Utilities	Ensure positive effects from installation of distributed PV (DPV) system	Prosumer: Installing a DPV system, choosing a tariff structure Utility: Setting solar compensation	4

Figure 1.1: Sankey diagram of electricity output flow from source to generation sources to end-use



Source: EIA Annual Electricity Data, 2018.

Notes: IPP – Independent power producers (includes distributed generators); CHP – Combined heat and power generators; HVAC – Heating, ventilation, and air conditioning/cooling.

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Chapter 2

Policy payoff: Are Aggressive State Electricity Policies Beneficial in the Context of Federal Re-engagement?

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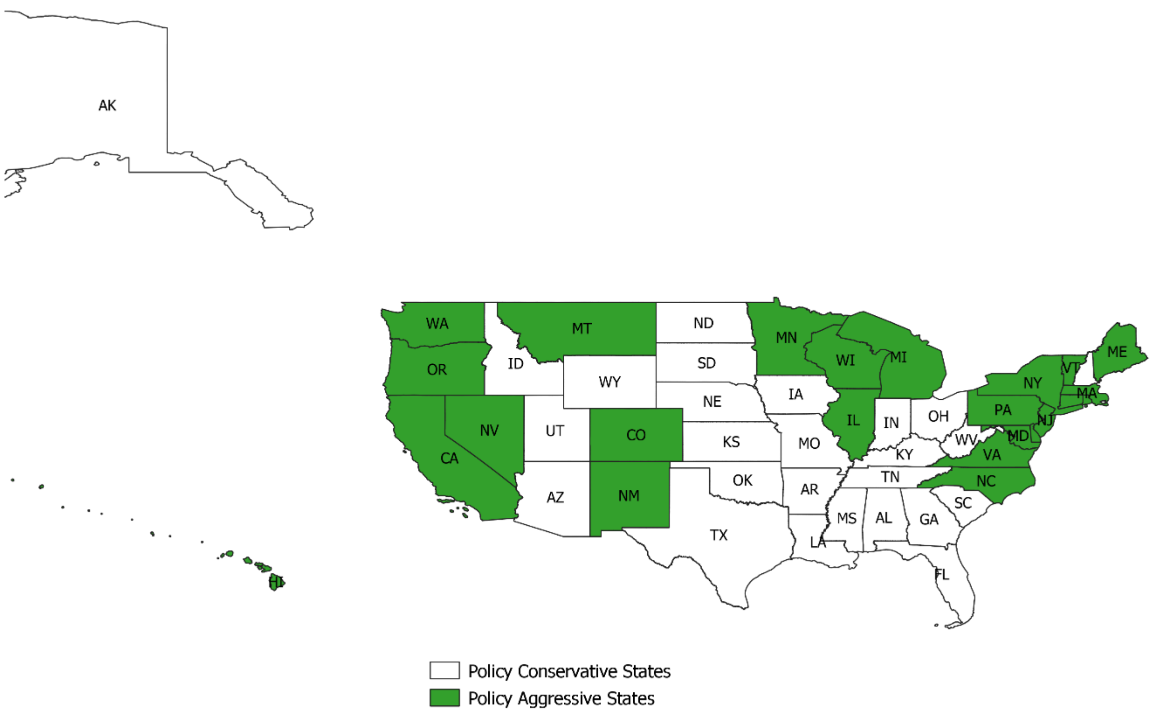
2.1 Introduction

In order to mitigate the most significant impacts of global climate change, 195 nations including the United States adopted the Paris Agreement ("Agreement") in the United Nations Framework Convention on Climate Change (UNFCC) on December 12, 2015("Historic Paris Agreement on Climate Change: 195 Nations Set Path to Keep Temperature Rise Well Below 2 Degrees Celsius | UNFCCC" n.d.). The President of the United States, Barack Obama was regarded as instrumental. United States, the second largest emitter of CO2 and GHG in the world(Boden, Marland, and Andres 2017), made commitments to reduce GHG emission by 26-28 per cent from 2005 levels by 2025 (Schreurs 2016). However, on June 1, 2017, the current U.S. President, Donald Trump announced the withdrawal of United States from the Agreement("Statement by President Trump on the Paris Climate Accord" n.d.) citing the economic disadvantage the U.S. faced under the agreement. A bipartisan coalition committed to meeting the objectives of the Agreement was formed by governors of several U.S. states and territories, known as the United States Climate Alliance (USCA)("Inslee, New York Governor Cuomo, and California Governor Brown Announce Formation of United States Climate Alliance | Governor Jay Inslee" n.d.). The Alliance currently represents 24 U.S. states (See Figure 2.1), in total accounting for over 40 per cent of the national CO2 emissions in

2017("Environment - U.S. Energy Information Administration (EIA) - U.S. Energy Information Administration (EIA)" n.d.).

Figure 2.1: Climate Alliance States



This research study asks - are states with aggressive policies better equipped to meet long-term U.S. GHG emission goals in the event of federal action? Does the Federal Government and Electricity sector benefit from more intensive aggregated state policies?

To answer these questions, the study analyzes the interaction between different levels of state policy action and a possible federal re-engagement starting from 2025, with the assumption being that with a maximum of two terms of the Trump Administration concluding at the end of 2024, a new administration will take up the challenge of emission reduction and institute federal actions to meet nationwide reduction targets. Given the long-term agenda of the USCA, it is also assumed that the member states will continue to aggressively pursue climate policies, and at a minimum the non-member states will not deviate from their current climate policy trajectories. The primary focus of the study is the electricity sector of the United States. Electricity accounted for 28 per cent of U.S. GHG emissions in 2017(US EPA 2015) and is the second largest contributor, behind transport. Electricity sector emissions have actually decreased substantially in the past two decades("Monthly Energy Review – March 2020" 2020) primarily due to the changing generation mix that has resulted in more gas and renewable energy in the grid and the flattening of electricity consumption. That being said, a number of studies find that the power sector is likely to contribute the largest GHG reductions, at least in the near-term, ,[16] and thus the sector merits a deep dive in terms of the interaction effects of state and federal policies.

2.1.1 Literature Review

The literature in the context of analyzing federal and state policies generally tend to focus on either state or on federal policies, either downscaling or aggregating their impacts on the other. Some studies analyze the impact of federally imposed emission restrictions or carbon prices on subnational entities(McFarland et al. 2015; Cole et al. 2018; Rausch and Karplus 2014). Other studies suggest what subnational entities can achieve on an aggregate in terms of GHG emission reduction without analyzing differences at the regional level(Nathan Hultman 2020; Kuramochi et al. 2017). Wiser et al. (2017)(Wiser et al. 2017) does both to some extent, with an analysis of an aggressive renewable portfolio standards (RPS) scenario deployment to meet the targets of the then-relevant Clean Power Plan (CPP) and what benefits and costs that entails in terms of electricity prices, air quality improvement, GHG emission reduction, and water use reduction. These numbers are reported both at a regional and at the national level. There is a third strand of studies which qualitatively discusses the implications of state-federal policy interactions (Rabe 2008; Peterson and Rose 2006; Goulder and Stavins 2011), but does not explicitly answer the quantitative impact of such interactions.

The literature surveyed does not answer the question whether or not the states that were already ahead of the curve in meeting their emission targets were better positioned in the more aggressive GHG reduction scenario in terms of their benefits and costs. This is important in the context of understanding state-federal policy interaction as a positive answer is likely to induce the states to make more of an effort to step up their policies and a negative answer is likely to induce them to maintain or even reduce their policy efforts.

This study analyzes the efforts of policy aggressive and conservative states in reducing GHG emissions in the electricity sector with and without federal intervention using integrated assessment modelling. It aims to determine whether or not the trajectory of state efforts alter significantly with federal intervention and how that alteration is related to the existing policy aggressiveness of the states concerned. We find that electricity grid regions comprised of policy aggressive states will not need to significantly alter the trajectory of their efforts in response to federal intervention which benefits them in terms of needing to not substantially alter the generation mix and face less price shocks in the marginal electricity prices at the wholesale market.

2.2 Methodology (Overview)

2.2.1 Grid Region Classification

The present study considers RPS as one of the state electricity policy, along with energy efficiency. We assume that other factors ("market factors") that impact electricity sector emissions such as fuel prices, GDP growth rate, coal power plant retirement, generation technology costs, building electrification, and vehicle electrification are based on projections from external studies. While state-level policies are modelled, our results are reported at the national level and at the grid level (See Figure 2.2 for U.S. Grid Region Map as defined in the GCAM-USA). Electricity is heavily traded within a certain grid and as such electricity consumption-focused policies of some states will impact that the grid as a whole in terms of potential leakages and reshuffling(Bushnell and Chen 2009). If USCA members contribute to more than 50 per cent of greenhouse gas emissions to a particular grid, we term that grid as Policy Aggressive, otherwise the grid is known as Policy Conservative (See Table 2.1 for the designation of U.S. electricity grids into Policy Aggressive and Policy Conservative Grids based on 2017 CO2 emission data). We have 8 policy conservative grids, and 7 policy aggressive grids with the former accounting for about two-thirds of the emissions.

Figure 2.2: U.S. Grid Regions

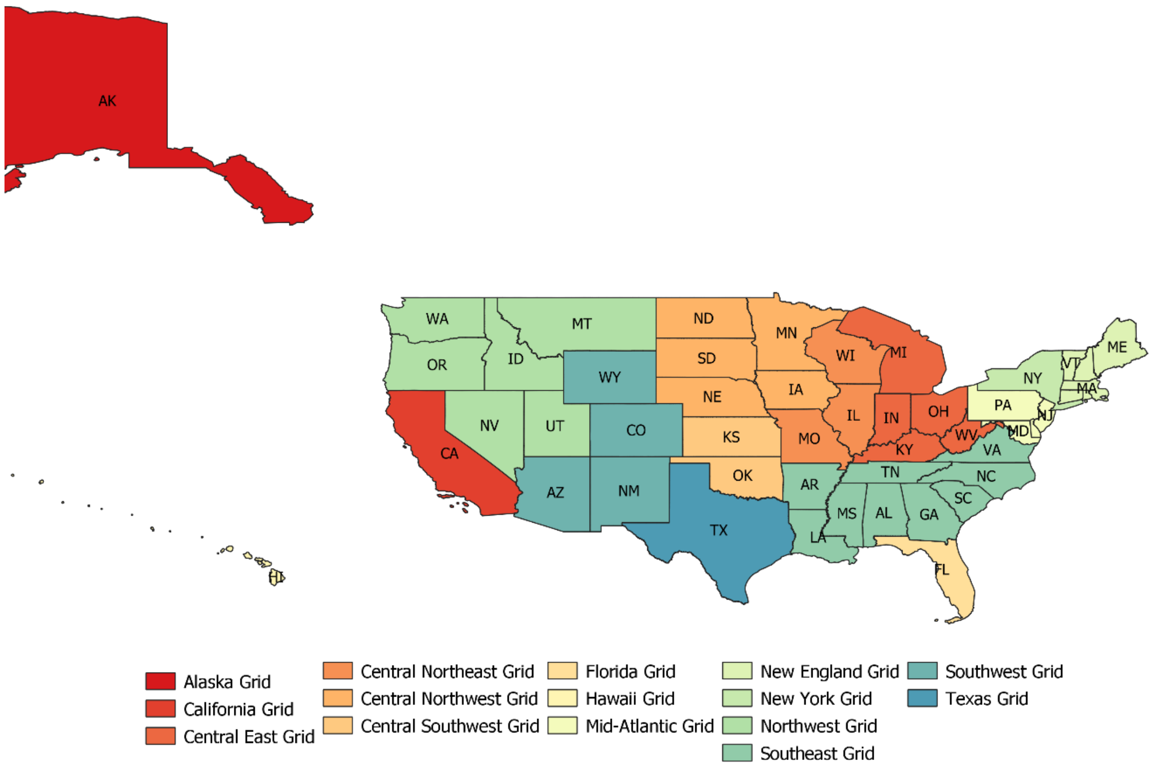


Table 2.1: Classification of Grids by Policy Aggressiveness

Grid Region	Climate Alliance States	Contribution to GHG emissions	Grid Status
Alaska	None	0%	Policy Conservative
California	All	100%	Policy Aggressive
Central East	Michigan	21%	Policy Conservative

Central Northeast	Illinois, Wisconsin	71%	Policy Aggressive
Central Northwest	Minnesota	31%	Policy Conservative
Central Southwest	None	0%	Policy Conservative
Florida	None	0%	Policy Conservative
Hawaii	All	100%	Policy Aggressive
Mid-Atlantic	Delaware, Maryland, New Jersey, Pennsylvania	99%	Policy Aggressive
New England	Connecticut, Maine, Massachusetts, Rhode Island, Vermont	91%	Policy Aggressive
New York	All	100%	Policy Aggressive
Northwest	Montana, Nevada, Oregon, Washington	70%	Policy Aggressive
Southeast	North Carolina, Virginia	22%	Policy Conservative

Southwest	Colorado, New Mexico	48%	Policy Conservative
Texas	None	0%	Policy Conservative

2.2.2 Overview of Analytical Tool

The analysis of electricity sector trajectories in response to state and federal policy measures is undertaken through a modified version of the open-source integrated assessment model Global Change Assessment Model USA (GCAM-USA), known as GCAM-AP. The benefit of an integrated assessment model is that although we primarily focus on the electricity sector, the results reflect its interplay with other sectors as well, which is beneficial given that federal intervention in the context of our research is not sector-specific. GCAM-USA has been used in the literature to analyze the sectoral impact of long-term climate targets in the United States(Iyer et al. 2017), analyze the impact of air pollutants at the state level(Shi et al. 2017), and water demand at a state level(Liu et al. 2015). GCAM-AP has been used for the America’s Pledge series of reports(N Hultman and Calhoun 2018). GCAM-AP enhances the capabilities of GCAM-US by effectively aggregating the effects of different actions at the state-level to avoid double counting, while also being calibrated to the GCAM-USA baseline data. The version of GCAM-AP used in this study improves upon the original in two aspects. First, it extends the formulation till 2050, and second – it adds an explicit Federal Re-engagement component rather than simply assuming that the states will increase their commitments in response to a Federal re-engagement scenario. (See Methods and Supplementary Materials for additional details.)

2.2.3 Overview of Scenario Design

Six scenarios are analyzed starting from 2020 till 2050 (See Table 2.2 for summary, Methods section for details on scenario construction including explicit numerical assumptions for each of the parameters, and Supplementary Materials for additional clarifications). We assume that in 2020, all scenarios have the same starting point in terms of key input variables. Three of the scenarios are dependent on intensity of policy actions by both the USCA and the non-member states, as well as the degree to which market factors are favorable towards GHG emission reduction. We term the least ambitious of these scenarios as the **“BAU”** scenario and the most ambitious as the **“High”** scenario with the **“Medium”** scenario in between. Collectively we term them as the **“Non-Tax Scenarios”**. The three additional scenarios simply involve federal action on top of state policies and underlying market factors through the institution of a carbon price from 2025 till 2050. These scenarios are termed as **“BAU + Tax”**, **“Medium + Tax”**, and **“High + Tax”**. Collectively we term them as the “**Tax Scenarios”**. It is to be noted that “Tax” is merely used as a convenient shorthand, and the actual implementation of carbon price may be either a direct tax or some kind of a carbon market which determines a price of carbon. GCAM calculates the appropriate carbon price given an emission constraint for a certain time period calculated at five-year intervals starting from 2025 to 2050. The emission constraint for each time period is set using a using a linear emission cap from 2025 to 2050 that ensures that the U.S. emissions from all economic sectors in 2050 is 80 per cent of the emissions of the 2005 level (Please see Section 6 and Table 2.4 for more details). The 2050 target is based on the U.S. Mid Century Strategy devised during the Obama Administration(Iyer et al. 2017) and is actually considered a conservative target given the recent push towards net zero GHG emissions by 2050 by some U.S. legislators(Carper et al., n.d.). However, as the literature suggests that U.S. will have trouble to meet the 2025 Agreement target apart from the most optimistic scenarios(Nathan Hultman 2020), it makes realistic sense to set the more modest target for 2050.

Table 2.2: Summary of Scenario Design

Scenario	**USCA Policy Aggressiveness**	**Non-Member Policy Aggressiveness**	**Market Conditions favorable to GHG Emission Reduction**	**Carbon Tax Applied**
BAU	Low	Low	Low	No
Medium	Moderate	Moderate	Moderate	No
High	High	High	High	No
BAU + Tax	Low	Low	Low	Yes
Medium + Tax	Moderate	Moderate	Moderate	Yes
High + Tax	High	High	High	Yes

2.3 Results

For all the scenarios, this study analyzes the following outcomes at national and grid levels. At the national level, we look at the emissions from the electricity sector between 2020 and 2050 and the carbon pricing (acting as a proxy for federal intervention) required to achieve those emission trajectories. At the grid level, we look at emission trajectories, electricity prices, and generation mix in terms of – i. Renewables to Fossil Fuel generation ratio in the grid and ii. CCS to Renewables ratio in the grid. The point of interest here is to compare the changes in these metrics both within and between grid regions in response to carbon pricing on the Non-Tax Scenarios.

At the national level, more aggressive state policies make federal intervention easier, which can be interpreted as requiring lower carbon prices in order to achieve the 80% GHG reduction from 2005 level by 2050 (Figure 2.3). In 2050, the "High + Tax" scenario required the application of two thirds of the tax compared to the "Low + Tax" scenario in order to achieve the same economywide GHG outcome. This is because the carbon price acts as a complementary measure to existing state policies and market factors. Even with the lower price levels, the more aggressive tax scenarios actually end up reducing more emissions in the electricity sector (Figure 2.4), which means that with higher level of state policy, the electricity sector takes the pressure of other sectors to contribute to GHG reductions. In 2050, the "High + Tax" scenario has a 30 per cent reduction of the emissions in the electricity sector compared to the "Low + Tax" scenario. It is also interesting to note that the most aggressive non-tax scenario, "High" has slightly lower emissions to that of the "Low +Tax" scenario till 2045, demonstrating the effectiveness of strong policies and market factors in the electricity sector even without a carbon tax.

Figure 2.3: Carbon tax (Taxes in $2018/ tonne of carbon dioxide equivalent)

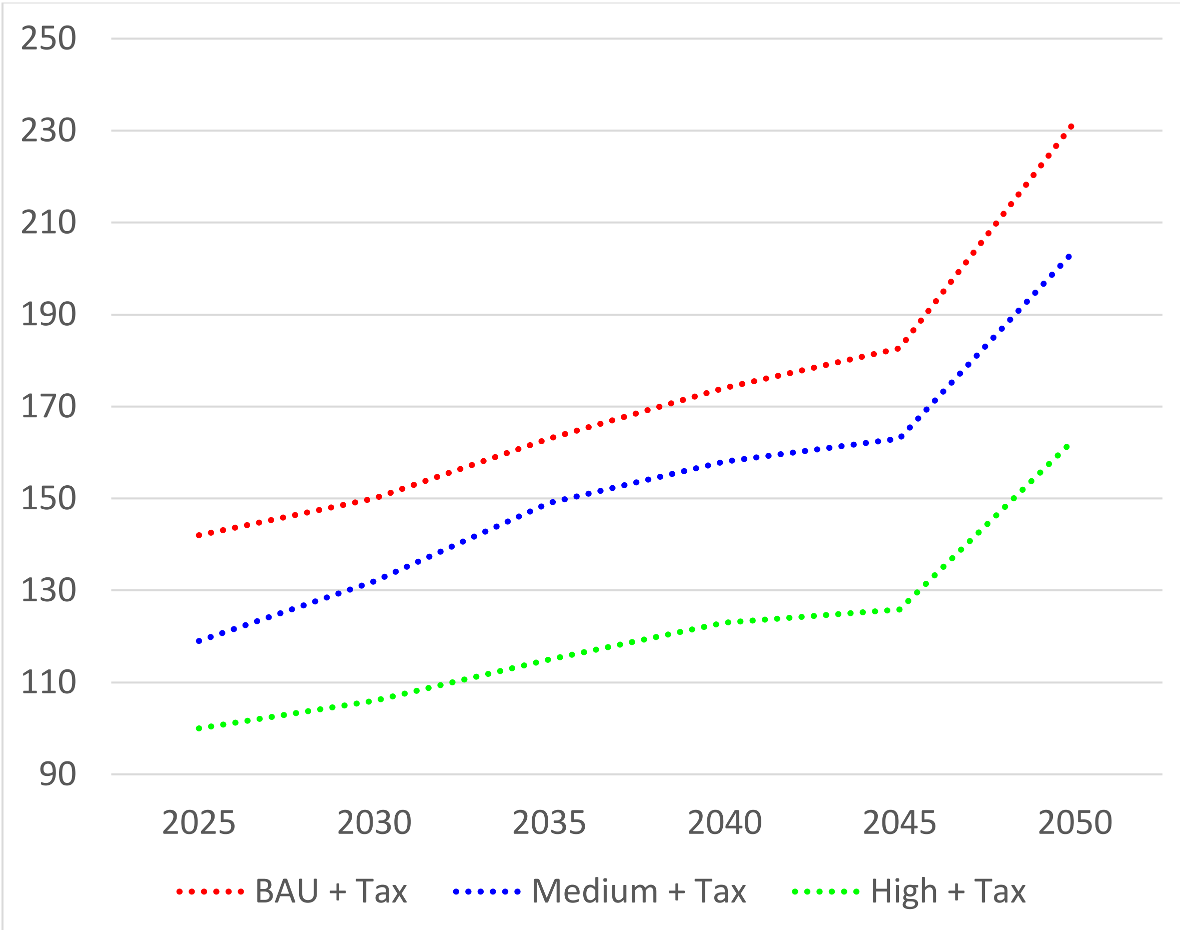
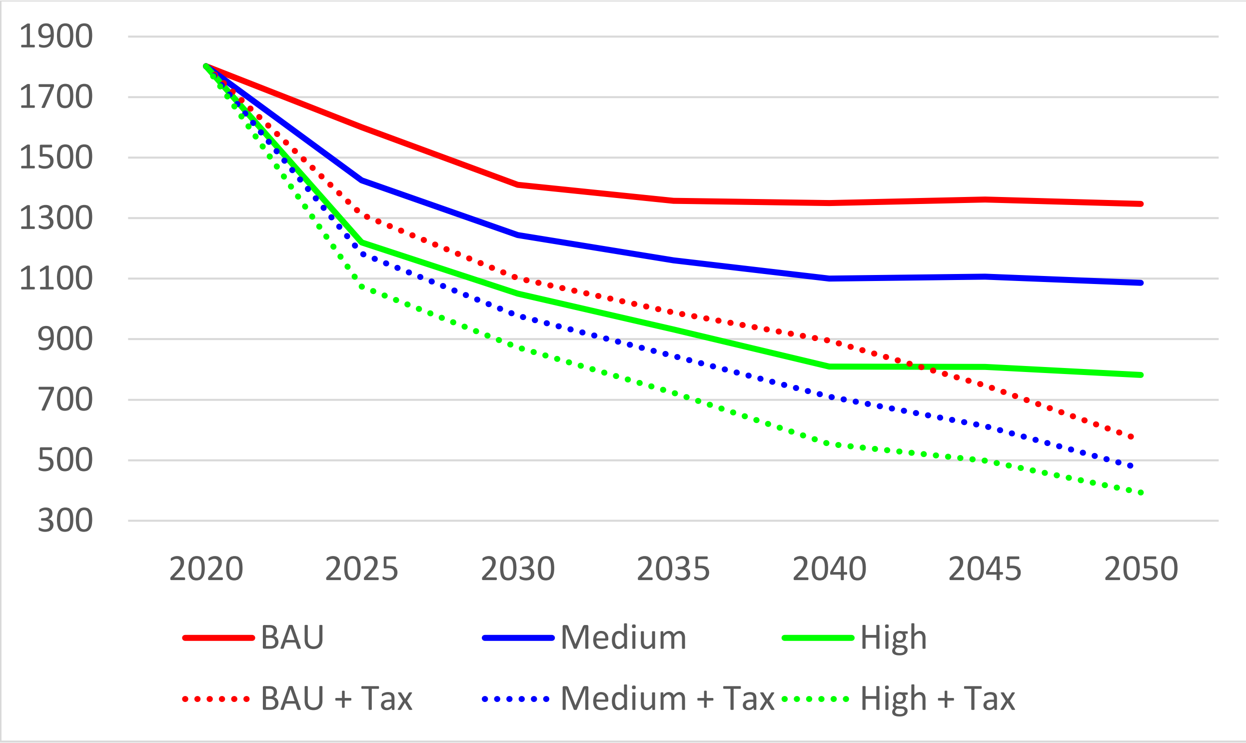


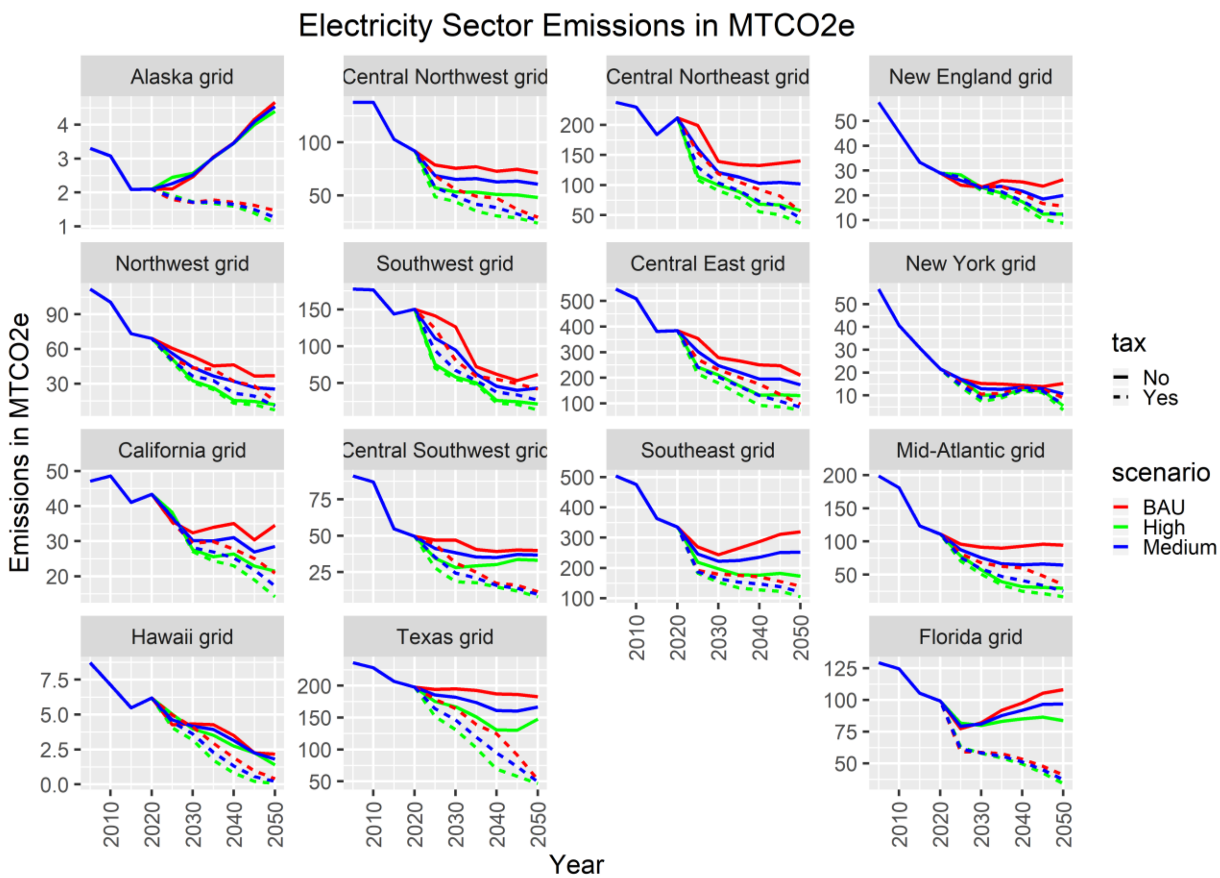
Figure 2.4: National Electricity Sector Emission Pathways (Emissions in million tonnes of carbon dioxide equivalent)



In all the federal intervention scenarios, Policy Aggressive Grids effectively take a leadership role in emission reduction and increasing the deployment of renewables in the electricity grid which means that while Policy Conservative Grids will have to make substantial adjustments, they have at least some cushion in terms of the work already done by the Policy Aggressive Grids. Additionally, because the Policy Conservative grids are marginally increasing their policy contributions in more aggressive non-tax scenarios, they are much better off than they would have been if they stuck to their BAU level of policy aggressiveness.

In terms of emission pathways, in the "High" scenario, the pathways of most Policy Aggressive Grids overlap with the "High + Tax" scenario indicating that the tax doesn't change a whole lot in the electricity sector generation mix for these grids (Figure 2.5). New York is an interesting case where emissions pathways from every scenario, tax or non-tax, practically overlap one another, indicating strong baseline policies. Meanwhile, for grid regions such as Florida, Texas, Southeast, there’s a clear divergence in the emission pathways of the non-tax scenarios and the tax-scenarios, with the best cases being some overlap of the “High” and “BAU + Tax” scenario emission pathways. This implies that these grid regions, in response to a carbon tax need to change their underlying generation mix more drastically than the Policy Aggressive grid regions. At an aggregate in 2050, there’s a 60 per cent difference in emissions in the “BAU + Tax” versus “BAU” scenario for Policy Conservative Grids compared to about 55 per cent for Policy Aggressive grids. Comparing “High + Tax” scenario to “High” scenario, the difference is 52 per cent for Policy Conservative grids compared to 38 per cent for Policy Aggressive grids.

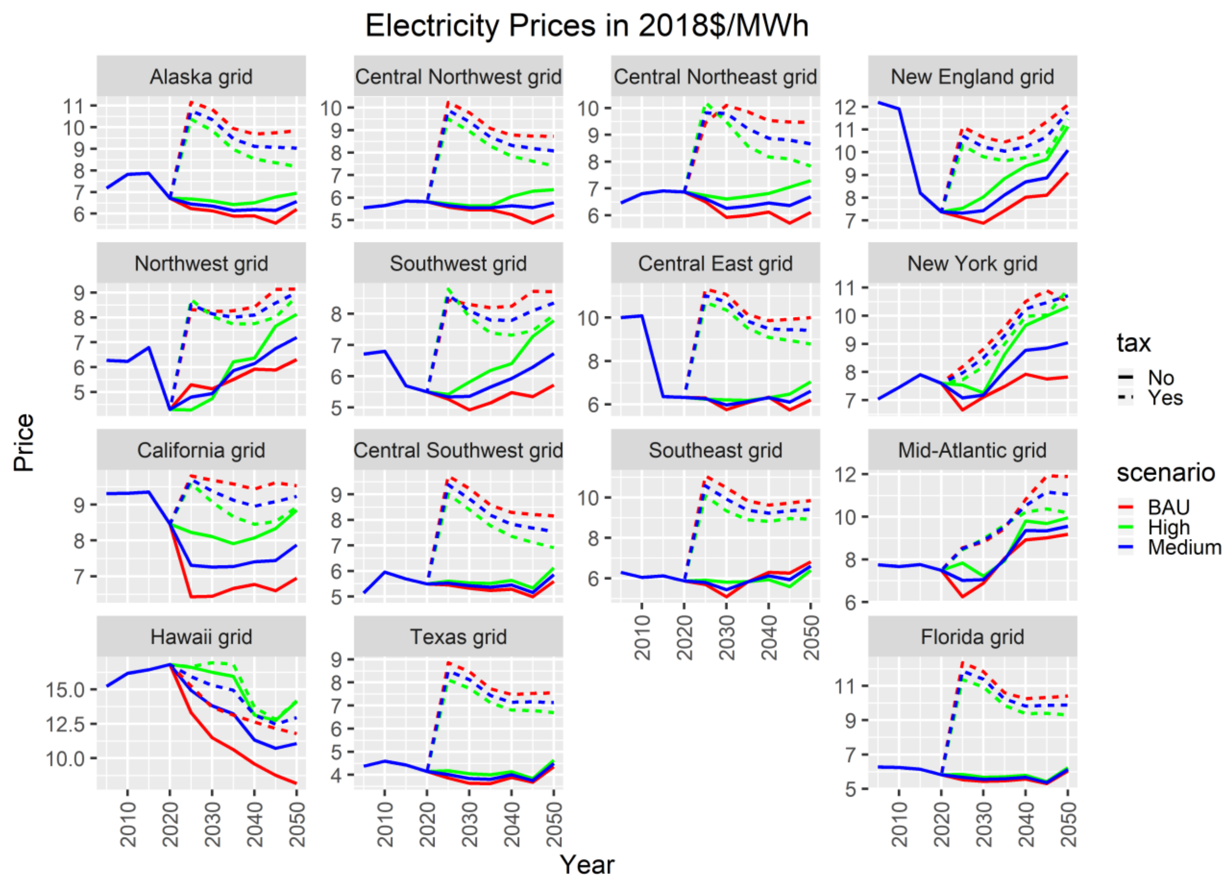
Figure 2.5: Emission by Grid Region



The changes in electricity prices also illustrates the insights gained from analyzing relative emission trajectory changes. In response to a price on carbon, all grids will face a price shock, but the degree of shock is far lower in the Policy Aggressive Grids compared to the Policy Conservative Grids (Figure 2.6). The contrast is especially evident when we compare grid regions such as Florida and Southeast with regions such as New York and Mid-Atlantic. In both cases there exists a bunching of the non-tax scenario pathways and the tax scenario pathways, but in the former cases, there are no overlaps between the two, indicating a greater degree of price adjustments for the Policy Conservative Grids. On an aggregate, prices in the “BAU+Tax” scenario are higher than the BAU scenario in 2050 by 58 per cent in the Policy Conservative Grids and by 38 per cent in the Policy Aggressive

Grids. For “High+Tax” versus High scenario, the increases are 25 per cent and 4 per cent respectively.

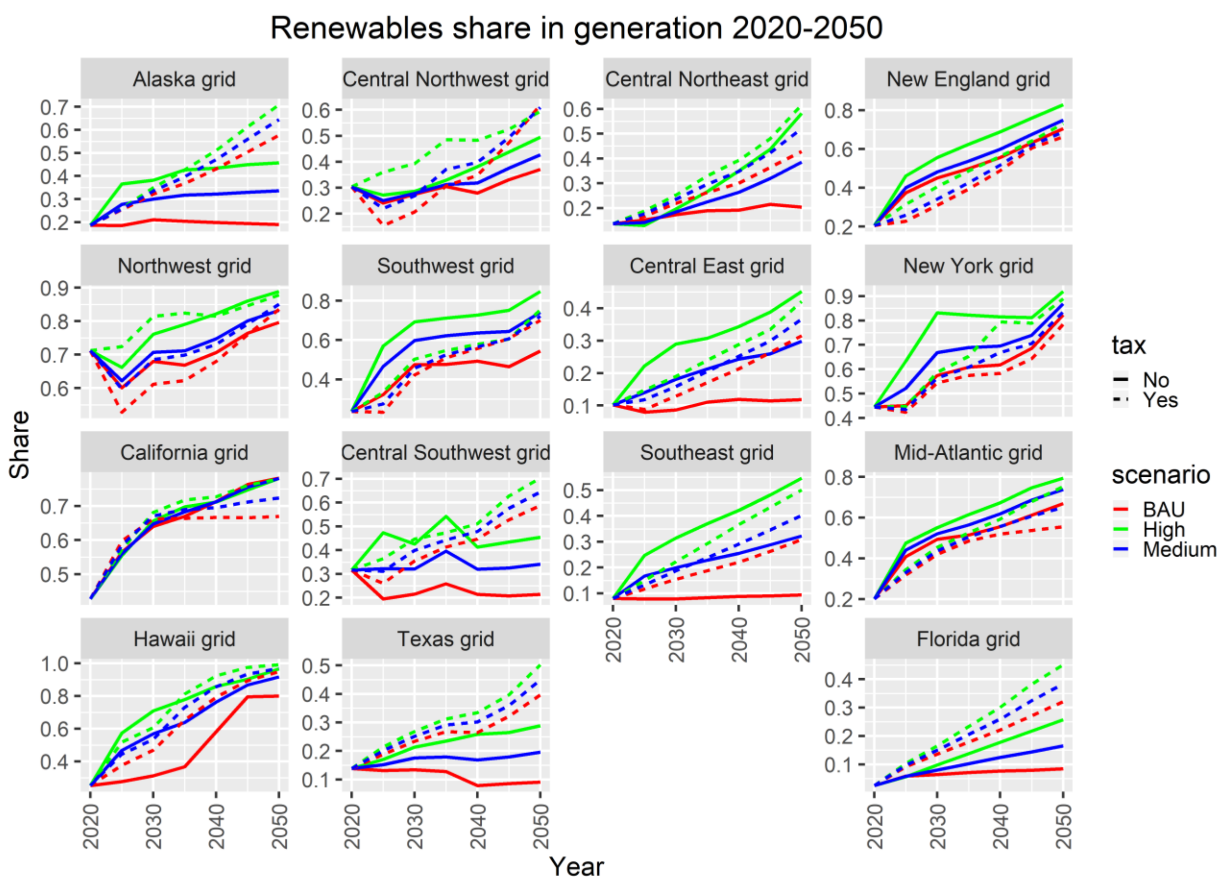
Figure 2.6: Prices by Grid Region



The underlying generation mix plays a major role in determining emissions and prices. Three aspects of the generation mix – share of renewables, share of fossil fuels, and share of CCS in the mix are analyzed in order to provide insight the level of adjustments states will have to make with the imposition of a federal policy. For most Policy Aggressive Grids, deployment of renewables tends to be higher in the non-tax scenarios compared to their respective tax scenarios due to some CCS being installed in the tax scenarios (Figure 2.7). Examples include New York, New England and Mid-Atlantic. In most Policy

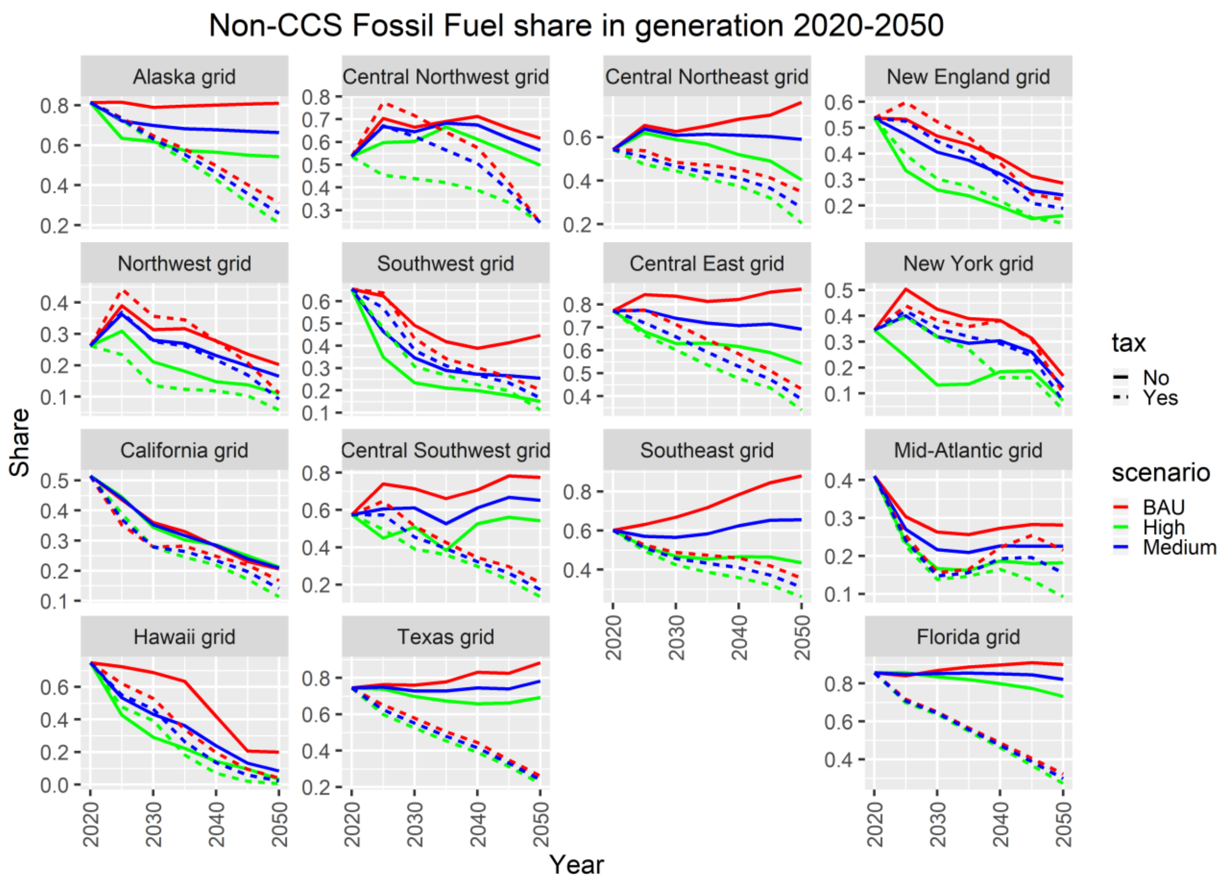
Conservative grids, there is a dramatic increase in renewables deployment in response to tax compared to the corresponding non-tax scenario, e.g. in Florida, Texas and Central Northwest. That being said, some Policy Conservative grids do well in deploying renewables in the "High" scenario, e.g. Southeast, Central East, and Southwest even if their efforts are lacking in the lower ambition scenarios. In 2050, the average share of renewables in a Policy Conservative Grid is about 55 per cent higher in the "BAU +Tax" case compared to BAU, and is only about 3 per cent higher for Policy Aggressive Grids. For "High+ Tax" case compare to High, the differences are 20 per cent and -2 per cent (i.e. renewables are deployed more in the High case than High + Tax) respectively.

Figure 2.7: Share of renewables in the generation mix (excluding CCS)



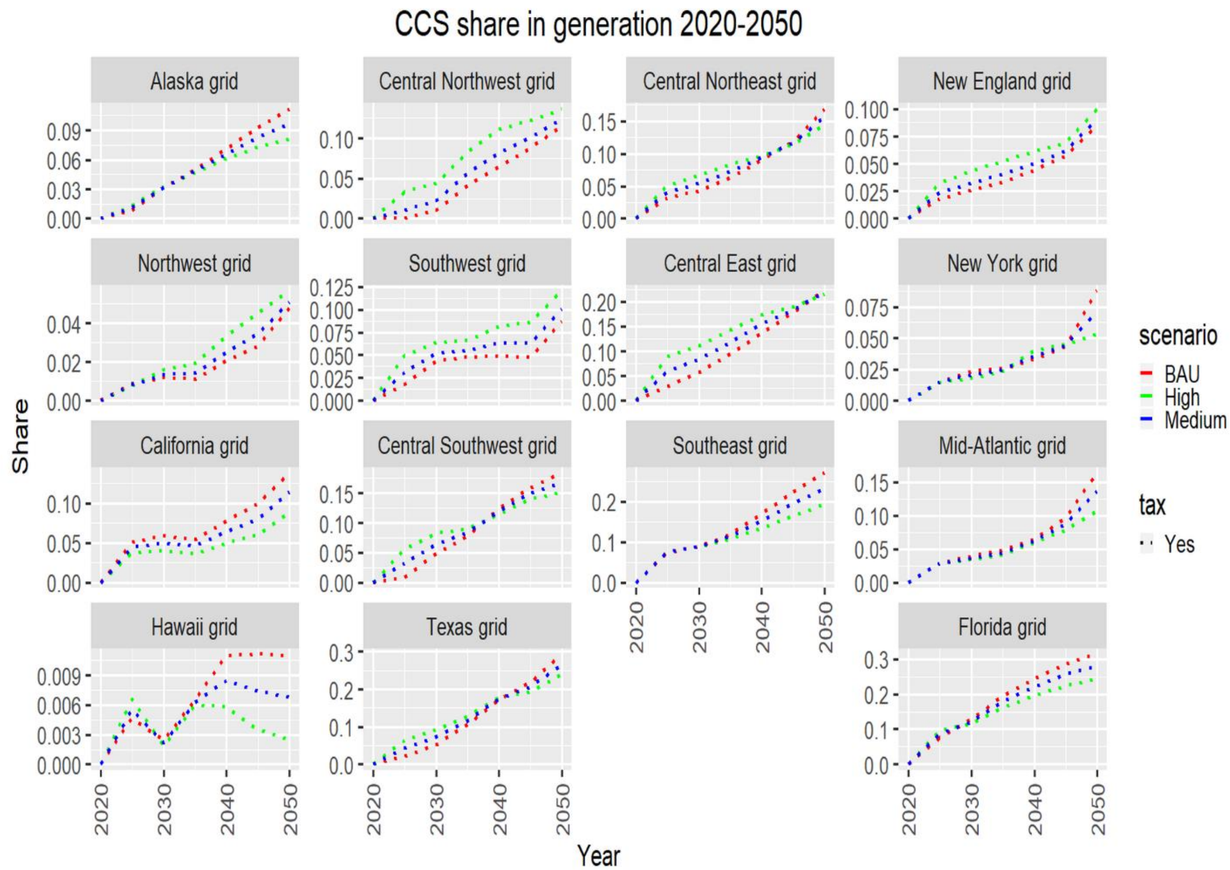
Most Policy Conservative Grids will need to dramatically reduce their dependence on fossil fuels in response to a federal intervention compared to Policy Aggressive Grids (Figure 2.8). In 2050, the average share of fossil fuel in a Policy Conservative Grid is about 63 per cent lower in the "BAU +Tax" case compared to BAU, and is about 45 per cent lower for Policy Aggressive Grids. For "High+ Tax" case compare to High, the differences are 57 per cent and 43 per cent respectively. It should however be noted that numerically, the average shares are much lower in Policy Aggressive Grids to begin with (30 per cent in BAU and 17 per cent in High compared to 77 per cent and 52 per cent for Policy Conservative Grids), so even a relatively high percentage reduction implies a relatively modest reduction as far as generation is concerned.

Figure 2.8: Share of non-CCS fossil fuel in the generation mix



CCS is only deployed in GCAM when there is a direct financial incentive do so, which is provided by a direct pricing of carbon. The key takeaway from analyzing CCS share in the generation mix of various grid regions (Figure 2.9) is that Policy Conservative Grids (e.g. Texas, Florida, Central East) will tend to deploy more CCS than Policy Aggressive Grids (Mid-Atlantic, New England, Northwest). This is partially because of the already entrenched renewables generation portfolio in most Policy Aggressive Grids although as noticed earlier, CCS will displace some of the renewables at higher tax scenarios. Policy Conservative Grids also may find it effective to retrofit some of their existing fossil fuel fleet (which are generally more substantial than those in the Policy Aggressive Grids) with CCS in addition to installing renewables capacity, given the challenge of decreasing their fossil fuel generation at a much rapid rate compared to Policy Aggressive Grids.

Figure 2.9: Share of CCS in the generation mix (tax scenarios only)



2.4 Discussion

In determining whether policy aggressive grids are better off when federal intervention is introduced to reduce GHG emissions and if more aggressive state actions in general reduce the degree of federal intervention required, the results have a few implications. First, in general if the country as a whole is pursuing more aggressive policies even at a differentiated rate by states, it will lower the burden of federal action and increase the contribution that the electricity sector makes in lowering national emissions. Second, Policy Aggressive grids will have to adjust considerably less in terms of their generation pattern, prices, and emission mix in response to federal intervention. Thus, aggressive policies at the state level make sense for benefits to the states themselves and the grid regions they are part of, in addition to the national context.

The study has some limitations that can serve as future avenues of research. Firstly, state policies can be extended to sectors other than electricity and results of federal intervention can be analyzed on a per sector basis to determine which sectors share most of the reduction burden at the state level and at the federal level under different levels of state policy aggressiveness. Secondly, we do not account for additional scenarios where the Policy Conservative Grids consistently "Free Ride", i.e. never changes their contributions from the BAU level irrespective of what the Policy Aggressive Grids are doing. When a tax is applied on these free-rider scenarios, our hypothesis is that the policy conservative grids would have to do much more in terms of reducing emissions and face more price shocks than the scenarios where Policy Conservative Grids increase their own contributions as well. Thirdly, market factors play a significant role in determining the emission, price and generation pathways in our scenarios. The reason why the market factors were allowed to vary was to give us a sense of the "relatively pessimistic" and "highly optimistic" bound of scenarios that can exist without federal policy intervention, and our hypothesis is that every other possibility will be represented by pathways that fall somewhere in the middle, of which we modelled one (the Medium scenario). However, certain market factors such as coal power plant retirement economics (discussed in detail in Supplementary Materials) and cost of technologies do play a significant role in determining our outcomes of interest. This is especially true for Policy Conservative Grids which have substantial coal power generation capacity and in the absence of very aggressive policies even in the most aggressive scenarios, coal power shutdown and cost of competing technologies may have a bigger role in determining generation mix (and consequently prices and emission trajectories) than policies alone. Additional scenarios can be constructed holding the market factors constant for different levels of policy aggressiveness. Fourthly, Detailed sensitivity analysis can also be done for each of the policy factors and market factors to determine which plays the biggest role in determining the outcomes of interest. Fifthly, the study can also be extended to add scenarios where federal intervention is applied and withdrawn at different time periods and withdrawn due to changes in political landscape instead of a straightforward implementation from 2025 to 2050. The relative aggressiveness of the intervention can also be altered based on recent political developments. Sixthly, From the current set of scenarios alone, the role of declining fossil fuel and increased CCS in tax scenarios can also be studied further in terms of determining the additional cost of retrofitting fossil fuel plants with CCS and the cost of stranded assets in Policy Conservative Grids in particular where there is significant fossil fuel generation reduction. The distributional impact of such costs can also be studied at the grid region level to determine potential economic ramifications of having or not having aggressive state policies when faced with significant federal GHG emission reduction mandates.

This study highlights that states and market forces alone can achieve a great deal in the decarbonization of the U.S. electricity grid, but the final push towards a substantial impact in the long-term climate ambitions make federal directives necessary. However, it is also in the own interest of the non-Federal actors to make a significant contribution to the long-term climate ambitions through their own actions to make the transition easier for the Federal government where the latter can play a supporting role instead of having to be the main architect of climate policy. This has significant impact in terms of changes the subnational entities must make to their electricity sector and the shocks they will face as well as determining the direct burden of the taxpayers under federal action. Pro-active actions of subnational entities will help themselves and help the United States in the longer run to efficiently achieve ambitious climate goals ensuring the long-term prosperity of all.

2.5 Detailed Methodology

This study analyzes six scenarios to determine whether or not policy aggressive states will have to face less adjustments to their electricity sector emissions, prices, and generation mix when a federal re-engagement in terms of carbon tax is introduced. A two-step analytical approach was used for modeling, largely following the methodology outlined by Hultman et al. (2020)(Nathan Hultman 2020). In the first-step termed as **"Sectoral Analysis"**, climate policies were translated into activity data using the Athena tool, e.g. the state-level renewable generation resulting from state and city renewable energy policies. The primary focus of this step was to aggregate state-level data without double counting and taking into account the most high impact actions in each sector GCAM-AP data served as the baseline for some parameters, e.g. energy efficiency – which is explicitly modelled as percentage change in electricity consumption reduction from the baseline. In the second step termed as **"Economic Analysis"**, results of the first step were converted into inputs for the GCAM-AP model (Please see Supplementary Materials for additional details in the case of both Sectoral Analysis and Economic Analysis). The electricity sector of GCAM-AP consists of state-level representations of the U.S. electricity sector, accounting for different technologies with varying economic and technical attributes such as costs and capacity factors, vintages (years when plants became operational), and load segments. Market equilibrium is calculated over 5-year period intervals between 2020 and 2050 and is achieved when the model finds a set of prices that creates equality of demand and supply in all markets.

Apart from scenario parameters that were explicitly modified for this study (discussed below), assumptions regarding all other sectors such as agriculture, oil and gas production, hydrofluorocarbons, land use are used as is from the reference version of the GCAM-AP model (Please see Supplementary Materials for additional details).

The discussion of scenario assumptions consists of two parts. Firstly, to clarify what "Low", "Medium" and "High" mean for each of the parameters specified in Table 2.2 (Please see Table 2.3 for a numerical summary) and Secondly, how these parameters were calculated. For additional details on these parameters and their calculations, please refer to Supplementary Materials.

- **Low**
  - USCA Policies: This is the extension of current level of policies for USCA member states in terms of RPS and Energy Efficiency (EE) targets. Since these are percentage targets, we simply assume that these targets, if not currently set till 2050, will continue to apply till 2050 beyond the last policy date, e.g. if a state has a RPS of 35% set till 2030, we assume that 35% will be applicable from 2035 to 2050. **The USCA states contribute to 25% effective RPS of their total generation in this scenario in 2050.**
  - Non-Member Policies: Same as USCA policies. This also means that states without a RPS/EE policy (Oklahoma) or states that have explicitly set a termination data for their RPS/EE policies (Ohio) will continue to have zero policy targets for the entirety of the model period or beyond the end date,

whichever is applicable. **The non-member states contribute to 3% effective RPS of their total generation in this scenario in 2050.**

- Market conditions:
  - Coal Retirement: Based on profitability of plants between 2012-2017 as calculated by BNEF(N Hultman and Calhoun 2018). We assume that beyond existing confirmed retirements, the plants with six years of consecutive losses shut down in 2025, five years of consecutive losses shut down in 2030, and so on, until only plants that have been consistently profitable between 2012 and 2017 remain open in 2050. Our assumption is that the plants which have been unprofitable for many years are unlikely to turn a profit in the future given that the trend of coal power plant profitability has been consistently going downward. Coal power generation capacity at the end of 2050 is 38 GW, about 14 per cent of the present capacity. No new conventional coal capacity is constructed (as based on current evidence, there are no conventional coal-fired plants under construction in the United States).
  - Capital Cost: Capital cost trajectory between 2020 and 2050 is directly inputted from National Renewable Energy Laboratory (NREL)'s Annual Technology Baseline (ATB)'s 2019 version of "Low Improvement" costs(Vimmerstedt et al. 2019).
  - Fuel Prices: Fuel price (natural gas and crude oil) trajectory between 2020 and 2050 is used from U.S. Energy Information

Administration (EIA)'s Annual Energy Outlook 2019(U.S. Energy Information Administration, n.d.). The Low Cost case is used. For natural gas, the Henry Hub spot prices are used. For Crude Oil, West Texas Intermediate Prices are used.

    - GDP Growth: Assumed at 2 per cent per year on an average, based on Congressional Budget Office's 2019-2029 projections(U.S. Congressional Budget Office, n.d.).
    - Building Electrification: Based on NREL's Electrification Future Study(Mai et al. 2018), about 300 TWh of electrification increase between 2020 and 2050.
    - Vehicle Electrification: Based on the same NREL study, assuming an increase of about 475,000 vehicles miles travelled on electric vehicles between 2020 and 2050.

- **Medium**
  - USCA Policies: **The USCA states contribute to 50% effective RPS of their total generation in this scenario in 2050.** Doubling their existing commitments in such a way that any state already above this rate in terms of existing commitments will not have to increase their commitments, but states that have fallen short in terms of existing commitments will have to match the trajectories to the dominant states in the coalition.
  - Non-Member Policies: **The non-member states contribute to 10% effective RPS of their total generation in this scenario in 2050.** Same

principle of adoption as USCA states, although with a large number of non-member states not having any RPS policies or that well below 10 per cent, most states will have to adopt the 10 per cent mark.

- Market conditions:
  - Coal Retirement: Accelerate retirement by one period from Existing, i.e. by 2025 all plants with five years or more accumulated losses retire, by 2030 all plants with four years or more accumulated losses retire and so on. In 2050, every conventional coal-fired power plant shut down.
  - Capital Cost: Capital cost trajectory between 2020 and 2050 is directly inputted from National Renewable Energy Laboratory (NREL)'s Annual Technology Baseline (ATB)'s 2019 version of "Medium Improvement" costs(Vimmerstedt et al. 2019).
  - Fuel Prices: Fuel price (natural gas and crude oil) trajectory between 2020 and 2050 is used from U.S. Energy Information Administration (EIA)'s Annual Energy Outlook 2019(U.S. Energy Information Administration, n.d.). The Reference Case is used. For natural gas, the Henry Hub spot prices are used. For Crude Oil, West Texas Intermediate Prices are used.
  - GDP Growth: Assumed at 2 per cent per year on an average, based on Congressional Budget Office's 2019-2029 projections(U.S. Congressional Budget Office, n.d.).

        - Building Electrification: Based on NREL's Electrification Future Study(Mai et al. 2018), about 500 TWh of electrification increase between 2020 and 2050.
        - Vehicle Electrification: Based on the same NREL study, assuming an increase of about 975,000 vehicles miles travelled on electric vehicles between 2020 and 2050.

- **High**
    - USCA Policies: **The USCA states contribute to 75% effective RPS of their total generation in this scenario in 2050.** A linear increase in commitments over medium results in effectively all states contributing at or close to 75% RPS mandate individually.
    - Non-Member Policies: **The non-member states contribute to 25% effective RPS of their total generation in this scenario in 2050.** This brings non-member states in terms of contributions to the "Low" policy contribution of the USCA states.
    - Market conditions:
        - Coal Retirement: Accelerate retirement by one period from Medium, i.e. by 2025 all plants with four years or more accumulated losses retire, by 2030 all plants with three years or more accumulated losses retire and so on. In 2045, every conventional coal-fired power plant shut down.
        - Capital Cost: Capital cost trajectory between 2020 and 2050 is directly inputted from National Renewable Energy Laboratory

(NREL)'s Annual Technology Baseline (ATB)'s 2019 version of "High Improvement" costs(Vimmerstedt et al. 2019).

- Fuel Prices: Fuel price (natural gas and crude oil) trajectory between 2020 and 2050 is used from U.S. Energy Information Administration (EIA)'s Annual Energy Outlook 2019(U.S. Energy Information Administration, n.d.). The High Cost case is used. For natural gas, the Henry Hub spot prices are used. For Crude Oil, West Texas Intermediate Prices are used.
- GDP Growth: Assumed at 2 per cent per year on an average, based on Congressional Budget Office's 2019-2029 projections(U.S. Congressional Budget Office, n.d.).
- Building Electrification: Based on NREL's Electrification Future Study(Mai et al. 2018), about 800 TWh of electrification increase between 2020 and 2050.
- Vehicle Electrification: Based on the same NREL study, assuming an increase of about 1.475 million vehicles miles travelled on electric vehicles between 2020 and 2050.

Table 2.3: Comparison of Scenario Parameters

Parameter	BAU	Medium	High
USCA Policy (% of generation in RPS)	25	50	75

Non-Members Policy (% of generation in RPS)	3	10	25
Coal Retirement (GW remaining in 2050 vs 2020)	38/281	0/281	0/281
Capital Cost (NREL assumptions used)	Low Improvement	Medium	High Improvement
Fuel Price (Oil and Gas price in 2020 vs 2050 – Oil in $2018/barre, Gas in $2018/MMBtu)	Oil: 69.72/ 49.71 Gas: 11/3.39	Oil: 69.72/ 104.52 Gas: 11/4.87	Oil: 69.72/ 208.11 Gas: 11/8.24
GDP Growth (annual %)	2	2	2
Building Electrification (TWh in 2050 over 2020)	300	500	800

Vehicle Electrification (VMT in 2050 over 2020)	475,000	975,000	1,475,000

Carbon pricing application: Carbon pricing was calculated for each of the scenarios using the emissions trajectory between 2025 and 2050 outlined in Table 2.4. The 2005 GHG emission in the United States was 7339 MTCO2e(US EPA 2017). We assume the 2020 GHG emissions to be roughly below 15% that level, an optimistic projection based on preliminary 2019 emissions data("Preliminary US Emissions Estimates for 2019" n.d.) which estimates a 12% reduction from 2005 level. For reference, the Agreement target was a 17% reduction from 2005 levels(Belenky 2015). The 2020 emission assumption is the starting point of the linear pathway of emission reduction, with an ending point of 80% GHG reduction from 2005 level in 2050.

Table 2.4: Carbon tax emission trajectory

Year	Emission Cap (GHG in CO2e)
2025	5,443
2030	4,648
2035	3,853
2040	3,058
2045	2,263
2050	1,468

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Chapter 3

Energy Strategy: Aggregate household behavior in heating and cooling control strategy and energy efficient appliance adoption

Arijit Sen and Yueming Qiu

3.1 Introduction

Energy efficiency has long been considered to be one of the most cost-effective way to reduce greenhouse gas (GHG) emissions [1], particularly in the residential sector which was responsible for around 20% of the total energy consumption in 2017 (U.S. Energy Information Administration (EIA) 2018). The residential sector has long been targets of policies and incentives to promote energy efficiency (Nejat et al. 2015). These include policies identifying appliances that would reduce long-term electricity consumption, and reduce the payback period of purchasing these appliances through financial incentives (Jones, Fuertes, and Lomas 2015). These appliances are termed as energy efficient appliances. Once a consumer purchases such an appliance, their energy usage behavior plays a significant role in determining the actual energy savings (Lopes, Antunes, and Martins 2012). Electricity consumption in general is influenced by a myriad of other factors (Kavousian, Rajagopal, and Fischer 2013) such as – physical characteristics of the dwelling including type of building, house size, house age; demographic characteristics of the occupants including income, race, gender, age distribution, and level of education. The distinction between appliances that are "always on" and those that operate in accordance with differing occupant behavior patterns is also important. There exists a fair bit of research on the linkage between occupant behavior and energy efficiency. Kavousian et al.

[6] notes that households who tend to buy energy efficient appliances are generally those with higher levels of consumption and tend to be wealthier. Income is considered as a potential factor for both higher level of consumption and the ability to buy higher priced energy efficient appliances. A meta study by Karlin et al. (Karlin et al. 2014) demonstrates two strong behavioral dimensions – curtailment and efficiency, with curtailment measures being easier to adopt but less effective on a longer time horizon compared to efficiency measures.

The theory of occupant behavior and its relationship to energy efficiency can be used as a backdrop to formulate the research questions for this paper – *How can household behavior in terms of adoption of energy efficient white goods*[1] *appliances and temperature control strategy of space heating and cooling equipment be jointly categorized (white goods refer to large electrical appliances)? What are the factors associated with households being categorized into different behavioral groups?*

Following research parameters set up by Hong et al. (Hong et al. 2017), it is important to identify both technical and social factors of occupant behavior. From the technical side, adoption and usage must both be considered for relevant appliances, given the asymmetric impact of appliances such as heater and air conditioning on total energy usage (Santos et al. 2018) with rebound effects being a larger concern for such appliances (A. Greening, Greene, and Difiglio 2000). However, it is also to be noted that the way people use temperature control for heating and cooling can differ significantly among people given that effective use of thermostats is considered difficult (Meier et al. 2011). A number of

[1] White goods - A class of consumer durables that includes washing machines, dishwashers, refrigerators, tumble-dryers, deep-freezers, and cookers; they are so named because they are usually finished in white enamel paint… (Oxford Reference)

studies report that thermostats in general are improperly utilized (Pritoni et al. 2015) (Peffer et al. 2011). If temperature setting of heating/cooling equipment and adoption of other energy efficient appliances are considered as joint variables of interest, statistical analysis (Liao, Farber, and Ewing 2015) (Gibbons and Wilcox-Gök 1998) can enable us to determine the share of households that are using energy efficient appliances but not using thermostats effectively versus those that are doing both.

From a social perspective it is important to consider the factors that are closely associated with different behavioral patterns, e.g. demographics, household characteristics, or potential financial incentives (Abrahamse and Steg 2011). Patterns demonstrated through the behavioral classification and characterization process can be used to improve smart home demand response or demand management algorithms by providing data for better load segmentation and demand forecasting (Beaudin and Zareipour 2015) (Pipattanasomporn et al. 2014). The patterns can be used by policymakers to identify characteristics of households that have significant shortcomings in the adoption of energy efficient appliances and temperature control strategy. This information can be utilized to develop more effective targeting strategies on behavioral change. (Fischer 2008) (Markandya, Labandeira, and Ramos 2015).

The remainder of the paper is structured as follows. The next section of the paper looks at the relevant existing literature that informs the research question and relevant gaps. The paper then describes the dataset and methods to answer the research question, followed by the key results. A discussion section outlines how the key results of the paper can be used as valuable inputs to several engineering and policy problems regarding residential energy efficiency, concluding the paper.

3.2 Literature Review and Motivation

Several studies look at the physical and social characteristics of households with regards to energy efficiency. A number of studies find that it is easier to undertake simple and short-term technical changes rather than long-term behavioral changes (e.g. buying an energy efficient appliance vs optimally setting up a thermostat) (Poortinga et al. 2003) (Karlin et al. 2014) (Pothitou, Hanna, and Chalvatzis 2016). More in-depth studies into social and other demographic factors (Jones, Fuertes, and Lomas 2015) (Frederiks, Stenner, and Hobman 2015) find that statistically significant energy efficient behavior is often associated with better economic and housing situation, higher education, relatively young age, and urban residency. Utility incentives are generally strong predictors of energy efficient behavior (Alberini and Towe 2015) (Datta and Filippini 2016). Behavioral intervention programs have been employed with varying degrees of success – and meta analyses of the literature finds that benefits often tend to be short-term (Abrahamse et al. 2005). That being said, regular feedback is a good way to ensure that backsliding is minimized and long-term habits are formed (Allcott and Rogers 2014). The cost-effectiveness of such programs tends to vary, with literature estimates ranging between 1.1 cents per kWh to 47.9 cents per kWh per a 2018 meta study (Gillingham, Keyes, and Palmer 2018), although the authors find that the national average is around 2.8 cents per kWh in terms of net savings.

A potential application of understanding occupant behavior with regards to efficient use of electrical appliances is the area of smart home demand management. This enables utilities and enrolled households to improve energy efficiency and lower the cost of energy consumption through two-way digital communications (Anvari-Moghaddam, Monsef, and

Rahimi-Kian 2015). Smart home demand management relies on effectively characterizing and forecasting energy demand on the basis of dwelling and socio-demographic characteristics (Vassileva, Wallin, and Dahlquist 2012) (Kavousian, Rajagopal, and Fischer 2013). The design of such a demand management system also requires understanding the usage pattern of different appliances which can be used to design effective pricing strategies (Zhou et al. 2016). This can help schedule an application usage efficiently while minimizing user discomfort and cost (Barbato and Capone 2014) and maximizing demand response opportunities (Pipattanasomporn et al. 2014). There are however also concerns that smart home technologies “may reinforce unsustainable energy consumption patterns in the residential sector” and lock out low income and vulnerable consumers (Tirado Herrero, Nicholls, and Strengers 2018). In particular it has been found that a number of households which do have smart appliances are not effectively able to use them, e.g. improper use of programmable thermostats (Pritoni et al. 2015).

Thermostat usage data has been used by several studies to gauge the effectiveness of thermostat use. Temperature setpoint and setback strategies both have significant impact on energy consumption (Huchuk, O’Brien, and Sanner 2018), especially in colder or humid climate (Moon and Han 2011). If the setpoint is only set slightly higher than what people generally do, significant reduction in energy consumption can be achieved (Kwong, Adam, and Sahari 2014). Smart thermostats can be effective in saving more energy compared to manual operation (De Bock et al. 2017) (Lu et al. 2010) (Shann et al. 2017), however in the US context it has been found that most people do not use the advanced features of their thermostats, which is somewhat related to their perceived complexity (Peffer et al. 2011) (Meier et al. 2011).

The current literature regarding appliance energy efficiency, household behavior and predictors have several gaps that this paper seeks to address. While there has been literature dealing with effect of having energy efficient appliances or usage pattern of appliances on consumption (Mansouri, Newborough, and Probert 1996) (Young 2008) (Sanchez et al. 2008), there does not exist a lot of research that tackle the issue of identifying patterns of households which do purchase energy efficient appliances and engage in certain usage patterns jointly. There is research regarding household types and adoption of energy efficient appliances, but these do not provide a clear classification of households engaging in certain behavioral pattern compared to another. This paper also extends on several studies that does try to look at multiple parameters of interest such as knowing efficient appliances and purchasing them (Mills and Schleich 2010); or types, strategy and financial value of energy efficient measures adopted by households (Poortinga et al. 2003). Households are classified through the statistical procedure of Latent Class Analysis ("Latent Class Analysis" 2004). The factors that affect classification of a particular household into one category over another are then determined. Additionally, the paper contributes to the growing literature analyzing the U.S. Energy Information Administration (EIA)'s Residential Energy Consumption Survey (RECS) database as well as the Latent Class Analysis literature, which are discussed at greater detail in the next section.

3.3 **Data and Methods**

The EIA's RECS 2015 dataset is utilized for this study. RECS is the only household level survey of a nationally representative sample of households which are asked questions regarding their energy consumption-related behavior and relevant socio-demographic information. This is known as the Housing Characteristics part of the RECS dataset (U.S.

Energy Information Administration n.d.). The households are selected through a multistage sampling process. Of the 12,753 households sampled, only 5,686 responded ("2015 RECS Technical Documentation" 2015). Note that information on the primary sampling unit is not available in the public database. The RECS dataset provides final sample weight, with the weight associated with each individual household adjusted for different probabilities of selection and rates of response. The final weight associated with each household is the number of households in the population the particular sample household represents. There is a total of approximately 118.2 million households in the US represented by the RECS dataset ("2015 RECS Technical Documentation" 2015).

3.3.1 Dataset and Research Questions

The EIA RECS 2015 dataset has several peculiarities in the response variables which influenced the research questions, in addition to the pre-existing literature on the topic. Ideally, the classification process should have used adoption and usage data for all appliances considered, but since such data was not often available from the survey responses, several analytical choices were made.

Adoption data on energy efficient space heating and cooling equipment is not available, unlike appliances such as washing machine, clothes dryer, refrigerator, and dishwasher. This means that temperature setting strategy is not only useful as an indicator of occupant behavior, but also as a proxy for adoption of space heating and cooling equipment. This is a distinct change from the 2009 version of the survey, where household adoption of these appliances was a survey question("Residential Energy Consumption Survey (RECS) - Data - U.S. Energy Information Administration (EIA)" n.d.). There are a number of indirect variables in the 2015 survey that may give us better understanding of the type of heating and cooling equipment owned such as presence of any thermostats, presence of programmable thermostats, and presence of smart thermostats. However, it's not clear whether they are applicable to heating or cooling systems apart from specific variables on the presence of thermostats and programmable thermostats for central air conditioner.

Non-space heating and cooling appliances do not have a lot of energy efficient usage related questions associated with them in the 2015 survey. The closest to this is the variable "Dishwasher cycle type used most of the time" in which "Energy Saver" is an option. However, unlike thermostats, the literature is relatively thin on the merits and demerits of various dishwasher cycle on energy efficiency compared to the actual work that gets done. One study (Finn, O'Connell, and Fitzpatrick 2013) uses a specific dishwasher model to assess demand side management option, but the cycle choices aren't easily replicable to a generic dishwasher model. A second study (Richter 2011) looks at temperatures associated with cycle choices in general, but does not explicitly quantify the associated energy use. For this reason, the "Dishwasher cycle type used most of the time" is not a variable chosen in this study.

Of the energy efficient appliance adoptions that are considered – water heaters are excluded, specifically because there is no usage information associated with water heaters in the survey responses. Residential Consumer End-Use Data from the same survey ("EIA's Residential Energy Survey Now Includes Estimates for More than 20 New End Uses - Today in Energy - U.S. Energy Information Administration (EIA)" n.d.) shows that water heating is almost important in terms of share in total energy consumption (14%) as space heating (15%) and air conditioning (17%). As a result, the authors are of the opinion that simply including adoption of energy efficient water heater as a reasonable proxy for energy efficient behavior was insufficient.

Specific utility incentives were not available from the dataset, and the responses only pertained to generic incentives such as “Received utility or energy supplier rebate for new appliance or equipment” or “Received tax credit for new appliance or equipment”. This limited the analysis in terms of finding specific associations with household classifications and exact type of incentives received.

Lastly, because the survey data is a snapshot of the sampled households at a given moment of time, the research question and the analysis could not consider the change in classification patterns or responses to incentives over time.

3.3.2 Variables

The following variables are utilized from the survey. Most of the variables were reconstructed in order to simplify the analytical process and to provide more effective interpretation of the results. Summary statistics of the variables are presented in Table 3.1.

3.3.2.1 Dependent Variables

Unless specified otherwise, the first option for each variable is the base category. In Table 3.1, the order of possible values is listed as Category 1-4 as applicable, following the order listed in this section.

- Temperature setting strategy for cooling equipment (USEAC) – The survey has separate questions regarding “Central air conditioner household behavior” and “Most-used individual air conditioning unit household behavior”. If a household was indicated to have a central air conditioner, then responses to the first question were considered in constructing the variable. If a household was indicated to have window air conditioners (and NOT central air conditioners) then the responses to the second questions were considered in constructing the variable. The strategy options are:

    - Keep AC temperature unchanged
    - Manually change AC temperature (this includes turning the AC on and off as needed)
    - Program the thermostat to automatically adjust the temperature during the day and night at certain times
    - No Control over Temperature (this is typical in the case of apartment buildings where building management controls air temperature)

- Temperature setting strategy for heating equipment (EQUIPMUSE): The survey has only one variable related to the temperature setting of heating equipment, "Main heating equipment household behavior". The possible strategies are the same as the air conditioner case.

- Adoption of non-cooling/heating energy efficient appliances (EFFICIENT): The responses regarding the adoption of several appliances are combined (energy efficient versions as denoted by presence of an Energy Star qualification) – namely refrigerators, clothes dryer, dishwashers, and clothes washers. This was done to reduce the number of dependent variables in the classification process and simplify the analytical process and provide more meaningful interpretations. From a purely statistical point of view, having more indicators can improve the quality of the classification process (Wurpts and Geiser 2014).

The possible options are

- Adoption of zero energy efficient appliances, i.e. the household in question does not own an energy efficient version of any of the four appliances
- Adoption of one or more energy efficient appliances, i.e. the household in question owns an energy efficient version at least one of the four appliances
- Uncertain adoption of all applicable energy efficient appliances, i.e. the household in question is uncertain regarding the adoption of an energy efficient version for any of the four appliances

3.3.2.2 Independent Variables

The number of categories were condensed from the original RECS survey responses for easier computation, specifically in the case of categories that had a numerical value attached to it, e.g. year of house construction and income. Unless specified otherwise, the first option for each variable is the base category. In Table 3.1, the order of possible values is listed as Category 1-3 as applicable, following the order listed in this section.

- Type of House (TYPEHUQ): Not a single-family home (i.e. apartment or mobile home)/ Single family home
- Adoption status (KOWNRENT): Non-renter (i.e. owner or living without rent but not an owner)/ Renter

- Year of house construction (YEARMADERANGE): Before 1980/After 1980
- Energy audit status (AUDIT): No Energy Audit/ Energy Audit taken place/ Uncertain audit status
- Respondent gender (HHSEX): Female/ Male
- Respondent race (HOUSEHOLDER_RACE): Non-White (includes mixed race)/White
- Respondent education (EDUCATION): Below college education/ College educated or above
- Household income (MONEYPY): Below $60,000 per annum/$60,000 per annum or higher
- Incent (INCENT): Received no utility incentives/ Received at least one utility incentive/ Uncertain regarding receipt of utility incentives.

The utility incentive responses considered are: rebate for new appliance or equipment, free recycling of old appliance, tax credit for new appliance or equipment, any other benefit or assistance.

- Electricity payment responsibility (ELPAY): household not fully responsible for separate payment electricity/ Household fully responsible for separate payment for electricity
- Number of household members (NHSLDMEM): Continuous variable – total number of household members. The summary statistics for this variable are specified in Table 3.1.

Table 3.1 Summary Statistics for variables – categorical variables and number of households in possible categories (N=5686)

Variable	Category 1	Category 2	Category 3	Category 4
USEAC	2,030	2,127	781	748
EQUIPMUSE	2,156	2,176	972	382
EFFICIENT	1,753	3,519	414	-
TYPEHUQ	1,455	4,231	-	-
KOWNRENT	3,928	1,758	-	-
YEARMADERANGE	2,895	2,791	-	-
AUDIT	4,630	458	598	-
HHSEX	3,189	2,497	-	-
HOUSEHOLDER_RACE	3,189	2,497	-	-
EDUCATION	3,644	2,042	-	-
MONEYPY	3,147	2,539	-	-
INCENT	4,646	955	85	-
ELPAY	328	5,358	-	-
Variable	Mean	Median	Minimum	Maximum

NHSLDMEM	2.577383	2	1	12

3.3.3 Methods

A schematic workflow diagram that outlines the methodological structure of the analysis is presented in Figure 3.1. Table 3.2 presents the structure of the multivariate probit model that is outlined in Figure 3.1. Further details on each of the methods can be found in the Supplementary Materials.

Figure 3.1 – Schematic Workflow Diagram Outlining Methodological Approach

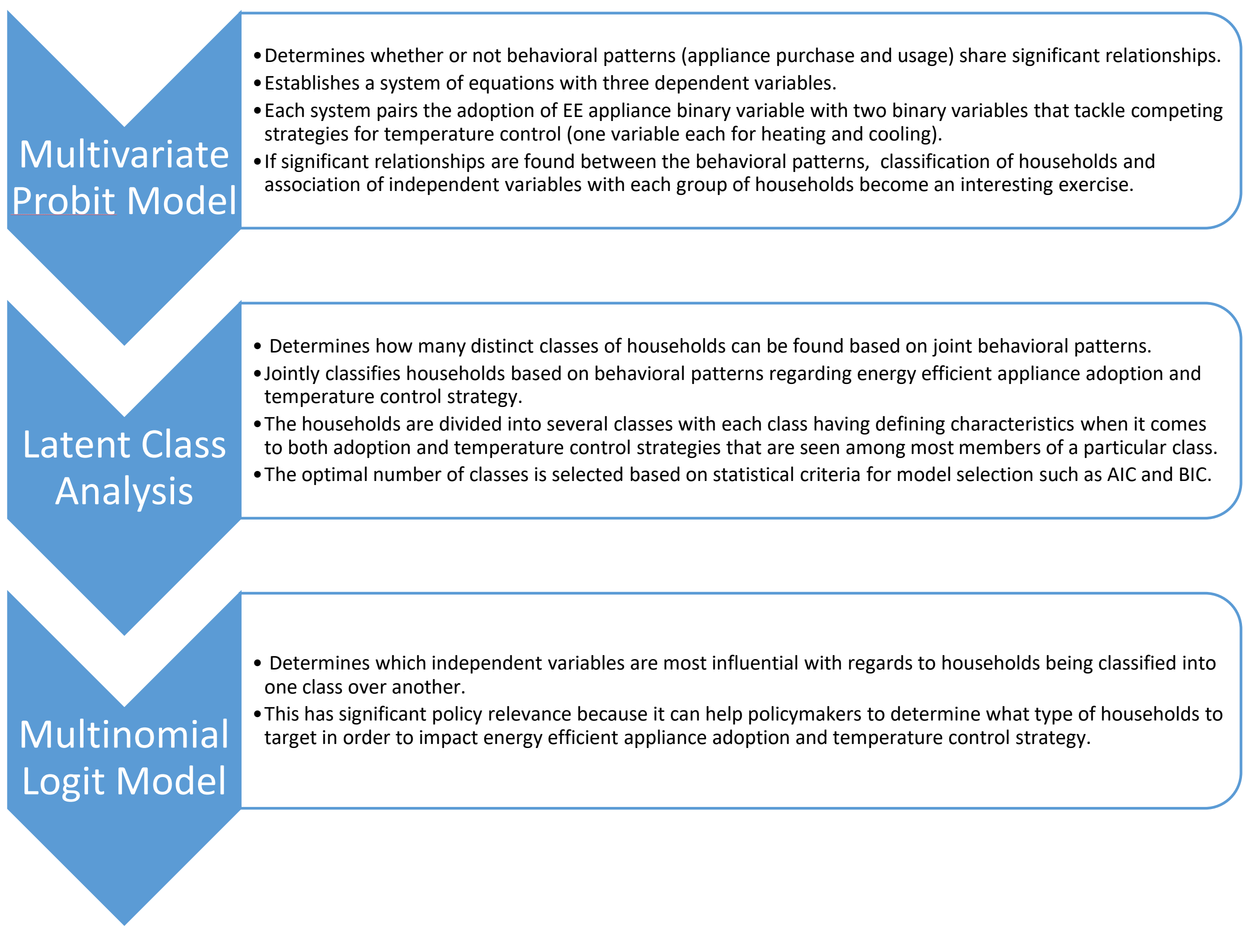


Table 3.2 – Representation of the Multivariate Probit Model

System	Dependent Variables (Binary)	Independent Variables
System 1	USEHEAT1 (Manual or Single Temperature in Heating vs Use of Programmable Thermostat) USECOOL1 (Manual or Single Temperature in Cooling vs Use of Programmable Thermostat) EFAPP (Adoption of zero/uncertain energy efficient appliances vs Adoption of one or more energy appliances)	These variables are common for all dependent variables across all three systems TYPEHUQ KOWNRENT AUDIT HHSEX HOUSEHOLDER_RACE EDUCATION INCENT ELPAY NHSLDMEM
System 2	USEHEAT2 (No Control of Temperature in vs Control of Temperature in Heating) USECOOL2 (No Control of Temperature in Cooling vs Control of Temperature) EFAPP (Adoption of zero/uncertain energy efficient appliances vs Adoption of one or more energy appliances)	
System 3	USEHEAT3 (No Thermostat Use in Heating vs Use of Programmable Thermostat) USECOOL3 (No Thermostat Use in in Cooling vs Use of Programmable Thermostat) EFAPP (Adoption of zero/uncertain energy	

	efficient appliances vs Adoption of one or more energy appliances)	

3.4 Results

Multivariate probit model: The first system had reduced number of samples due to eliminating no-control households from USEAC1 and USHEAT1 variables, hence only 68 draws were used.

For all systems, marginal effects are reported, as these are easier to interpret in the case of a probit model. The marginal effect with categorical independent variables can be interpreted as the change in odds of the household being part of the non-base category for all three dependent variables, given a change to a certain category for the categorical independent variable from the base category. The results are summarized in Table 3.3.

Table 3.3 – Marginal Effects of independent variables on changing odds of the household being part of the non-base category for all three dependent variables, given the change to a certain category for the categorical independent variable from the base category

Independent Variable	**System 1**	**System 2**	**System 3**
	Marginal Effect (Standard Error)		
TYPEHUQ_SINGLEFAMILYHOME	0.238** (0.073)	0.019 (0.065)	0.301*** (0.075)
KOWNRENT_RENTER	-0.327*** (0.076)	-0.192** (0.064)	-0.303*** (0.068)
AUDIT_AUDITED	0.117 (0.095)	-0.232** (0.084)	0.079 (0.091)
AUDIT_UNCERTAIN	-0.016	-0.255**	-0.016

	(0.0.84)	(0.074)	(0.072)
HHSEX_MALE	0.127** (0.048)	0.034 (0.049)	0.119** (0.044)
HOUSEHOLDERACE_WHITE	-0.037 (0.066)	-0.249*** (0.060)	-0.069 (0.058)
EDUCATION_COLLEGE	0.276*** (0.052)	0.070 (0.056)	0.230*** (0.050)
MONEYPY_60K	0.305*** (0.053)	0.158** (0.057)	0.330*** (0.052)
INCENT_RECEIVED1+	0.158* (0.062)	-0.052 (0.067)	0.125* (0.059)
INCENT_UNCERTAINED	0.109 (0.162)	0.086 (0.209)	0.053 (0.173)
ELPAY_FULLYPAY	-0.106 (0.121)	-0.009 (0.098)	-0.194 (0.132)
NHSLDMEM	-0.014 (0.018)	-0.001 (0.019)	-0.008 (0.017)

Note: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

For System 1 - Residents of single family homes, a male respondent to the survey, college educated respondent, a household with an income exceeding $60,000 per annum, and a household receiving one or more energy efficiency related utility incentives were more likely to be using thermostats for heating and cooling as well as adopt one or more energy efficient appliances, compared to using single/manual temperature control strategy and not having any energy efficient appliances (or be uncertain). However, being a renter decreased these odds. The relationships are generally in-line with what is seen in the literature, although with the respondent not necessarily being the head of the household, the gender and education link cannot be interpreted as strongly.

For System 2 – only income over $60,000 seemed to increase the odds of the household belonging to the control temperature/having an efficient appliance category, which makes sense given the link between income and energy consumption and affordability of expensive appliances. There are a large number of variables that seem to decrease the odds of the household belonging to the control temperature/owning an efficient appliance category – being a renter, doing a home energy audit, uncertain status of home energy audit, and the respondent being white. Being a renter makes sense from the empirical literature because rented houses often have their temperature controlled by management companies and there is limited opportunity to replace existing appliances or having uncertain audit status. There is little evidence to support the relationship between auditing and having no control over temperature/not buying an appliance and the respondent being white.

For System 3 –results are similar to that of System 1, which suggests that adding back the no-control group does not impact the relationships of the independent variables to thermostat usage/efficient appliance adoption very significantly.

Table 3.4: Correlation coefficients of the three dependent variables under three different tri-probit systems with standard errors in parentheses.

System	**Correlation between Heating and Cooling temperature**	**Correlation between Cooling strategy and EE appliance adoption (Standard errors)**	**Correlation between Heating strategy and EE appliance adoption (Standard errors)**

	strategy (Standard errors)		
System 1	0.92*** (0.01)	0.06*** (0.01)	0.06*** (0.02)
System 2	0.34*** (0.04)	0.08** (0.03)	0.01 (0.03)
System 3	0.89*** (0.01)	0.07*** (0.02)	0.07*** (0.02)

Note: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

An analysis of the three sets of correlation coefficients (Table 3.4) -1. between heating/cooling temperature control strategy; 2. Between heating temperature control strategy and EE appliance adoption; 3. cooling temperature control strategy and EE appliance adoption suggests that, predictably households will have fairly similar heating and cooling temperature control strategies. However, there is low (albeit statistically significant) correlation between their heating or cooling strategy with appliance adoption. This suggests that households may be as a whole purchasing one or more energy efficient appliances but that does not necessarily inform their temperature control strategy.

Latent Class Analysis Model: The AIC and BICs of 3-5 class models are presented in Table 3.5. Only the class specification with the lowest AIC/BIC is discussed in detail.

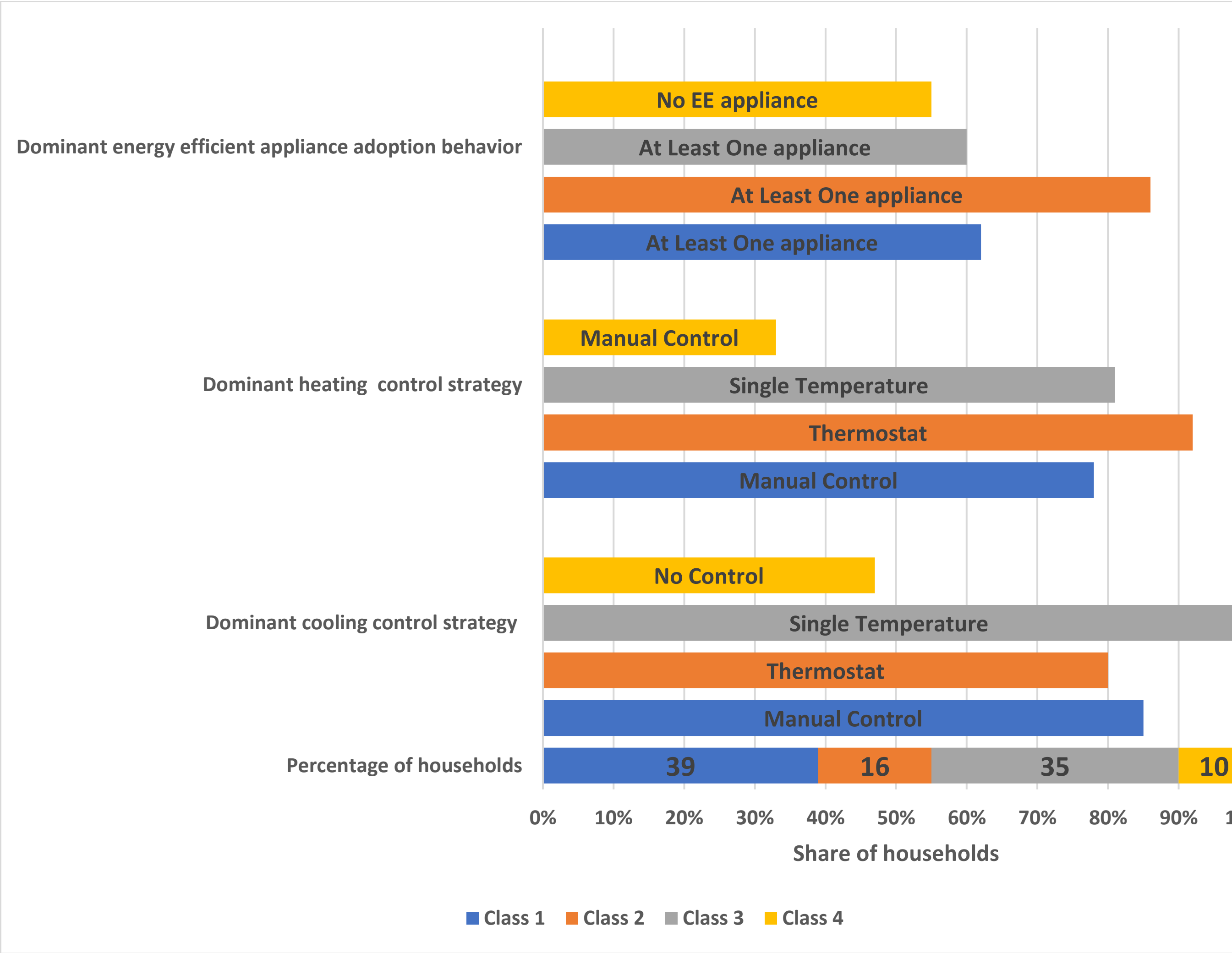
Table 3.5 – AIC and BIC comparison for different LCA specifications

Measure	3-Class	4-Class	5-Class
AIC	34032	**33912**	33915
BIC	34205	**34144**	34208

Endnote. AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion. AIC and BIC are used to evaluate relative quality of statistical models, with lower values indicating lower information loss in the specification concerned. Please see Supplementary Materials for more details.

The four-class model is the optimum one. The outcome of the model is summarized in Figure 3.2.

Figure 3.2 – Summary of Four Class Specification of Household Energy Efficient Behavior



Note: All strategy and adoption numbers are in percentages. To be interpreted as percentage of households within a particular class engaging in a particular type of behavior.

Effectively the four classes are largely separated based on temperature control behavior. Apart from Class 4 – most members of the other classes tend to own at least one energy efficient appliance. The manual (Class 1) and single temperature (Class 3) strategy households dominate the sample in terms of percentage of households being class members, which is in line with the literature. However, it is interesting to note that the programmable thermostat preferring class (Class 2) has a higher percentage of members owning one or more energy efficient appliance compared to that of Class 1 and Class 3, suggesting some link between high percentage of EE appliance adoption and exhibiting more sophisticated temperature control behavior. The joint categorization into one class alone isn't enough to draw conclusive evidence. Class 4 is also interesting to analyze, and apart from the slight majority of its members not owning (or uncertain about owning) an energy efficient appliance – it is the only class where heating and cooling temperature behavior is split. About half of the members don't have control over cooling strategy and there's an even split between manual and single temperature strategy for heating. Much like Class 2, we can generally say that there seems to be a link between less-sophisticated temperature control strategy and low adoption percentage of energy efficient appliances.

Multinomial Logit Model: The model uses the four-class prediction for each household as the dependent variable, with Class 1 (Manual temperature strategy and EE appliance owning households) as the base class[2]. This means that the change in relative log-odds of

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[2] Class 1 is chosen as the base case because it is the most common category. We want to estimate what are the characteristics which are related to a deviation from the norm, especially the case where households use thermostats and the case where households do not own any EE appliance/have no

being in Class X (where X ≠ 1) compared to Class 1 will increase/decrease by a certain value if moving from the base category of that independent variable to another category. In Table 3.6, only the independent variables which have a statistically significant relative log-odds of impacting a class change are reported (either positive or negative), along with the absolute numerical value of the odds in parentheses. A visual representation can be found in the Supplementary Materials.

Table 3.6: Multinomial logit analysis of independent variables affecting the relative log-odds of membership of a behavioral class compared to the base behavioral class (Class 1)

Membership change to	Increased relative log-odds due to (odds specified in parentheses)	Decreased relative log-odds due to (odds specified in parentheses)
Class 2	TYPEHUQ_SFH (0.696)***	KOWRENT_RENTER (0.796)***
	YEARMADE_1980+ (0.173)*	HOUSEHOLDERACE_WHITE (0.265)*
	AUDIT_AUDITED (0.309)*	-
	EDUCATION_COLLEGE (0.373)**	-
	MONEYPY_60K (0.538)***	-

control strategy. This is relevant from a policy perspective because potentially, these households can be targeted to improve thermostat usage/ promote EE appliance ownership. The reason why Class 2 (Owns EE Appliance/ Thermostat users) is not chosen as the base class is because we want to identify the characteristics that make the odds of not being in this class less likely (renters primarily), and potentially target these households for potential behavior change incentives.

	INCENT_AVAILED (0.309)*	-
Class 3	HHSEX (0.130)*	EDUCATION (0.481)***
Class 4	KOWRENT_RENTER (0.404)**	TYPEHUQ_SFH (0.409)***
	AUDIT_UNCERTAIN (0.384))*	YEARMADE_1980+ (0.684)***
	-	EDUCATION (0.325)*
	-	INCENT_AVAILED (0.476)*

Notes: Class 1 – EE appliance owning manual temperature control class; Class 2 – EE appliance owning thermostat temperature control class; Class 3 – EE appliance owning single temperature class; Class 4 – Non-EE appliance owning mostly no control/manual temperature control class

The variables that are likely to increase the relative log-odds of being a part of Class 2 (thermostat user/EE adoption) compared to Class 1 are residence in a single family house, living in a house made after 1980, completion of a home energy audit, college educated respondent, household income above $60,000 per annum, and use of at least one utility incentive. Renters and white respondents are likely to have decreased relative log odds of being a part of Class 2. By and large the results are comparable to the first system of multivariate probit equations, where the base class was Manual/Single temperature strategy households and the alternate class was thermostat users. The only differences are the statistical significance of audit status in the multivariate probit analysis and the significance of being a white respondent in the multinomial logit analysis. However, the impact of race or gender of the respondent on behavior cannot be measured properly if we do not know whether the respondent is the head of the household.

Between Class 1 and Class 3 (Single temperature strategy/Efficient appliance owners) there are very few variables that can affect membership relative log-odds, which is to be expected given the similarities in behavioral structure of the two classes. However, it does seem that gender of the respondent (being Male) and education level (College educated) impact the relative log-odds of membership, positively and negatively respectively. While the relationship with gender is hard to interpret, having at least a college-educated household member may mean that there is some influence of NOT switching from a more sophisticated strategy (actually changing the temperature, albeit manually) from a less sophisticated one (keep a single temperature).

Changing relative log-odds of membership between Class 1 and Class 4 (limited control/no EE appliance adoption) is positive as a result of being renters and uncertain audit status and negative due to living in a single family home, living in a home constructed after 1980, having a college educated respondent, and availing an utility incentive. The results make intuitive sense, given that renters and households with little knowledge about audits are likely to be correlated with those who have limited control over setting temperature of their devices and not purchase any energy efficient appliance. It is also likely that those living in a single family home (typically not operated by management companies), newer house, having a college educated respondent, and availing an utility incentive are less likely not to buy an energy efficient appliance or not have control over temperature. This compares somewhat favorably with the second system of multivariate probit equations, where no control of heating and cooling temperature strategy was the base case and having any type of control being the alternative case. There are two key differences. Variables that decrease the log-odds in the multinomial logit case are not found to be significant in the multivariate probit system. Additionally, variables such as Audit status positive and white respondent being not found significant in the multinomial logit analysis. These discrepancies can be explained by the fact that the multivariate probit system looked at all possible alternatives to no control as the counterfactual while in the latent class analysis, the base class only comprises of manual temperature controlling households.

3.5 Discussion

The joint analysis implies that while the majority of the sampled households' own energy efficient appliances, only a small percentage control temperature through thermostats, which in a residential setting can lead to significant energy savings. Therefore, adoption of one more energy efficient appliance is not highly correlated with a consistent temperature control strategy. The four-class categorization provides greater clarity in appliance usage even when adoption patterns are similar. In incentivizing households to adopt more energy efficiency measures, policymakers should ensure both adoption and proper usage of energy efficient appliances. In determining whether households are using their appliances properly and helping households with regards to ease of use, engineering solutions such as smart meters and smart thermostats are likely to be useful. These provide information on the thermostat usage patterns of individual consumers for the thermostat manufacturers.

The factors that are associated with the usage of programmable thermostats are – home ownership, single family home dwelling, higher income, college education, use of utility incentives and completion of a home energy audit; and one factor explicitly reducing the odds of use of thermostats or increasing the odds of not controlling the temperature is renting. These factors are also generally in line with households that in the literature are generally classified as "pro-environmental" (Abrahamse and Steg 2011) (Poortinga et al. 2003). Renters meanwhile have been studied in the literature as a subgroup of interest when it comes to energy efficient and stand out as a group when it comes to less effective energy efficiency outcomes (Davis, n.d.) (Bird and Hernández 2012).

From the policy perspective, literature that has analyzed the issue of energy efficiency adoption shortfalls (Markandya, Labandeira, and Ramos 2015) assert that policies should be tailored based on the failures that are noted in the system. For example, if there are market failures such as imperfect information, policies to improve the quality of information to consumers should be developed and agents should be targeted as far as possible to improve efficiency of investments. Based on our results, we make the following observations. Firstly, a small percentage of population use the programmable features of thermostats and can be considered as the leaders in terms of effective usage of temperature control equipment. However, the question of whether they were using the thermostat properly was not asked in the RECS survey, but it is an important policy question that needs to be addressed. Secondly, this segment of the population tends to be educated and wealthy homeowners living in single family homes – factors that themselves are highly interconnected (e.g. education and wealth, wealth to home ownership, and preference of SFH in the case of home ownership). On the assumption that more people should use the programmable features of thermostats in order to improve energy efficiency, policies should be designed to target those households (or the laggards) which do not have factors that are associated with thermostat users – i.e. households that are low-income, apartment dwelling (or mobile home dwelling), renters with less than college level of education, and those who typically do not avail any utility incentives or complete home energy audit. High level information such as Energy Star labels do improve consumer awareness (Mills and Schleich 2010) but that does not necessarily help consumers who are low-income or have other demographic issues that contributes to low regional ratings by organizations such as the American Council for an Energy-Efficient Economy (Murray and Mills 2011). Hence states, utilities and local authorities should consider additional level of policy support for consumers in their jurisdiction exhibiting these demographic characteristics. Motivational tools that have been generally used include nudge-style interventions such as home energy reports which do have positively demonstrated effect on welfare (Allcott and Kessler 2015), improvement of information provision that is relevant to the demographics under consideration (Abrahamse et al. 2005), and setting incentive compatible contracts as well as financing options. Identifying the demographic characteristics of households that are not effectively exhibiting ideal energy efficiency behavior is also the first step towards for designing intervention trials to evaluate new policies. It can also be used to design more sophisticated consumption disaggregation techniques such as nonintrusive load monitoring to improve stakeholder decision-making (Carlson, Scott Matthews, and Bergés 2013).

From an engineering perspective, the insights may improve in managing and forecasting demand for smart home energy management. Some appliances such as dryers, air conditioners and dishwashers may offer significant opportunity when it comes to demand response, so ascertaining the adoption and usage patterns of these appliances among households can be useful (Pipattanasomporn et al. 2014). When it comes to creating complex optimization algorithms for home energy management systems, well-being of consumers can be better modelled by understanding broad usage patterns and demographical trends of the target households (Beaudin and Zareipour 2015). Analysis of smart meter data through clustering techniques have shown that demographic patterns are powerful predictors of daily usage patterns of electricity which in turn can be used to generate effective load profiles (McLoughlin, Duffy, and Conlon 2015). While not as extensive as daily or hourly data gathered from smart meters, the RECS dataset is extensive enough for predicting further patterns in the context of electricity usage and household behavior by using machine learning techniques such as clustering, and can be used to make further contribution to the existing literature (Tsanas and Xifara 2012) (Zhao and Magoulès 2012).

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Chapter 4

Pricing Prosumers: Can distributed solar tariffs jointly make sense for prosumers and utilities?

Arijit Sen, Yueming Qiu, and Leon Clarke

4.1 Introduction

One of the key reasons behind the decrease of emissions in the U.S. electricity sector in the recent years("Power Sector Carbon Dioxide Emissions Fall below Transportation Sector Emissions - Today in Energy - U.S. Energy Information Administration (EIA)" n.d.) is the increase of renewable energy-based electricity generation in the grid, particularly solar. Solar power generation from utility scale sources alone have increased by about 60 times between 2010 and 2019("EIA - Electricity Data" n.d.). As defined by the U.S. Energy Information Administration (EIA) as "distributed … generation technologies produce electricity near the particular load they are intended to serve… being connected to the electricity grid and meant to directly offset retail sales"("EIA - Distributed Generation in Buildings" n.d.). As per EIA's 2018 Electric Power Annual report("Electric Power Annual 2018," n.d.), over 1.2 TWh of electricity from net metered photovoltaic (PV) systems was sold back to the grid and in the same year, about 30 TWh of electricity was generated from small-scale facilities (which would include facilities that are not grid-connected as well)("EIA - Electricity Data" n.d.). Small-scale residential and non-residential solar PV installations have increased from a little over 7 GW in 2014 (when they were first tracked by EIA) to around 20 GW in 2019("Electric Power Annual 2018," n.d.). This can be partially explained by the dramatic reduction of per watt installation costs(O'Shaughnessy et al. 2019), estimated over \$3.50 in 2014 but well under \$3.00 in 2019, mostly due to falling hardware costs(“Solar Industry Research Data” n.d.). However, incentives such as the 30 per cent investment tax credit(“Residential and Commercial ITC Factsheets” n.d.) and the net metering provision afforded by main utilities are also regarded as key drivers for this growth(Eryilmaz and Sergici 2016). The analysis of compensation[1] that can be afforded to rooftop PV installers[2] is one of the key drivers of this paper. The most common form of compensation is net metering, the details of which are discussed in the next section.

4.2 Net metering and the associated value of solar literature

Net metering compensates the prosumers for the electricity sold back to the grid at the retail rate of electricity tariff, thus the effective or net consumption is electricity demanded (which is always at the retail rate) minus electricity sold. An example of how the mechanism works is illustrated as follows -

Assume that a prosumer and a utility are contracted under a monthly billing cycle and that the prosumer only pays for the electricity that is bought from the utility. In a given month, assume that the demand of the prosumer is 1,000 kWh, a shade over the average household electricity consumption in the United States(U.S. Energy Information Administration (EIA) 2018), and the PV system installed by the prosumer is capable of generating 1,200 kWh (about what a 8 kW system would generate in the month of July on a downtown San Diego rooftop per a PVWatts(“PVWatts Calculator” n.d.) simulation). Then for this month, the 1,000 kWh of the 1,200 kWh generated can be used to completely offset the demand of the prosumer, and the remaining 200 kWh can be sold to the grid. Assume that

[1] termed by utilities and regulators the “Value of Solar”(9)
[2] henceforth termed as prosumers(10) – entities who both produce and consume electricity

the retail rate for the prosumer is 35 cents per kWh (considering only a single tier for simplification purposes), without the system they would have paid $420 to the utility. With the system and the excess electricity sold, the utility instead pays $70 to the prosumer.

As of October 2019, 39 states in addition to the District of Columbia and a handful of territories have net metering rules in place(DSIRE 2019). However it also has come under a fair bit of controversy in the recent years, with one of the arguments of the utilities being that prosumers are overcompensated for their sale to the utility given that

(a) it would cost the utility far less to buy the same amount of electricity from the wholesale market (Szmolyan 2019); and
(b) because the utility is buying electricity at the retail rate, there is no money to support the transmission and distribution expenses of the utility while selling this electricity to other consumers. Additionally, when selling excess electricity back to the grid, the prosumer is still making use of the transmission and distribution infrastructure which they are not being charged for (Brown and Sappington 2017).

A phenomenon that has been discussed in the literature at some length is the possibility of a utility "death spiral". The "death spiral" hypothesis suggests that because utilities lose money from net metering, it would have to raise its rates on the non-net metered prosumers to remain profitable, but this rate increase makes the economics of defecting more favorable to some of these non-not metered prosumers, which forces the utility to raise its rate further, ending up in a situation where the utility is driven out of business(Costello and Hemphill 2014). Quantitative examination suggests that while only extreme (and unrealistic) cases of grid defection and utility costs may actually lead to such a death spiral happening(Laws et al. 2017), it is well established that net metering will dent the profitability of utilities(Janko, Arnold, and Johnson 2016) which will mean at least some rate increase for the non-metered households(Satchwell, Mills, and Barbose 2015) which has serious distributional concerns(Brown and Sappington 2017). In real-life, there has been a twofold response this on the utility and regulator side. First, there are some utilities and regulators who have come out against net metering and have decided to move on from the system(Davies and Carley 2017) . Second, there has been a growing number of regulator and utility sponsored “Value of Solar” studies which try to determine the optimal value of distributed solar from the utility point of view, taking an avoided cost approach – aggregating the avoided fuel, transmission, distribution, capacity, operation and maintenance, and environmental compliance costs from purchasing electricity from distributed PV sources rather than the wholesale market. Of note are studies by Institute of Self Reliance for the regulators in Minnesota(Farrell, n.d.) and Clean Power Research for Austin Energy(Rábago et al., n.d.) which demonstrated that the value of electricity purchased from prosumers lies between the wholesale and retail rates. Whether not value of solar studies adequately account for all costs and benefits for all parties while still incentivizing rooftop PV deployment is up for debate(O’Shaughnessy and Ardani 2020). However, the wholesale generation cost (or perhaps what the utility regards as the generation expenses in its retail bill) can be regarded as an effective floor in terms of compensation by the utility.

The prosumer economics of net metering, specifically in response to changes by the utility to its tariff system has been discussed at length in the literature. Almost any deviation from the net metering status quo will dampen the benefits of the prosumer, such as two-part tariffs with a fixed customer charge or switch to a wholesale compensation structure (Laws et al. 2017). The feedback effect from dampened benefits is likely to cause a decline in distributed solar PV adoption(Darghouth et al. 2016), although estimates vary on the magnitude of impact(Gagnon et al. 2017). Several studies have also attempted to come up with an optimal solar rate that would maximize the benefits of prosumers or utilities (Satchwell, Mills, and Barbose 2015) (Woo and Zarnikau 2017) (Singh and Scheller-Wolf 2017) (Vaishnav, Horner, and Azevedo 2017). Optimistic estimates suggest that there should not be any changes in deployment of rooftop PV so long as the overage electricity is credited above the levelized cost of electricity (Comello and Reichelstein 2017).

The literature in general does not do a good job in assessing the relative benefits of utilities and prosumers in response to different valuations of distributed solar generation and reports aggregated benefits from both parties or benefits for one party but not the other. As a result, the literature does not focus on valuations that might be beneficial for both parties, rather than simply focusing on maximizing combined benefits. For example, Singh and Scheller-Wolf(Singh and Scheller-Wolf 2017)'s numerical examples which calculate combined financial welfare for the prosumer, non-adopter consumers, and utility, as well as the environmental welfare for the society -only provides a combined number, and does not provide a breakdown of the winners and losers from various tariff arrangements. Janko et al. (Janko, Arnold, and Johnson 2016) consider at various penetration rates - utility revenue losses, optimal system sizes for prosumers, and electric rate increase required to cover losses, but does not discuss prosumer benefits changes. Laws et al. (Laws et al. 2017) focus on adoption/defection rates and the effective retail price at various solar compensation rates, but does not demonstrate what benefits are accrued by the prosumer and the utility at each of those compensation rates. Other studies cited in the previous paragraph tends to focus on the benefits of either the utility (Woo and Zarnikau 2017) (Satchwell, Mills, and Barbose 2015) or the prosumer (Darghouth et al. 2016) (Vaishnav, Horner, and Azevedo 2017) (Comello and Reichelstein 2017) .

4.3 Research Question

The previous section identifies two major limitations of the literature – the lack of distinct quantification of prosumer and utility benefits in response to different valuations of distributed solar generation, and the tendency of the literature to either consider the utility or the prosumer when their benefits are distinctly quantified. The research questions are designed to address both issues.

1. For the median prosumer[3] served by an electric utility, what is a range of valuations of distributed solar generation that ensures that utilities do not pay excess cost to acquire energy from the prosumer and the wholesale market compared to a no distributed PV system case and that the prosumer still receive enough monetary benefits to ensure payback for the installed system within its lifetime?
2. How are these valuations affected in response to a different utility retail tariff structure?
3. What explains the differences in these valuations between median prosumers of different utilities?

4.4 Methods

[3] A median prosumer is an artificially constructed household based on Tracking the Sun(Barbose et al. 2019) database that has the average characteristics of all rooftop PV installations in a certain zip code that is served by a certain utility. In this study, each combination is denoted by the utility is served, e.g. if the zip code 93940 is served by Pacific Gas & Electric (PG&E), the prosumer-utility combination PG&E is a household that is a representative of all households in that zip code with a rooftop PV installation.

The research design involves finding an optimal valuation for distributed solar generation (VDSG) to solve the optimization problems for each median prosumer and retail utility tariff structure. Candidate VDSG values are defined in Table 4.1.

Min VDSG

such that P = (Es * VDSG – Ed * VRTP) – (Ed + Eg - Es) * VRTP – CO > 0 ……(1).

and **Max VDSG**

such that U = Em * VMEC – (Em – Es)* VMEC – Es * VDSG > 0…. (2)

P and U are prosumer and utility benefits respectively. Prosumer benefit arises from savings in retail costs due to the installation of the PV system reducing consumption requirement compared to a no-PV situation as well as compensation received for excess solar generation. We assume that prosumer demand will remain unchanged over the years and is invariant of tariff structure alteration, which is unlikely to happen in real life. This assumption is made due to the static nature of the model and these feedbacks can be explored in future studies. A positive prosumer benefit ensures that the system cost is paid back for within its lifetime, assumed at 30 years.

Positive utility benefit arises if the cost of purchasing energy from the wholesale market exceeds the valuation of distributed solar generation. Because of lack of transmission and distribution related cost data, utility benefits calculations are considerably stylized compared to real life.

The various terms in the two equations are defined as follows:

Es = Lifetime energy sold to the utility by the prosumer

Eg = Lifetime of energy generated by the solar PV system

VDSG = Levelized Value of Distributed Solar Generation

Ed = Leftover energy demanded by the prosumer from the utility

VRTP = Levelized Value of Retail Tariff Price paid to the utility

Ed + Eg - Es = Total energy demand in the case of a PV scenario (Leftover energy plus net solar generation

CO = Cost of system including tax-payer funded incentives

Em = Energy bought from the wholesale market in a no-PV scenario, equals Ed + Es

VMEC = Levelized cost of energy bought from the market

Em – Es = Leftover energy bought from the market in a PV scenario, equals Ed

A valid minimum VDSG that solves (1) is the Floor (F). A valid maximum VDSG that solves (2), provided that a solution of (1) is not incompatible with the solution (2) is the Ceiling (C). If there exists a F that solves (1) and a C ≥ F[4] that solves (2), then an optimal VDSG is any value between F and C, or F ≤ Optimal VDSG ≤ C.

We also consider the societal benefit, which is the aggregate of the prosumer and the utility benefit, plus any air quality related benefit (defined as avoided healthcare cost due to improved air quality) from additional PV electricity in the grid assumed to replace an

[4] If C ≤ F, it means that the maximum that the utility can afford to pay without losing money does not meet the minimum compensation required by the median prosumer to pay off the system, i.e. the system would not be built.

equivalent amount of fossil-fuel based generation, minus the taxpayer expenses that are borne by the society when rooftop PV systems are subsidized. This is defined as:

S = P + U + LCAPD * Es – I

Where, LCAPD = Levelized cost of avoided pollution damage

I = Tax-payer funded incentives for the system, typically at 30 per cent of the system cost.

The society is said to benefit from a given valid valuation $VDSG_0$, if for $VDSG_0$, S>0.

Table 4.1: Details of candidate valuations of distributed solar generation

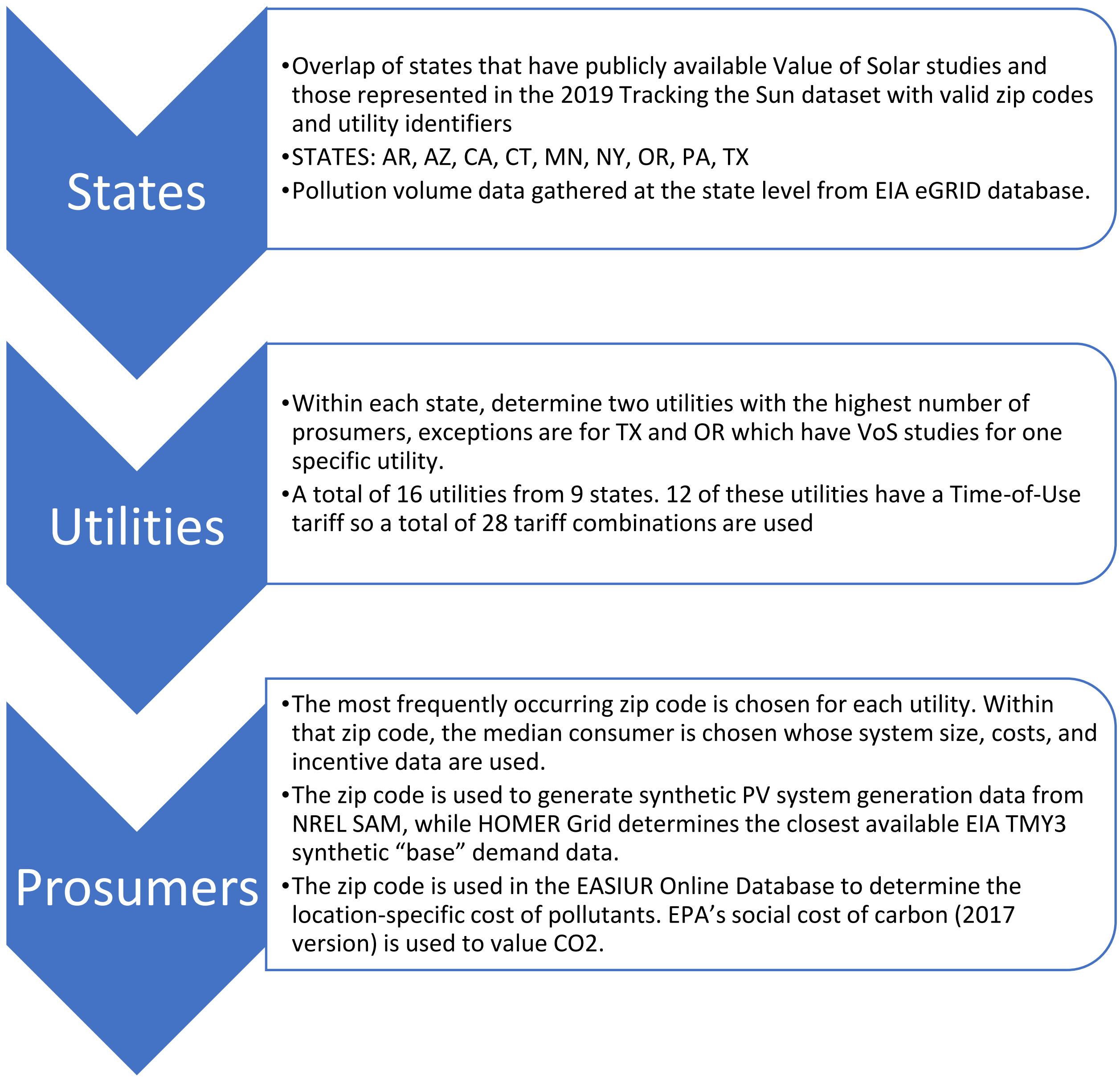
VDSG name	**Explanation**
Net Metering (NM)	Present value of retail rate
Floor (F)*	A rate that ensures a positive payoff for the prosumer. This is the minimum compensation necessary to ensure that the PV system is built.
Ceiling (C)*	A rate that imposes no additional energy costs to the utility compared to a no-rooftop PV situation. This is the maximum compensation that the utility can afford without having to increase its tariffs for other consumers to compensate for excess energy payments.

Value of Solar (VoS)	A rate that is calculated by existing studies for a given state or utility. Used for benchmarking purposes.

* A 1 cent minimum is chosen because it is unlikely the fractions of a cent will be used as a payoff.

4.5 Data

Figure 4.1: Data selection process workflow



Data collection for this study followed a sequential process outlined in Figure 4.1. Details of the process is provided below. All calculations start from the year 2019, and then a 25-year time consistent with the lifetime of a PV system horizon is analyzed. Values are reported as net present values (NPVs). Additional details can be found in Supplementary Materials.

1. Identification of States and pollution volume data: System level data for a large section of rooftop PV installations across the United States can be obtained from the Tracking the Sun (TTS) database, updated annually by the Lawrence Berkeley National Laboratory (LBNL). This study uses the 2019 edition of the database, which tracked households till the end of 2018(Barbose et al. 2019). The states whose residential rooftop PV systems (our target group in this analysis) are tracked by the database include: Arizona, Arkansas, California, Connecticut, Delaware, Florida, Massachusetts, Maryland, Minnesota, New Hampshire, New York, Oregon, Pennsylvania, Texas, Vermont and Wisconsin. As a reference point of comparison, this study includes VoS VDSG for comparative purposes and not all of these states have VoS studies done by their regulators/utilities/ a third party. By using the VoS meta-studies developed by ICF International("The Hunt for the Value of Distributed Solar" n.d.) and SEIA("Solar Cost-Benefit Studies" n.d.), we narrow down the states that have such studies with quantifiable VoS numbers and find commonalities with those in the TTS database. We find the following overlap: Arizona, Arkansas, California, Connecticut, Massachusetts, Maryland, Minnesota, New Hampshire, New York, Oregon, Pennsylvania, Texas and Vermont. Of these, households in Maryland and Vermont weren't identifiable by zip codes (which are required for generating synthetic generation and demand patterns), so those two states were dropped. The three New England states had very similar characteristics in terms of their average sizes, costs and even utility tariff structure, and as a result only Connecticut was chosen – primarily due to the fact that it was the only state among the three with utilities having two different type of tariff structures (baseline and time-of-use). So the final tally of states considered

for this study ended up being: Arizona, Arkansas, California, Connecticut, Minnesota, New York, Oregon, Pennsylvania, Texas, and Vermont. For pollution-related calculations, state level power system pollution data (calculated at pound of CO_2e, SO_2, and Annual NO_X per MWh) from U.S. Environmental Protection Agency (EPA)'s eGRID database was used("EGRID2018 Summary Tables," n.d.). PM2.5 data was collected at a grid level from a eGRID presentation as state level PM2.5 data is yet to be incorporated in the model(Cooley, n.d.).

2. Identification of Utilities and tariff data: For each state, the aim was to identify two utilities which served prosumers with the most rooftop PV installations. In order to accomplish this, a simple frequency Table 4.2 with utility name was generated for each state. For the nine states, this resulted in the identification of 18 utilities. However, for Oregon and Texas, the Value of Solar studies were explicitly for a specific utility – Portland General and Austin Energy respectively, and hence only those utilities were considered for those two states, bringing the total to 16. For comparative purposes, two sets of tariffs were used for each utility, a baseline one (generally tiered with seasonal variations) and a time-of-use (ToU) one. Twelve out of the sixteen utilities offered a ToU tariff. The exceptions were: Carroll Electric (Arkansas), Minnesota Power (Minnesota), PECO (Pennsylvania), and Austin Energy (Texas). We assume that the retail rates escalate at the average rate of escalation between 2009 and 2018 at the state level, per EIA data(U.S. Energy Information Administration n.d.). We assume the energy cost of a utility to be the same as the generation charge which is present in utility bills, and that these costs escalate at the same rate as the tariff. Since transmission and distribution charges are also separately accounted for retail rate, we do not assume that

this is a part of the generation charge. Utilities will buy electricity from the wholesale market at a price that is generally better approximated by the locational marginal price (LMP)(“Wholesale Power Price Maps Reflect Real-Time Constraints on Transmission of Electricity - Today in Energy - U.S. Energy Information Administration (EIA)” n.d.). However, these tend to fluctuate wildly and as such obtaining a long-term prediction for these are problematic(“Wholesale Electricity Prices Were Generally Lower in 2019, except in Texas - Today in Energy - U.S. Energy Information Administration (EIA)” n.d.). Since utilities already explicitly specify a generation charge in their retail rate as a proxy for their energy costs, this study uses the same data as its proxy for utility energy costs.

3. Identification of Zip code and demand/generation data: For each utility, a frequency table was created to identify the zip code which was associated with the greatest number of installations. These zip codes were then used to generate average system size, cost, and subsidy data creating a prosumer-utility combination. Some households have incomplete or missing subsidy data and, in these cases, the standard 30 per cent investment tax credit (ITC) reduction is assumed as the subsidy value. The TTS database does not have demand data associated with the households. Hence the zip code was also used to generate a synthetic hourly demand profile for the prosumer using the “Base” DOE TMY3 Load Profile data(“Index of /Datasets/Files/961/Pub/RESIDENTIAL_LOAD_DATA_E_PLUS_OUTPUT” n.d.). Almost always the actual zip code did not have a TMY3 Load Profile data associated with it, so the nearest location was used, as determined by analyzing the zip code concerned using Homer Grid(“OpenEI Load Profiles” n.d.). The synthetic hourly

generation profile for a rooftop PV system installed in a given zip code was determined using the default assumptions of the National Renewable Energy Laboratory (NREL)'s Solar Advisory Model (SAM)(Gilman et al. 2018). Table 4.3 and Figure 4.2 summarize the results obtained from Steps 2 and 3. Because synthetic demand is used, in several cases the median prosumer's tends to generate more or less electricity than the demand calculated over the period of a year, where in real life the system will be appropriately sized. The appropriate sizing of the system (i.e. ignoring TTS data) is used as a sensitivity case. More details on the actual tariffs can be found in Supplementary Materials.

4. Calculating costs of pollution: The cost of carbon dioxide is estimated using EPA's social cost of carbon from its Obama Administration days(US EPA n.d.). The 2020 value with 3 % average discount rate is used, which estimates the cost of one metric ton of carbon dioxide in 2007 dollars at $42. The cost of local pollutants are calculated by zip code using the Estimating Air pollution Social Impact Using Regression (EASIUR) model(Heo, Adams, and Gao 2016). Dollar year, income year, and population year are all calculated as 2010. The marginal social cost data (measured in terms of $ per metric tonne) for the pollutants (PM2.5, SO_2, and NO_X) are gathered on a seasonal basis rather than an annual basis, accounting for monthly or hourly granularity in generation and demand data. Data is reported at four different altitudes, but the ground level data is selected given that we have little knowledge regarding the actual terrain conditions of an average household in the zip code with a rooftop PV system installed. All reported dollar values at converted to present day (December

2019) dollars using U.S. Bureau of Labor Statistics Inflation Calculator("CPI Inflation Calculator" n.d.).

5. Discount rate: A 4 per cent base discount rate is assumed. This rate is chosen on the basis of the peak long-term treasury interest rate over the last decade(Organization for Economic Co-operation and Development 1955).

Table 4.2: List of States, Utilities, Zip codes, Tariff Structures, and Escalation Rate

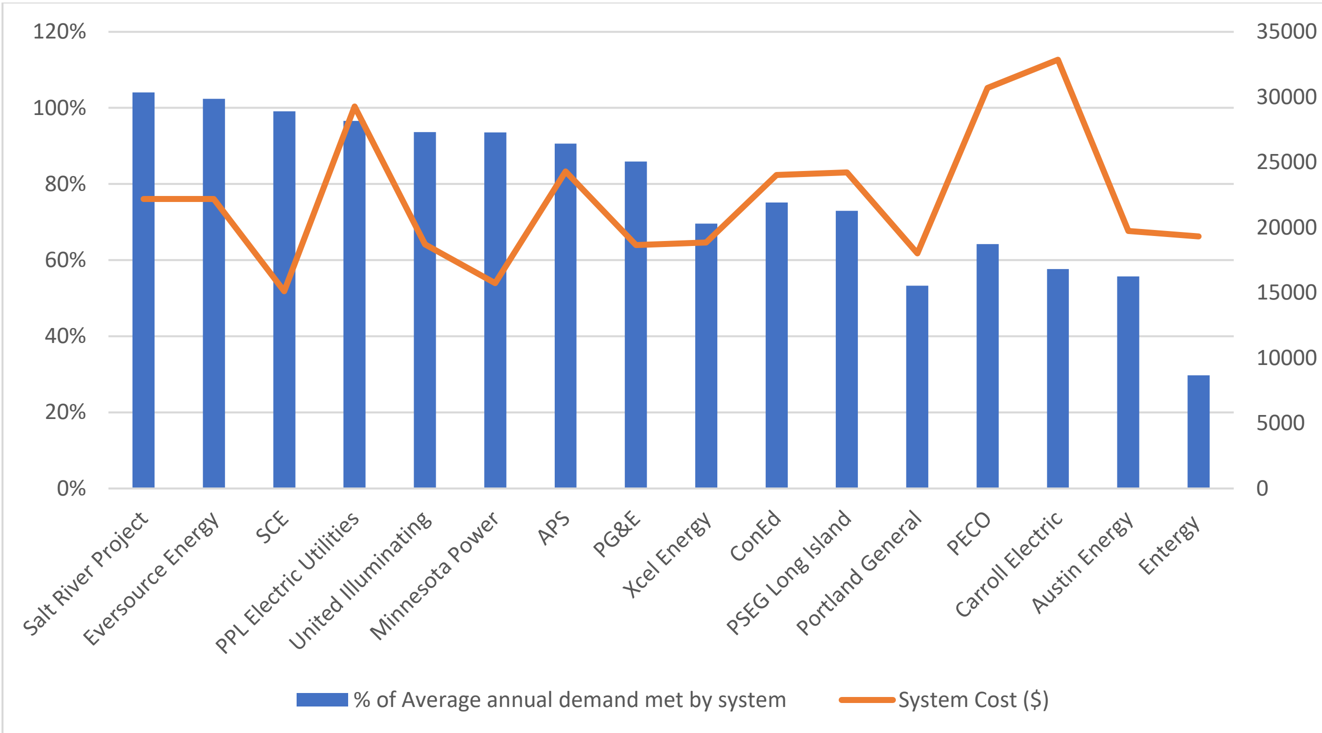
Utility	**State**	**Chosen Zip code**	**ToU**	**Tariff Escalation Rate**
Entergy	AR	71909	Yes	0.7%
Carroll Electric	AR	72641	No	0.7%
APS	AZ	85383	Yes	1.8%
Salt River Project	AZ	85140	Yes	1.8%
PG&E	CA	95648	Yes	2.5%
SCE	CA	92563	Yes	2.5%
Eversource Energy	CT	6010	Yes	0.4%
United Illuminating	CT	6516	Yes	0.4%
Xcel Energy	MN	55406	Yes	2.7%
Minnesota Power	MN	55804	No	2.7%
PSEG Long Island	NY	11704	Yes	0.6%

Consolidated Edison	NY	10562	Yes	0.6%
Portland General Electric	OR	97215	Yes	2.4%
PPL Electric Utilities	PA	17601	Yes	1.8%
PECO	PA	19426	No	1.8%
Austin Energy	TX	78701	No	-1.0%

4.6 Results

We start by comparing the effective demand met (ratio of average annual generation to average annual demand) and the total system cost in Figure 4.2 to determine whether or not the most expensive systems are actually effective in meeting the requisite demand of the median prosumer. We find that an expensive system does not ensure that more of the effective demand is met, owing to substantial variation in the per kW cost faced by median prosumers depending on their utilities.

Figure 4.2: Comparison of System Cost vs Demand met through system

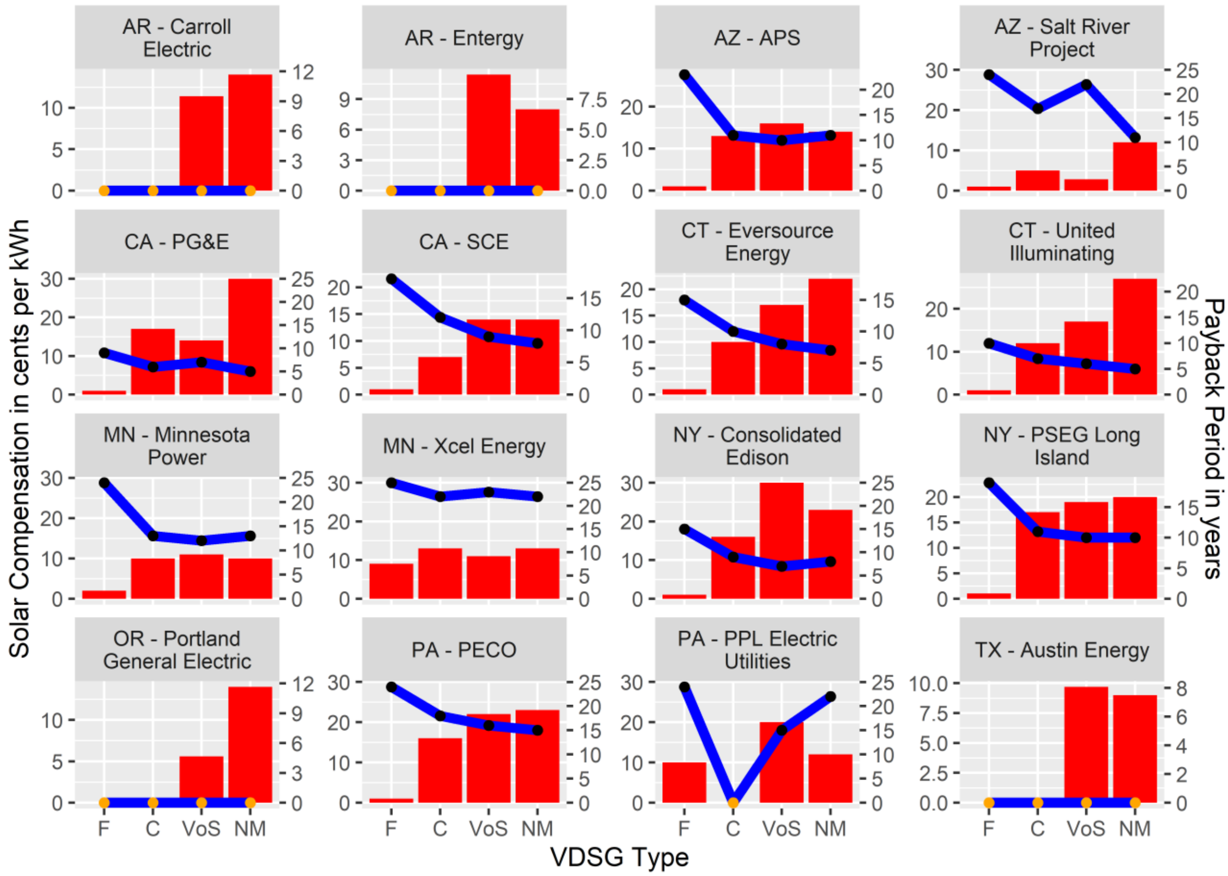


Notes: Primary axis – Percentage of Average Annual Demand met by system. Utilities arranged by ascending order of this percentage. Secondary axis – System cost for the median prosumer served by the utility.

The correlation between the demand met by system percentage and system cost is -0.11, suggesting a weak inverse relationship, i.e. more expensive systems meeting less demand which is counterintuitive. The correlation between demand met by system percentage and system cost per kW is -0.69, suggesting a stronger inverse relationship. There are however caveats in interpreting these relationships, given the fact that a synthetic demand profile is used, and we have no way of knowing the actual demand pattern of the zip code associated. However, the system cost and system cost per kW data which are based on real life data, show considerable variations across utilities, and as such there is only a 0.36 correlation between the two, suggesting that while in general the more expensive system suggests a higher generation capacity, the relationship isn't very strong. For example, a 3 kW system at the Entergy service area costs about $19,000 on average, and at that price point, the PG&E service area zip code can install a system with a capacity of 6 kW. More expensive systems per dollar, inability of expensive systems to meet a higher share of effective demand, and low retail rates are often cited as some of reasons why distributed PV might not be financially viable for some consumers (Darghouth, Wiser, and Barbose 2016), and for preliminary analysis we see some of these factors present across the chosen sample of utilities. Utilities of interest are Carroll Electric (Ranked Highest in system cost but 13th highest in demand met) and PECO (Ranked second highest in system cost but 12th highest in demand met). On the flip side, utilities with a high rank in demand met but low rank is system costs include SCE (3rd and 16th respectively) and Minnesota Power (6th and 15th respectively).

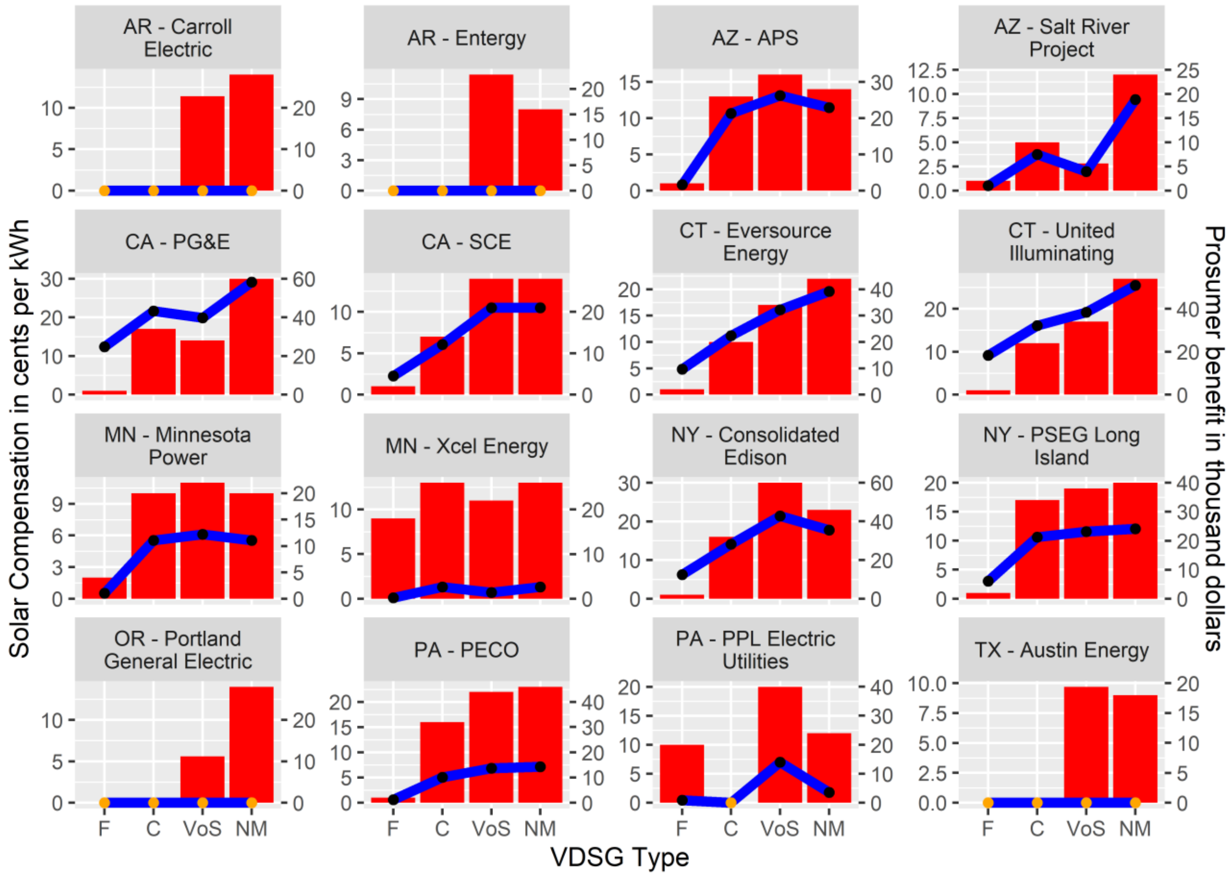
Figures 4.3 -4.5 summarizes the key findings for the base tariff (non-ToU) cases. In Figure 4.3 we see the impact of different solar compensation mechanisms (bars on the primary axis) on the payback period of the installed PV systems (line). An, i.e. when an acceptable floor and ceiling compensation cannot be found, is denoted by an orange dot, and no payback is possible within 25 years of project lifetime. For benchmarking purposes, even if the VoS and Net Metering tariff correspond to an invalid payback period, the tariffs are still graphically plotted, but the payback period is denoted using an orange dot. Most utilities do have valid payback periods for all types of tariffs with the notable exceptions being the previously flagged Carroll Electric, as well as Entergy, Portland General, PPL, and Austin Energy. Cost issues aside for Carroll Electric, and to some extent for Austin Energy and Entergy as well, their low retail rate plays a major role in making the PV systems unprofitable, as there is not enough avoided cost in terms of retail energy demand savings to justify the investment in the system, regardless of the compensation offered for solar generation. For Portland General, the system cost and effective demand met are both towards the lower end (ranked 3rd lowest and 2nd lowest respectively). However, along with a middling retail rate, per kW cost is among the highest (4th highest) which explains the relative ineffectiveness of the system in being economically unviable. For PPL, only the ceiling compensation rate leads to an invalid payback which means that the compensation obtained would be lower than the 10 cents floor tariff (which is the highest among all valid floor tariffs), suggesting that while the relatively expensive system (3rd most expensive in total, 6th in per kW) does a good job in meeting the synthetic demand load, the compensation required to make it cost-effective is incompatible with the energy cost component of the utility tariff. It is to be noted that the VoS component for PPL is considerably higher than the floor and even net metering, suggesting that there might be ancillary benefits for the utility other than saving on energy costs, although given the generic nature of VoS tariffs, this cannot be said with certainty.

Figure 4.3: Solar Compensation and Payback period – Base Tariff



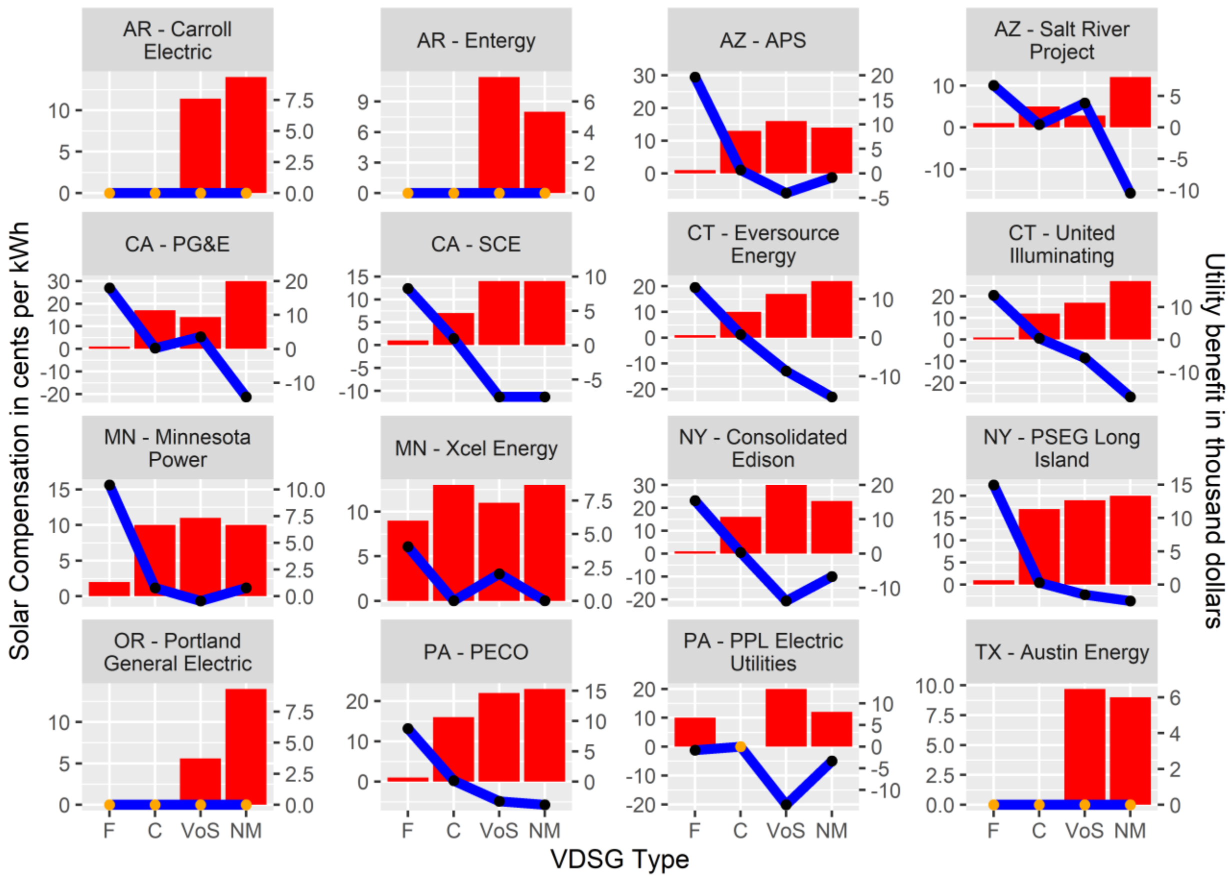
Notes: Primary axis (bar) – Compensation; Secondary axis (line) – Payback period. An orange dot indicates invalid payback period (which for Floor and Ceiling VDSG indicate invalid compensation). Value of Solar and Net Metering compensations are calculated for benchmark purposes even if there is no valid payback period within the 25-year lifetime of the project.

Figure 4.4: Solar Compensation and Prosumer Benefits – Base Tariff



Notes: Primary axis (bar) – Compensation; Secondary axis (line) – Prosumer benefit. An orange dot indicates negative prosumer benefit (which for Floor and Ceiling VDSG indicate invalid compensation). Value of Solar and Net Metering compensations are calculated for benchmark purposes even if there no valid payback period at the end of the 25-year lifetime of the project.

Figure 4.5: Solar Compensation and Utility Benefits – Base Tariff

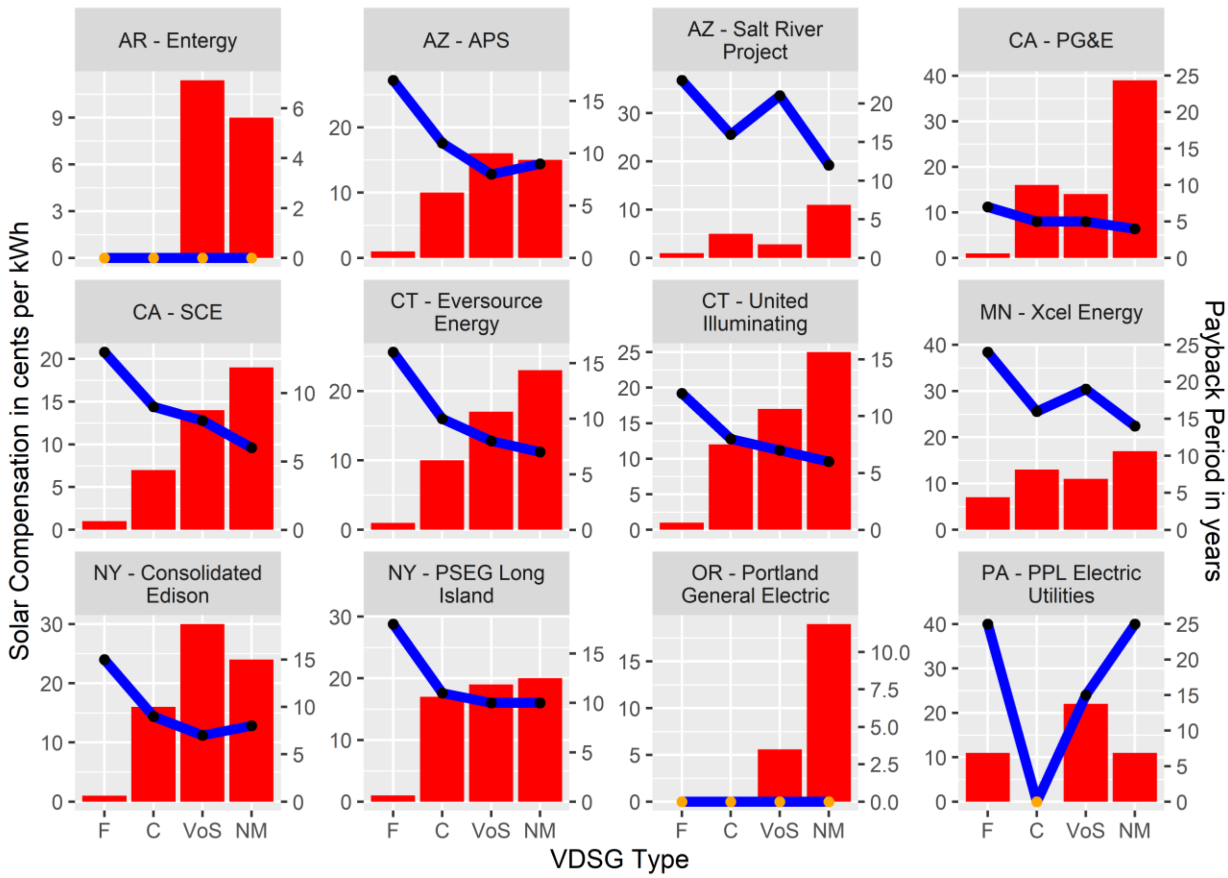


Notes: Primary axis (bar) – Compensation; Secondary axis (line) – Utility benefit. An orange dot indicates negative payback period (which for Floor and Ceiling VDSG indicate invalid compensation). Value of Solar and Net Metering compensations are calculated for benchmark purposes even if there is negative prosumer benefit at the end of the 25-year lifetime of the project.

In general, floor compensation rates are very low, often not exceeding the minimum threshold of 1 cent indicating that consumers do not require much incentive in terms of solar generation compensation to invest in the system. This is driven by high retail rates for most utilities, far exceeding the national average retail rate of 11 cents(“State Electricity Profiles - Energy Information Administration” n.d.) in all but two cases with valid compensation for every VDSG type (the two Minnesota utilities). The VoS tariff falls in between the floor and the ceiling in only 3 of the 11 complete cases, suggesting that most regulators believe that there is additional benefit to be gained by the utility than just avoided energy costs. Predictably, higher solar compensation means faster payback periods, so from a prosumer perspective, the net metering compensation for solar is the most suitable.

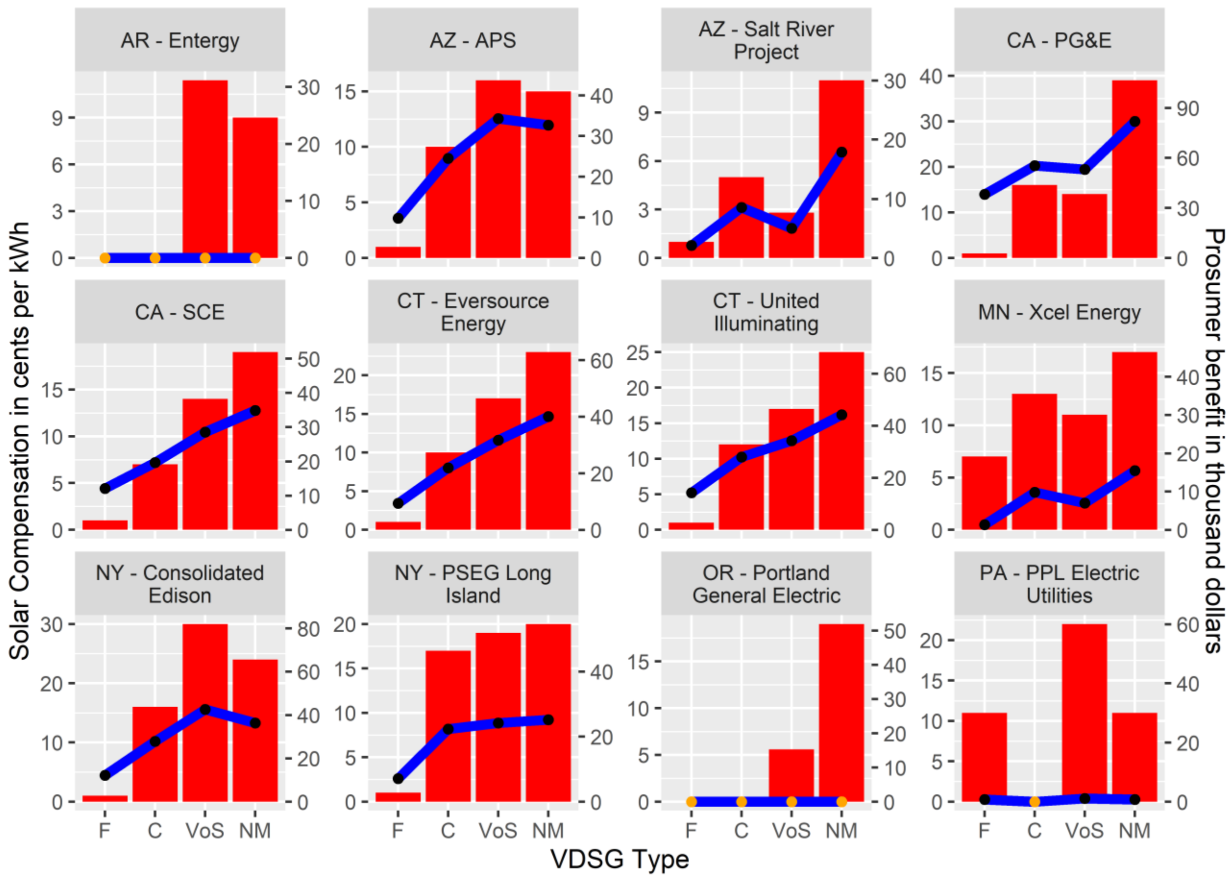
Figure 4.4 summarizes the prosumer benefits, and as expected we see that higher compensation correlates with higher benefits. Once again, invalid compensation means that there is no prosumer benefit, as the system will be infeasible in such a case. In Figure 4.5, we see the utility benefits going largely in the opposite direction of the prosumer benefits, and in a large number of cases when VoS or net metering compensations are adopted, they are negative.

Figure 4.6: Solar Compensation and Payback period – ToU Tariff



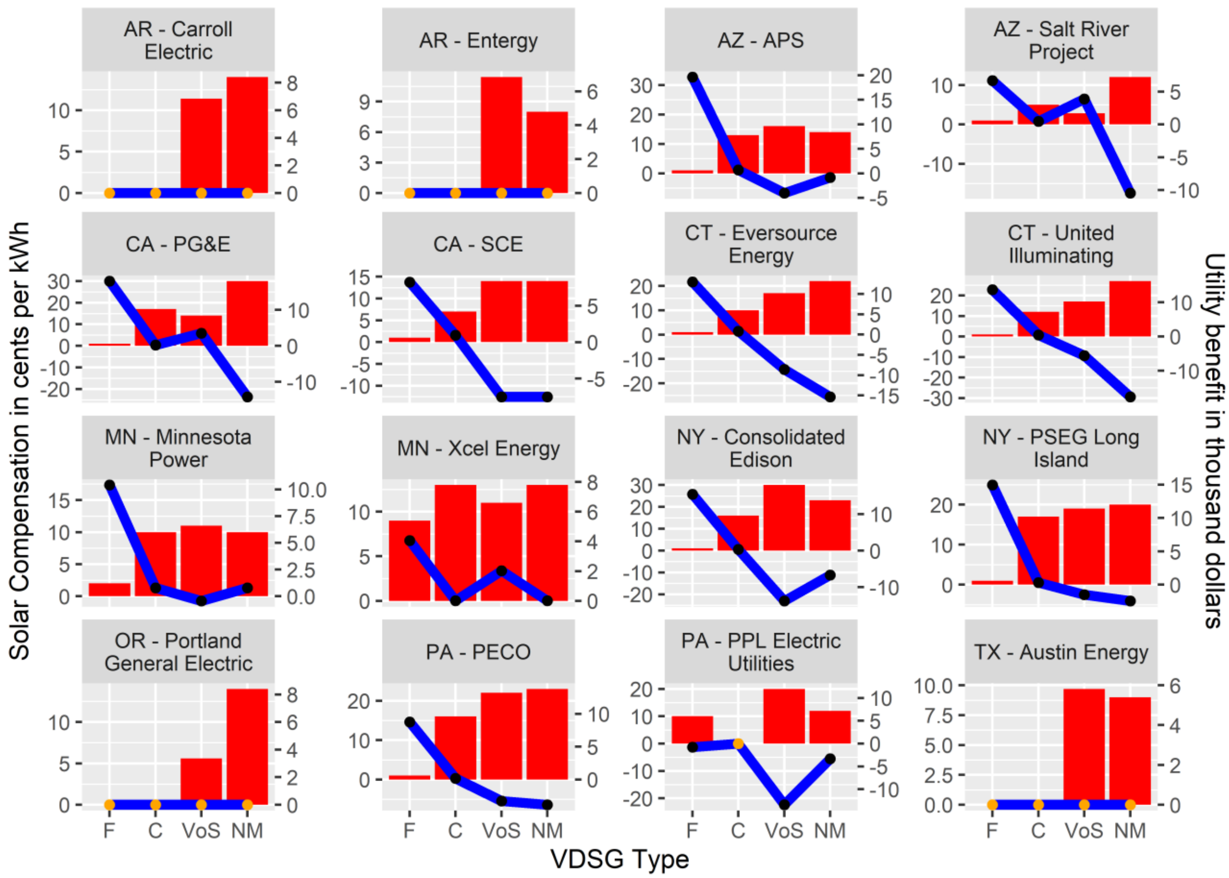
Notes: Primary axis (bar) – Compensation; Secondary axis (line) – Payback period. An orange dot indicates invalid payback period (which for Floor and Ceiling VDSG indicate invalid compensation). Value of Solar and Net Metering compensations are calculated for benchmark purposes even if there is no valid payback period within the 25-year lifetime of the project.

Figure 4.7: Solar Compensation and Prosumer Benefits – ToU Tariff



Notes: Primary axis (bar) – Compensation; Secondary axis (line) – Payback period. An orange dot indicates invalid payback period (which for Floor and Ceiling VDSG indicate invalid compensation). Value of Solar and Net Metering compensations are calculated for benchmark purposes even if there is no valid payback period within the 25-year lifetime of the project.

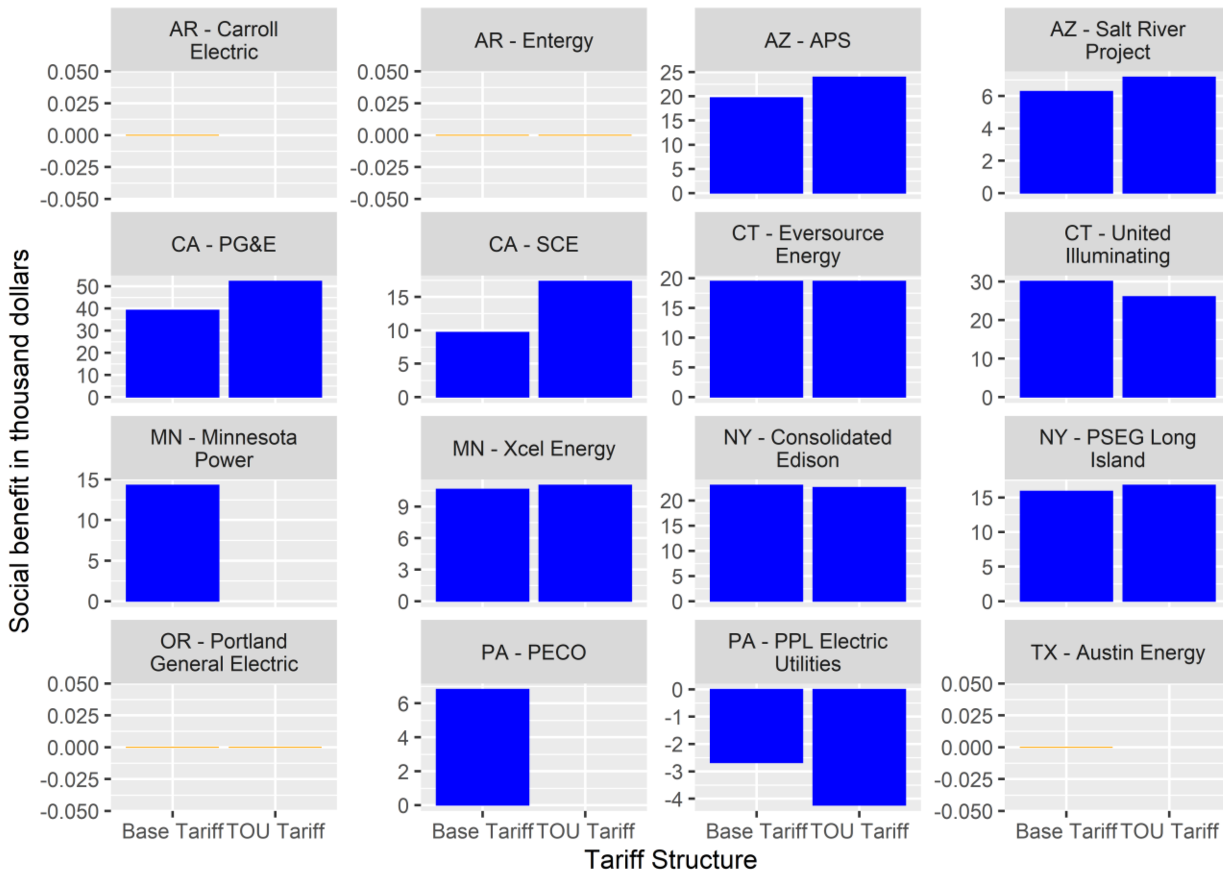
Figure 4.8: Solar Compensation and Utility Benefits – ToU Tariff



Notes: Primary axis (bar) – Compensation; Secondary axis (line) – Utility benefit. An orange dot indicates negative payback period (which for Floor and Ceiling VDSG indicate invalid compensation). Value of Solar and Net Metering compensations are calculated for benchmark purposes even if there is negative prosumer benefit at the end of the 25-year lifetime of the project.

Moving on to ToU tariffs, the basic trends are unchanged. However, ToU seems to be associated with slightly faster payback periods and slightly higher net metering and ceiling tariffs (Figure 4.6, please see Supplementary Materials for details on ToU tariff structure). This indicates consumers are certainly better off if solar compensation was still at a net metering rate, and the utilities can afford to pay more before the avoided energy cost equation becomes unfavorable to them. There are two important caveats. Firstly, it is likely that the demand pattern will change in response to a ToU tariff shift, and this cannot be replicated here as we are using synthetic demand. Secondly, we cannot generalize that a shift to ToU will be beneficial in terms of net metering and floor compensation because it is related to consumption pattern in these particular synthetic demand data points, and may not be applicable to the behavior of prosumers operating under ToU tariff. In Figures 4.7 and 4.8, we see similar trends, i.e. slightly higher prosumer benefits at all tariff levels and slightly higher utility benefits at the ceiling tariff level. However, it is to be noted that a shift to ToU does not mean utilities producing invalid compensation results now produce valid results. For these several basic assumption changes were required, which are tackled in Section 7.

Figure 4.9: Social Benefits – Base and ToU Tariff



Notes: A blank social benefit indicates absence of data (i.e. some utilities don't have ToU tariff structure). A social benefit depicted with a line instead of a bar indicates an invalid social benefit, because for that prosumer-utility combination – any VDSG fails to generate a valid payback period for the prosumer, making the PV system infeasible.

Figure 4.9 compares the compensation-invariant social benefit for all the utilities in the base tariff and the ToU tariff cases. Consistent with the prosumer and utility benefit observations we see that generally the society is better of under a ToU tariff, although United Illuminating and PPL seem to be exceptions. Once again, for invalid compensations – no social benefit is recorded, and these are represented by lines as compared to bars. Blank benefits are for utilities without ToU tariffs. The most interesting case here is that of PPL, which has negative social benefits in both cases, driven by the highly expensive system cost resulting in the society bearing a high subsidy burden which cannot be offset by pollution avoidance benefits and combined utility and prosumer benefits.

4.7 Key Sensitivities

For sensitivity purposes we alter the following parameters:

- Demand: Using Low and High demand from the TMY3 database that provided us with Base demand(“Index of /Datasets/Files/961/Pub/RESIDENTIAL_LOAD_DATA_E_PLUS_OUTPUT” n.d.)
- Discount rate: An alternate 7 per cent discount rate is chosen. This is roughly equivalent to the long-term rate of return of S&P 500(Maverick n.d.).
- Optimal sizing: Recognizing the fact that there might be a size-demand mismatch due to the use of synthetic demand data, we size the systems in accordance with the synthetic demand rather than taking the size as given. The only limit applied to sizing is that generation from the system must not exceed 120 per cent of the annual demand, which is applied by a number of state regulators(“State Net Metering Policies” n.d.). Re-sizing is done on the basis of the per kW cost obtained from the average system cost and installed capacity in the zip code.

In total for the 16 utilities considered, a total of 308 sensitivity cases were simulated (176 for base tariff cases and 132 for ToU tariff cases). The results from every single case are analyzed in the Supplementary Materials section. In the main body of the paper, we present the results of four of these 308 cases. The details of these cases are presented in Table 4.4.

Table 4.3: Results of selected sensitivity cases

State – Utility	VDSG_Type	Case	Solar Compensation (cents per kWh)	Payback Period (years)	Prosumer Benefit ($)	Utility Benefit ($)
AR - Entergy	F	Base	INV	INV	INV	INV
AR - Entergy	F	LD	INV	INV	INV	INV
AR - Entergy	C	Base	INV	INV	INV	INV
AR - Entergy	C	LD	INV	INV	INV	INV
AR - Entergy	VoS	Base	11.4	INV	INV	INV
AR - Entergy	VoS	LD	11.4	INV	INV	INV
AR - Entergy	NM	Base	8	INV	INV	INV
AR - Entergy	NM	LD	8	INV	INV	INV
CA - PG&E	F	Base	1	9	24812	17953
CA - PG&E	F	HD	1	9	28587	18838
CA - PG&E	C	Base	17	6	43259	215
CA - PG&E	C	HD	39	5	48109	67
CA - PG&E	VoS	Base	14	7	39799	3541
CA - PG&E	VoS	HD	14	9	31608	15933
CA - PG&E	NM	Base	30	5	58247	-14196
CA - PG&E	NM	HD	30	8	35237	12357
NY - Consolidated Edison	F	Base	1	15	12433	15462

NY - Consolidated Edison	F	HDR	1	19	3797	11422
NY - Consolidated Edison	C	Base	16	9	28159	342
NY - Consolidated Edison	C	HDR	15	11	15284	686
NY - Consolidated Edison	VoS	Base	30	7	42836	-13771
NY - Consolidated Edison	VoS	HDR	30	7	27591	-10816
NY - Consolidated Edison	NM	Base	23	8	35497	-6715
NY - Consolidated Edison	NM	HDR	23	9	21848	-5448
TX - Austin Energy	F	Base	INV	INV	INV	INV

TX - Austin Energy	F	OS	6	23	1771	-1532
TX - Austin Energy	C	Base	INV	INV	INV	INV
TX - Austin Energy	C	OS	INV	INV	INV	INV
TX - Austin Energy	VoS	Base	9.7	INV	INV	INV
TX - Austin Energy	VoS	OS	9.7	16	9704	-9161
TX - Austin Energy	NM	Base	9	INV	INV	INV
TX - Austin Energy	NM	OS	9	17	8204	-7718

Notes: LD – Low Demand; HD – High Demand; HDR – High Discount Rate; OS – Optimal Sizing; INV – Invalid

The following four cases are picked for illustrative purposes, all for base tariff structures:

- Entergy – Low demand. This is the utility which faired the worst in terms of the system meeting its demand. The low demand case improves the demand met percentage to 55 from 30.
- PG&E – High demand. This is the utility which fairs among the best (86 per cent) in terms of the system meeting its demand and in terms of prosumer benefit, it is ranked

the highest. The high demand scenario reduces the demand met percentage to 55 per cent.

- Consolidated Edison – High discount rate. Another highly profitable case for prosumers. The aim is to determine if higher discount rates reduce profitability significantly.
- Austin Energy – Optimal sizing. A utility with poor demand met percentage (56 per cent), low compensation rates and middling cost. The aim is to determine whether re-sizing the system is an effective technique to solve its issues.

The results suggest that for these cases, re-sizing is the only technique that significantly alters the pathway for the utility compared to the baseline. Even with a demand reduction, Entergy is unable to generate valid compensations. PG&E benefits are reduced somewhat but not by any substantial amount (although the ceiling compensation goes up considerably). Discount rate changes does substantially impact the benefits for Consolidated Edison prosumers and the utility, but the system still remains profitable for all parties. Austin Energy meanwhile generates valid compensation values for the floor with resizing, although finding a ceiling compatible with the floor is still problematic, likely due to cheap electricity generation costs. However the VoS and NM tariffs produce valid results in terms of benefits, but it seems that the prosumer is largely the winner, which is interesting to note because Austin Energy is one of the few utilities that actually uses VoS as a compensation mechanism. This perhaps indicate that the utility makes avoided cost gains from elsewhere in the system.

4.8 Discussion and Conclusions

There are several important policy lessons that can be learnt from the results of the stylized exercise. While utility and prosumer benefits tend to run in the opposite direction, the study establishes in most cases, valid ceilings and floors. Thus, the regulator has the option to pick a wide range of tariffs that will not leave the two parties worse off compared to a no rooftop-PV situation. Which tariff is picked depends on which side the regulator wants to favor. Ideally within the range of valid tariffs, a tariff that is exactly half-way down the middle will be picked or one will be picked to ensure relatively equitable benefits for both parties. The benchmark VoS values suggests that most utilities benefit significantly from factors other than avoided generation cost, although a direct comparison is probably inconclusive due to methodological differences in calculating the VoS values compared to values in this study.

We also find that the most significant determinants behind the validity of various types of compensations are system cost relative to size, percentage of demand fulfilled, the relative comparison between system cost and demand met, and the retail rate. With systems that are highly expensive for its size, which in turns means that a prosumer may not be able to install an optimal size of it to consistently offset their demand requirements, let alone sell excess power to the grid it is highly unlikely that any reasonable rate of solar compensation will work. The retail rate plays a major role as well, with the expensive prosumer-utility combinations in New York and California demonstrating that with the ability to offset significant amount of their demand with rooftop PV generation is beneficial to the point only a minor solar incentive is required to make installation of the system worthwhile.

A couple of caveats might be noted here – firstly, the use of synthetic demand may not be reflective of the actual demand conditions and secondly, since rooftop solar is considerably less expensive now as compared to what the median prosumer faces (the median value of PV system cost based on TTS data for existing systems), a prosumer might not face significant cost issues which may ease some of the financial constraints even if the retail rate is not favorable. However, given the vast differences in per kW costs with the existing rooftop PV systems, it is unlikely that these differences have been completely resolved with falling rooftop PV system costs. This is because while hardware costs have fallen dramatically, the balance of system costs have not, and these "soft costs" may vary considerably between states or even between utility service territories, making rooftop PV still prohibitively expensive for some consumers(O'Shaughnessy et al. 2019). The combinations that were worst affected such as the two Arkansas utilities and Portland General are both characterized by high costs relative to demand met and low retail tariff. Since lower capital costs will affect every utility and prosumer while retail tariffs increase fairly slowly, it is unlikely that these utilities will be relatively better off in the future than they are now unless soft costs specific to their service area or state come down dramatically. Policy efforts should probably be concentrated on reducing these soft costs for new installations and helping out existing installers with cost-effective re-sizing.

Expensive systems also mean greater burden on the society in terms of taxpayer-funded incentives, and this can ultimately offset or at the very least significantly reduce gains made by the prosumer and utility combined, even accounting for avoided pollution-related costs. This is precisely what happens in the case of PPL and even the Austin Energy sensitivity case with the resized system. Additionally, if generation is relatively inexpensive, then combined with low retail rates, and an expensive system, the Austin and the PPL case demonstrates that it may be hard to find a valid ceiling compensation for the utility as it may be below the minimum required compensation for the prosumer in order to guarantee a positive payout from the system.

This study can be extended to several future avenues of research. A dynamic model can be created that treats consumer response as endogenous. Which means we can model changing demand pattern in response to changes in tariff structure and compensation rates. More zip codes and utilities can be added to make state-level comparisons easier. Alternate compensation methods can be used to determine the effectiveness of certain methods under various solar compensation values and other factors such as system cost, system size, and retail price. New installations beyond the TTS database can be added to simulate the benefit proposition of consumers facing substantially lower system cost, although a mechanism must be created to preserve regional differences in cost per kW, which will require updates beyond the hardware cost. Custom-made demand profiles can also be used for new installations rather than sticking to synthetic data from TMY3. On the utility side, better accounting of benefits might be possible by gaining more data on potential benefits and costs due to distributed solar, making sure that the ceiling compensation is a more accurate reflection of the Value of Solar. The utility/prosumer benefit model may also be extended by accounting for other grid connected components that help offset electricity consumption and sell energy to the grid, e.g. battery storage and EV charging. These can dramatically alter the Value of Solar proposition and constitutes an important future research direction.

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Chapter 5

Conclusion: Building on the Achievements of Leaders and Motivating Laggards through Policy Levers key to decarbonization

The three previous chapters covered several entities in the U.S. electricity sector and their roles in grid decarbonization. In the process we have identified two distinct subset of entities (actors) that can be roughly classified as "leaders" or "laggards" based on their contribution to the specific objective outlined in each chapter. In order to summarize the outcomes of these chapters (The Three Essays) and how they answer the overarching questions answered in Chapter 1, this chapter is divided into five broad sections. The first section summarizes the actors and objectives analyzed, providing brief description of the outcomes and how certain subset of actors can be classified as leaders and laggards (**Table 5.1**). The second section circles back to the research questions that were asked in The Three Essays and summarizes their answers. The third section reiterates the overarching questions asked in Chapter 1 and answers them, drawing from the combined insights of The Three Essays. The fourth and final section outlines future work that can be undertaken based on these insights and some general policy suggestions related to the decarbonization of the U.S. electricity grid.

Table 5.1: Summary of Actors, Objectives, and Outcomes with Examples of Leaders and Laggards

Chapter	Actor	Objectives	Outcomes	Examples

2	States (through Grid Regions)	Institute state energy policies to set themselves up in case of a federal reengagement.	Grid regions with states that are aggressive in setting decarbonization policies face less adjustment or shocks to their generation, price, or emission pathways (**Leaders**) compared to the states that are more conservative (**Laggards**)	**Leaders:** New York, California, states in the Northwest Grid (Washington, Oregon etc.) **Laggards:** Florida, Texas, most states in the Southeast grid (Alabama, Tennessee etc.)
3	Households	Purchase and effectively use energy efficient appliances	Households that tend to be more educated, wealthier, and have their own single-family home are likely to purchase and effectively use energy efficient appliances (**Leaders**) compared to other households that do own and energy efficient appliance but don't tend to use them as effectively (**Laggards**)	**Leaders:** Households consuming about 15-20 per cent higher than average electricity **Laggards:** Households consuming at about or 2-5 per cent higher than average electricity
4	Prosumers and Utilities	Ensure positive effects from installation of distributed PV (DPV) system	Prosumer-utility combinations that benefit typically have suitably sized systems, high enough retail and energy market costs, and cost-effective systems (**Leaders**) compared to those with undersized systems, low retail and market costs and overpriced systems (**Laggards**)	**Leaders:** Specific prosumers and utilities analyzed in New York, California, Connecticut, Arizona, Minnesota. **Laggards:** Specific prosumers and utilities analyzed in Oregon, Texas, Arkansas.

5.1 Answering the Individual Research Questions

The research questions associated with these chapters and how the analysis in the dissertation chapters answered these questions are discussed in this section.

Chapter 2 asked – *"Is it worthwhile for the states to pursue aggressive climate policies with a federal policy on the horizon in terms of minimizing their deviation from existing electricity sector outcomes once a federal policy is instituted? Will federal policymakers and the U.S. electricity grid benefit when every state pursues relatively more aggressive policies compared to existing ones?"*

Chapter 2 finds that based on the effect of federal pricing of carbon on grid level emission trajectories, electricity generation mix, and electricity prices, grid regions that constitute of states with aggressive electricity sector policies will see a lower deviation in these outcomes with respect to a policy-only case compared to grid regions that constitute states with conservative electricity policies. This translates to policy conservative grids needing to drastically alter their emissions pathway by significantly ramping up renewable-based generation and install (or retrofit) costly carbon capture and storage (CCS) solutions under federal pricing scenarios compared to policy-only scenarios, which results in considerable price shocks in the electricity market. Meanwhile, if all states pursue more aggressive policies compared to their existing ones (albeit at a differentiated rate, given that policy aggressive states are likely to contribute more), then the federal policymakers benefit in having to price carbon lower compared to a less aggressive policy scenario in order to reach the same economy-wide GHG trajectory. The U.S. electricity grid benefits with more aggressive state policies as it enables the grid to decarbonize more at a lower federal price compared to a set of less aggressive state policies.

Chapter 3 asked – *"How can household behavior in terms of adoption of energy efficient appliances and temperature control strategy of space heating and cooling equipment be jointly categorized? What are the factors associated with households being categorized into different behavioral groups?"*

Chapter 3 finds that household behavior in terms of adoption of energy efficient appliances and temperature control strategy of space heating and cooling equipment can be roughly classified into four classes. Those households that own at least one energy efficient appliance and effectively use programmable thermostats to control their heating and cooling equipment only form about 15 per cent of the total sample. The two classes that own at least one energy efficient appliance but manually change their temperature/do not change it at all account for 75 per cent of the sample combined. A fourth class of households do not own an energy efficient appliance and tend not to control their heating and cooling equipment account for 10 per cent of the sample. The factors that tend to increase the odds of a household belonging to the programmable thermostat class over the classes favoring manual control/no change include higher education, owning a single family home, higher income, a newer house, and the completion of an energy audit of their house.

Chapter 4 asked – *"For given prosumer-utility combinations, what are the valuations of distributed solar generation that make sense for both prosumers and utilities – such that utility cost of energy acquisition for the prosumer remain unaffected and the prosumers still receive enough compensation to ensure payback for the installed system within its lifetime? What explains the differences in these valuations between and within certain prosumer-utility combinations?"*

Chapter 4 finds that for most of the prosumer-utility combinations analyzed, a range of valuations that meet the minimum requirements of both the prosumer and utility can be obtained. The upper bound of these values (representing the requirement of the utility) exceed the default net metering rate in almost every case. The Value of Solar benchmark studies that are likely to be more accurate measures of utility benefit from distributed generation at an aggregate level tend to be higher than the upper bound as well.

Prosumer-utility combinations for which valid valuations were obtained are characterized by many of the following parameters: high retail rate which ensures even at lower levels of compensation the prosumer has an incentive to install a rooftop PV system simply because of the electricity bill savings and the fact that high retail rates tend to correlate with higher energy costs which mean utilities will save on considerable energy costs when rooftop PV offsets some of the supply; and appropriately sized system with respect to demand as well as a moderate cost of the system on a per kW basis which reduces the financial burden of the prosumer. Lower system cost in total and on a per kW basis are also associated with higher societal benefits, ensuring that the avoided cost of pollution due to rooftop PV generated electricity exceeds the taxpayer burden the society has to bear by subsidizing the system.

5.2 Answering the Overarching Research Questions

The overarching research questions asked in Chapter 1 and their answers on the basis of the analysis in The Three Essays are discussed in this section.

Which actors are best positioned to contribute towards meeting objectives that would assist the transition of the U.S. electricity grid towards a sustainable future?

States with aggressive electricity sector decarbonization policies and a Federal Administration willing to price emissions appropriately, households adopting and effectively using efficient equipment, and prosumers who are able to install rooftop PV cost effectively in utility service areas where the cost structure allows both parties to find common ground for a suitable solar compensation. A common thread is that the **leaders are typically proactive and financially well-off members of their group**.

What is the impact of joint actions by actors in accomplishing their objectives?

Joint action by Policy Aggressive and Policy Conservative states in terms of both being relatively aggressive with their policies will aid in lowering the price that has to be applied by the Federal Government. Joint action by households in terms of adoption and effective usage of energy efficient appliance can lead to more energy efficient consumption outcomes, although this cannot be ascertained without further analysis. Finally, the joint determination of a valid range of tariffs provide opportunities for the utility to increase their renewables portfolio and the prosumer to save on their electricity bill. **Joint actions by all the actors help in achieving decarbonization objectives with greater effectiveness.**

What are the factors that make these actors better positioned than others in the same segment?

Policy aggressiveness at the state level is generally tied to the track record of the state government, and generally speaking – liberal(Brown and Hess 2016), highly educated(Snyder, de Brey, and Dillow 2019) and wealthier(Carley 2009). Chapter 2 shows that households are likely to be in the thermostat-usage class if they are wealthy and highly educated. Empirically speaking, prosumers tend to be wealthier and more educated than non-adopters (Soskin and Squires 2013), while states with favorable cost structures for both parties overlap somewhat with the policy aggressive states discussed in Essay 1. As such – policy positions of government, average wealth and level of education seem to play a significant role in determining the subset of actors that are better positioned to decarbonize the grid.

What policy options can be used to assist actors that are lagging behind?

Given the enormity of the task at hand however, it is important that effective policy options are considered in order to improve the contribution of the laggards. At the state-level, highlighting the benefits of aggressive policies to the states themselves can be a good first option. Policy conservative states are often concerned with the distributional impact of aggressive policies(Mathur and Morris 2014), and these can be mitigated to an extent with direct federal support. More targeted regional policies may also be applied specifically to make the most polluting elements of a grid region unprofitable, but these are likely to come under legal scrutiny. At the household level, information, technical and financial assistance should be provided to households that adopt energy efficient appliances but stick to manual temperature control, given that these households consume electricity at or close to the national average and account for 75 per cent of the sample. This is however contingent on additional studies on the thermostat user class to determine if their usage has resulted in reduction of consumption. For prosumers and utilities, it is important not to undermine the non-adopters by ensuring that utility revenue remain neutral as a result of increased rooftop PV adoption. On cases where this cannot be accomplished, proper sizing of the system can be ensured by financing retrofits, and cost of system on a per kW basis can be lowered by focusing on factors that impact soft costs(O'Shaughnessy et al. 2019).

5.3 Future Work and Overall Approach to Grid Decarbonizations

Several promising pathways of future research emerge from the results and analysis of this dissertation. First is a deeper dive into the demographic characteristics of states, prosumers, and utilities to empirically determine factors that affect grid decarbonization actions. Second is an in depth study of the households in Chapter 2 to determine to what extent their actions on adoption and usage of energy appliances can really drive national consumption of electricity to reduce per capita. A third strand of study can encompass other actors such as businesses, generators, manufactures, and installers and analyze their role in grid decarbonization and how it complements or competes with the goals of the actors discussed in this dissertation. A fourth strand of study can be an ambitious bottom-up analysis of all stakeholder actions (including households, utilities, and prosumers) and how enhanced actions can improve state policy outcomes and in turn improve national outcomes on cost effective grid decarbonization.

Given the complexity of the U.S. electricity grid, no single entity, no matter what their authority can effectively compel all the stakeholders to act appropriately to meet top-down decarbonization targets. Clear directives and education about the consequences of a heavily carbon-dependent grid and the benefits of a decarbonized one in terms of factors that are important to the actors themselves should be prioritized. If and only if all stakeholders in the system buy into the importance of decarbonization, the U.S. electricity grid can effectively solve the problem of decarbonization transformation.

5.4 References

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Appendices

Supplementary Materials for Policy payoff: Are Aggressive State Electricity Policies Beneficial in the Context of Federal Re-engagement?

GCAM-AP analyzed six scenarios of decarbonization through state policies, market actions, and federal pricing implemented through carbon tax.

These scenarios are:

BAU – Where existing measures of state policies and market actions are extended till 2050 to determine grid region contribution to electricity sector emissions, electricity sector prices, electricity generation mix, and national aggregate of electricity sector emissions

Medium – Slightly aggressive state policies and favorable market actions are assumed till 2050

High – Highly aggressive state policies and favorable market actions are assumed till 2050

BAU + Tax – A carbon tax implemented on top of the BAU scenario such that the U.S. economy meets its target of reducing 80 per cent GHG emissions from 2005 levels by 2050.

Medium + Tax – A carbon tax implemented on top of the Medium scenario such that the U.S. economy meets its target of reducing 80 per cent GHG emissions from 2005 levels by 2050.

High + Tax – A carbon tax implemented on top of the High scenario such that the U.S. economy meets its target of reducing 80 per cent GHG emissions from 2005 levels by 2050.

A two-step analytical approach was used for modeling, largely following the methodology outlined by Hultman et al. (2020)(Hultman 2020) [Henceforth referred to as the America's Pledge Study]. In the first step termed as "**Sectoral Analysis**", climate policies were translated into activity data using the Athena tool, e.g. the state-level renewable generation resulting from state and city renewable energy policies. The primary focus of this step was to aggregate state-level data without double counting and taking into account the most high impact actions in each sector GCAM-AP data served as the baseline for some parameters, e.g. energy efficiency – which is explicitly modelled as percentage change in electricity consumption reduction from the baseline. In the second step termed as "**Economic Analysis**", results of the first step were converted into inputs for the GCAM-AP model.

The methodology section of the main text described the components of the scenarios in detail. The supplementary section explains how certain assumptions for the components were reached and additional data tables that support the assumptions. The supplementary section focuses on Sectoral Analysis as the Economic Analysis component is largely similar to what has been described in the America's Pledge Study.

Sectoral Analysis:

For sectoral analysis, the basic principles outlined by the America's Pledge Study to aggregate data from plants, cities, businesses, and states without double counting were followed here. Changes were made to specific parameters of interest analyzed in the study (e.g. RPS and Coal Retirement) but other sectoral assumptions were imported as is and kept constant at the values equivalent to the Current Measures scenario of that study. By and large, an attempt was made to calculate the policy impacts of top-down targets at various levels, rather than attempting to quantify and aggregate granular measures that can contribute to top-down targets. This does mean some of the estimates are conservative, e.g. development of wind and solar capacity in excess of RPS targets isn't as pronounced as it can be (although in GCAM-AP, the RPS targets are not rigid, and if it is economically efficient, renewables will be installed anyway, as is seen in a number of states under high policy scenarios). In some cases, it may make estimates slightly aggressive, for example in coal retirement – where a strict economics-related retirement ruling may not be applicable given political or technical feasibility. For example, if the economics related rule shuts down a large number of baseload power plants in the state, which will have an destabilizing effect, and the rate of replacement by gas, CCS or renewables might not be economically feasible.

We discuss the implementation of the following technical parameters:

- RPS
- Energy Efficiency
- Coal Retirement
- Handling Nuclear Power and Gas
- Vehicle Electrification
- Building Electrification
- Technology costs
- GDP Growth
- Fuel price assumptions
- Existing Emission Policies
- Baseline assumptions for Non-CO2s (Methane, HFC, N2O)
- Carbon Tax Implementation

RPS: The RPS analysis was simplified from the America's Pledge Study in order to focus solely on state-level policies. As such any city or utility level policies that are already included in these numbers have been incorporated, but no additional efforts were made to incorporate city or utility level commitments. The baseline data of renewable portfolio standards till 2050 and their associated load projections are obtained from Lawrence Berkeley National Laboratory analysis(Barbose 2019) and were applied to GCAM-AP to form the BAU scenario. Note that LBNL and GCAM-AP calculates the effective RPS which is somewhat different than the official state RPS targets due to the fact states are often inconsistent on including or excluding hydro or other clean technologies, and GCAM-AP assumes that these are not included. Additionally, GCAM requires targets to be specified on the basis of generation and RPS targets are almost always based on consumption, which meant that RPS targets had to be adjusted for generation figures at the grid level to account for potential leakages. On dividing up the generation from RPS in GCAM-AP into those from Policy Aggressive States and Policy Conservative States, we find that about 25 per cent of the Policy Aggressive States output comes from renewables and about 3 per cent of the output of Policy Conservative States output comes from renewables. The optimistic target was that in the most aggressive scenario, Policy Conservative States would be able to match the generation mix of Policy Aggressive States in the BAU scenario with respect to renewables, i.e. 25 per cent. A straightforward linear increase is assumed for Policy Aggressive States as a whole, i.e. 50 per cent for the Medium scenario and 75 per cent for the High scenario. For Policy Conservative States the Medium Scenario assumption is 10 per cent, a round figure that is about as close to the High scenario target of 25 per cent as it is to the BAU scenario.

It is a complex exercise to figure out how should each Policy Aggressive State contribute to the increase in the Medium and High scenarios, given that some were far ahead of the others in the BAU scenario to begin with (example Colorado's contribution was about 21 per cent in 2050, while that of California was 65 per cent). Any state that was already exceeding 50 per cent commitment by 2050 was kept at that commitment level. It was then calculated from the GCAM electricity generation projections that every other state on an average would have to commit to 45 per cent of renewable electricity generation by 2050. The rate of increase from the 2020 level to the 2050 commitment is assumed to be linear. (Please see Table SM1.1 for RPS targets for every scenario by state). It is a little bit more straightforward for the High case, as none of the states had an effective RPS of 75 per cent by the end of 2050 in the BAU scenario, so it simply required all states to achieve that target by the end of 2050.

For the Policy Conservative States, many of them did not have RPS in the BAU case (only 7 did, one of them is the District of Columbia which is not part of the U.S. Climate Alliance but is radically different compared to most Policy Conservative States). One state, Ohio does have a RPS target presently but has decided to terminate its future commitments starting from 2027(Hall and Zoeller n.d.). Except DC, and New Mexico, none of the state targets exceeded 9.7 per cent. For the medium case, differential responsibilities were assigned to states based on where they were in the curve. DC and New Mexico were left alone, any state with an existing target was assigned to increase it to 15 per cent by 2050, and any state without a target in 2050 was assigned to increase it to 7.5 per cent by 2050. For High, DC and New Mexico were once again left alone, and every other state was assigned a target of 25 per cent, which brought the share of renewables in generation to approximately 25.3 per cent, rounded down to 25 per cent for our analysis. DC and New Mexico contributed 0.11 per cent and 2.37 per cent to the Policy Conservative State renewable energy generation mix respectively, demonstrating the lack of size of these states in relation to the others despite having high policy targets of their own .

Table SM1.1: RPS Targets by State and Scenario (Targets in percentage, `XY stands for the year 20XY, St. is State)

St.	RPS Existing Target (as share of generation)							RPS Medium Target (as share of generation)							RPS High Target (as share of generation)						
	‘20	‘25	‘30	‘35	‘40	‘45	‘50	‘20	‘25	‘30	‘35	‘40	‘45	‘50	‘20	‘25	‘30	‘35	‘40	‘45	‘50
AK	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
AL	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
AR	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
AZ	6	9	9	9	9	9	9	6	9	9	9	10	12	15	6	9	12	15	18	22	25
CA	35	47	65	65	65	65	65	35	47	65	65	65	65	65	35	47	65	65	65	65	75
CO	21	20	20	21	21	21	21	21	28	35	43	50	58	65	21	30	39	48	57	66	75
CT	11	16	21	21	21	21	21	11	17	23	28	34	39	45	11	22	33	43	54	64	75
DE	40	50	52	52	52	52	52	40	50	52	57	57	58	65	40	50	52	58	57	58	75
FL	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
GA	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
HI	20	20	27	28	49	70	70	20	20	27	28	49	70	70	20	20	27	28	49	70	75
IA	1	1	1	1	1	1	0	1	3	5	8	10	13	15	1	5	9	13	17	21	25
ID	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
IL	9	13	14	14	14	14	14	9	13	19	25	31	37	45	9	13	24	35	46	57	75
IN	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
KS	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
KY	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
LA	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
MA	18	27	36	40	45	50	54	18	27	36	44	51	59	65	18	27	36	45	55	64	75

MD	27	40	51	51	51	51	51	27	40	51	57	57	58	65	27	40	51	59	67	73	75
ME	25	42	64	64	65	65	66	25	42	64	64	65	65	66	25	42	64	64	65	65	75
MI	7	8	8	7	7	7	7	7	13	19	26	32	39	45	7	18	29	41	52	64	75
MN	24	26	26	26	26	26	26	24	31	37	44	51	58	65	24	32	41	49	58	66	75
MO	6	10	10	10	10	10	10	6	10	10	10	11	13	15	6	10	10	10	13	16	25
MS	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
MT	5	5	5	5	5	5	5	5	12	18	25	32	38	45	5	17	28	40	52	63	75
NC	8	10	10	10	10	10	10	8	14	21	27	33	39	45	8	19	31	42	53	64	75
ND	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
NE	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
NH	4	6	6	6	6	6	6	4	6	8	10	11	13	15	4	8	11	15	18	22	25
NJ	22	33	43	42	42	42	42	22	35	43	50	57	64	65	22	35	43	52	61	69	75
NM	10	24	30	30	43	43	47	10	24	30	30	43	43	47	10	24	30	30	43	43	47
NV	22	34	49	49	49	49	49	22	34	49	57	57	59	65	22	34	49	58	67	72	75
NY	27	44	62	62	62	62	62	27	44	62	62	62	62	65	27	44	62	62	62	62	75
OH	4	6	0	0	0	0	0	4	6	8	9	11	13	15	4	6	9	13	16	20	25
OK	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
OR	10	15	20	26	28	28	28	10	16	21	26	28	28	45	10	21	32	43	53	64	75

PA	5	5	5	5	5	6	6	5	11	18	25	32	38	45	5	16	28	40	52	63	75
RI	8	13	18	23	23	23	24	8	13	18	24	31	37	45	8	19	30	41	53	64	75
SC	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
SD	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
TN	0	0	0	0	0	0	0	0	8	15	23	30	38	45	0	13	25	38	50	63	75
TX	4	4	4	4	4	3	3	4	6	8	10	11	13	15	4	8	11	15	18	22	25
UT	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
VA	0	0	0	0	0	0	0	0	8	15	23	30	38	45	0	13	25	38	50	63	75
VT	33	38	49	55	56	58	59	33	38	49	55	56	58	65	33	38	49	55	62	69	75
WA	10	10	10	10	10	10	10	10	16	22	27	33	39	45	10	21	32	42	53	64	75
WI	9	9	9	9	9	9	9	9	15	21	27	33	39	45	9	20	31	42	53	64	75
WV	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
WY	0	0	0	0	0	0	0	0	1	3	4	5	6	8	0	4	8	13	17	21	25
DC	20	52	87	100	100	100	100	20	52	87	100	100	100	100	20	52	87	100	100	100	100

Energy Efficiency (Buildings): Energy efficiency numbers are based on building energy efficiency resource standards from states. These policies establish energy savings targets for electricity that utilities and other regulated entities are required to achieve. Using historical data from EIA on commercial and residential electricity demand(“EIA - Electricity Data” n.d.), projections through 2050 are made using GCAM’s growth trajectories to establish a no-policy baseline. Savings targets based on these projections are calculated on the basis of ACEEE’s 2018 State Energy Efficiency Scorecard(“The 2018 State Energy Efficiency Scorecard | ACEEE” n.d.).

When extending the current policies till 2050, the BAU scenario resulted in 1.5 per cent reduction in electricity consumption compared to GCAM no-policy baseline by 2050 for Policy Aggressive States and 0.4 per cent for Policy Conservative States. In the Medium Scenario, these targets were increased to 3 per cent and 1 per cent respectively. In the High Scenario, these targets were increased to 5 per cent and 3 per cent respectively. For Policy Conservative States, the leap from 0.4 per cent reduction to 1.5 per cent reduction following the logic of RPS target setting wasn’t deemed to be aggressive enough (only a 3.75-fold increase compared to 8.33-fold increase in RPS). Thus, the medium percentage reduction target of the Policy Aggressive States was chosen as the target in the High scenario for the Policy Conservative States. Similar to RPS, states that were already overachieving in BAU were not required to put additional effort in more aggressive scenarios. Tables SM1.2 and SM1.3 show the effective electricity reduction data (in EJ) for residential and commercial sectors respectively for the three policy scenarios.

Table SM1.2 – Residential Building Electricity Efficiency data by state and scenario (measuring EJ of electricity reduced from baseline through policy, ‘XY stands for year 20XY, St. = State)

St.	Residential – BAU							Residential - Medium							Residential - High						
	‘20	‘25	‘30	‘35	‘40	‘45	‘50	‘20	‘25	‘30	‘35	‘40	‘45	‘50	‘20	‘25	‘30	‘35	‘40	‘45	‘50
AK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AZ	.002	.012	.024	.024	.024	.024	.024	.002	.013	.025	.026	.027	.028	.030	.002	.013	.025	.027	.033	.038	.036
CA	.010	.032	.065	.065	.065	.065	.065	.010	.041	.070	.084	.099	.114	.097	.010	.051	.080	.101	.121	.141	.129
CO	.002	.006	.010	.010	.010	.010	.010	.002	.008	.011	.014	.016	.018	.016	.002	.010	.013	.016	.019	.023	.021
CT	0	.002	.005	.005	.005	.005	.005	0	.002	.006	.007	.008	.009	.008	0	.003	.007	.008	.010	.012	.011
DC	0	0	.001	.001	.001	.001	.001	0	.001	.001	.001	.001	.001	.001	0	.001	.001	.001	.001	.001	.001
DE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FL	.001	.004	.004	.004	.004	.004	.004	.001	.004	.004	.005	.005	.005	.005	.001	.004	.004	.005	.006	.007	.006
GA	.002	.004	.006	.006	.006	.006	.006	.002	.004	.007	.007	.007	.007	.008	.002	.004	.007	.007	.009	.010	.010
HI	0	.001	.002	.002	.002	.002	.002	0	.001	.002	.003	.003	.004	.003	0	.002	.003	.003	.004	.005	.005
IA	0	.001	.003	.003	.003	.003	.003	0	.001	.003	.003	.003	.003	.003	0	.001	.003	.003	.004	.004	.004
ID	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IL	.002	.014	.032	.032	.032	.032	.032	.002	.018	.035	.042	.050	.057	.049	.002	.023	.040	.050	.060	.071	.065
IN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

KS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KY	0	.001	.001	.001	.001	.001	.001	0	.001	.001	.001	.001	.002	.002	0	.001	.001	.001	.002	.002	.002
LA	0	0	.001	.001	.001	.001	.001	0	0	.001	.001	.001	.001	.001	0	0	.001	.001	.001	.001	.001
MA	.002	.009	.017	.017	.017	.017	.017	.002	.012	.018	.022	.026	.030	.025	.002	.014	.021	.026	.031	.037	.034
MD	.004	.014	.025	.025	.025	.025	.025	.004	.018	.027	.032	.038	.044	.037	.004	.022	.031	.039	.046	.054	.050
ME	.001	.003	.005	.005	.005	.005	.005	.001	.004	.006	.007	.008	.009	.008	.001	.005	.006	.008	.010	.011	.010
MI	0	.003	.020	.020	.020	.020	.020	0	.004	.022	.026	.031	.035	.030	0	.004	.025	.031	.037	.044	.040
MN	0	.003	.007	.007	.007	.007	.007	0	.004	.008	.009	.011	.013	.011	0	.005	.009	.011	.014	.016	.015
MO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ND	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NH	0	0	.001	.001	.001	.001	.001	0	0	.001	.001	.001	.001	.001	0	0	.001	.001	.001	.002	.002
NJ	.005	.022	.035	.035	.035	.035	.035	.005	.029	.038	.045	.053	.062	.052	.005	.036	.043	.054	.065	.076	.070
NM	0	.001	.003	.003	.003	.003	.003	0	.001	.003	.003	.003	.003	.003	0	.001	.003	.003	.003	.004	.004
NV	0	0	.002	.002	.002	.002	.002	0	0	.002	.002	.003	.003	.002	0	.001	.002	.003	.003	.004	.003
NY	.004	.017	.031	.031	.031	.031	.031	.004	.022	.034	.041	.048	.055	.047	.004	.027	.039	.048	.058	.068	.062

OH	.008	.025	.045	.045	.045	.045	.045	.008	.026	.047	.049	.051	.053	.057	.008	.026	.047	.051	.061	.071	.068
OK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OR	0	.002	.007	.007	.007	.007	.007	0	.002	.008	.009	.011	.012	.011	0	.003	.009	.011	.013	.015	.014
PA	0	.008	.020	.020	.020	.020	.020	0	.010	.021	.026	.030	.035	.030	0	.013	.025	.031	.037	.043	.040
RI	0	.001	.003	.003	.003	.003	.003	0	.002	.003	.004	.004	.005	.004	0	.002	.004	.005	.005	.006	.006
SC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TN	.001	.003	.005	.005	.005	.005	.005	.001	.004	.005	.006	.008	.009	.007	.001	.005	.006	.008	.009	.011	.010
TX	.004	.018	.036	.036	.036	.036	.036	.004	.019	.037	.038	.040	.041	.044	.004	.019	.037	.040	.048	.056	.053
UT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VA	.002	.002	.002	.002	.002	.002	.002	.002	.002	.002	.003	.003	.004	.003	.002	.003	.003	.004	.004	.005	.005
VT	0	.001	.002	.002	.002	.002	.002	0	.002	.002	.003	.003	.004	.003	0	.002	.003	.003	.004	.005	.004
WA	.002	.009	.018	.018	.018	.018	.018	.002	.012	.020	.024	.028	.032	.027	.002	.015	.022	.028	.034	.040	.036
WI	0	.003	.009	.009	.009	.009	.009	0	.004	.009	.011	.013	.015	.013	0	.005	.011	.014	.016	.019	.017
WV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WY	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	**.054**	**.222**	**.448**	**.448**	**.448**	**.448**	**.448**	**.054**	**.270**	**.480**	**.555**	**.635**	**.715**	**.641**	**.054**	**.320**	**.530**	**.642**	**.772**	**.902**	**.833**

Table SM1.3 – Commercial Building Electricity Efficiency data by state and scenario (measuring EJ of electricity reduced from baseline through policy, ‘XY stands for year 20XY, St. = State)

St.	Commercial - BAU							Commercial - Medium							Commercial - High						
	`20	`25	`30	`35	`40	`45	`50	`20	`25	`30	`35	`40	`45	`50	`20	`25	`30	`35	`40	`45	`50
AK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AL	0	.001	.001	.001	.001	.001	.001	0	.001	.001	.001	.001	.001	.002	0	.001	.001	.001	.002	.002	.002
AR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AZ	.003	.013	.025	.025	.025	.025	.025	.003	.014	.026	.026	.027	.029	.031	.003	.014	.026	.029	.034	.040	.037
CA	.012	.038	.079	.079	.079	.079	.079	.012	.049	.110	.114	.116	.117	.118	.012	.061	.141	.148	.153	.156	.158
CO	.003	.009	.016	.016	.016	.016	.016	.003	.012	.022	.023	.023	.023	.024	.003	.015	.028	.030	.030	.031	.031
CT	0	.003	.006	.006	.006	.006	.006	0	.003	.009	.009	.009	.010	.010	0	.004	.011	.012	.012	.013	.013
DC	.001	.002	.003	.003	.003	.003	.003	.001	.002	.003	.004	.004	.004	.004	.001	.002	.003	.004	.005	.005	.005
DE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FL	.001	.005	.006	.006	.006	.006	.006	.001	.005	.006	.006	.006	.007	.007	.001	.005	.006	.007	.008	.010	.009
GA	.003	.005	.007	.007	.007	.007	.007	.003	.005	.008	.008	.008	.009	.009	.003	.005	.008	.009	.010	.012	.011
HI	0	.002	.004	.004	.004	.004	.004	0	.002	.005	.006	.006	.006	.006	0	.003	.007	.007	.007	.008	.008
IA	0	.002	.003	.003	.003	.003	.003	0	.002	.003	.003	.003	.004	.004	0	.002	.003	.004	.004	.005	.005
ID	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IL	.007	.030	.059	.059	.059	.059	.059	.007	.039	.082	.085	.086	.088	.088	.007	.047	.105	.111	.114	.116	.118

IN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KY	0	.001	.001	.001	.001	.001	.001	0	.001	.001	.001	.001	.001	.001	0	.001	.001	.001	.002	.002	.002
LA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.001	.001	.001
MA	.004	.015	.027	.027	.027	.027	.027	.004	.019	.038	.039	.040	.040	.040	.004	.023	.048	.051	.052	.053	.054
MD	.004	.014	.026	.026	.026	.026	.026	.004	.018	.036	.037	.038	.039	.039	.004	.023	.046	.049	.050	.051	.052
ME	.001	.004	.006	.006	.006	.006	.006	.001	.005	.009	.009	.009	.009	.009	.001	.006	.011	.012	.012	.012	.012
MI	0	.007	.029	.029	.029	.029	.029	0	.009	.040	.041	.042	.043	.043	0	.011	.051	.054	.055	.057	.057
MN	.005	.018	.031	.031	.031	.031	.031	.005	.023	.043	.045	.046	.046	.047	.005	.028	.055	.058	.060	.061	.062
MO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ND	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NH	.001	.003	.005	.005	.005	.005	.005	.001	.003	.005	.006	.006	.006	.007	.001	.003	.005	.006	.007	.008	.008
NJ	.002	.018	.029	.029	.029	.029	.029	.002	.024	.040	.041	.042	.043	.043	.002	.029	.051	.054	.055	.056	.057
NM	0	0	.001	.001	.001	.001	.001	0	.001	.001	.002	.002	.002	.002	0	.001	.001	.002	.002	.002	.002
NV	.003	.010	.018	.018	.018	.018	.018	.003	.013	.025	.026	.027	.027	.027	.003	.016	.033	.034	.035	.036	.037
NY	.017	.057	.095	.095	.095	.095	.095	.017	.074	.133	.137	.140	.142	.143	.017	.090	.170	.179	.185	.188	.191

OH	.010	.032	.055	.055	.055	.055	.055	.010	.035	.057	.059	.060	.064	.069	.010	.035	.057	.064	.077	.089	.083
OK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OR	0	.003	.009	.009	.009	.009	.009	0	.004	.012	.012	.012	.013	.013	0	.005	.015	.016	.016	.017	.017
PA	.003	.014	.028	.028	.028	.028	.028	.003	.018	.039	.040	.041	.042	.042	.003	.022	.050	.052	.054	.055	.056
RI	0	.001	.003	.003	.003	.003	.003	0	.002	.005	.005	.005	.005	.005	0	.002	.006	.006	.006	.006	.007
SC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TN	.001	.003	.005	.005	.005	.005	.005	.001	.003	.007	.007	.007	.007	.007	.001	.004	.009	.009	.010	.010	.010
TX	.005	.019	.037	.037	.037	.037	.037	.005	.021	.038	.039	.040	.043	.046	.005	.021	.038	.043	.051	.059	.055
UT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VA	.002	.002	.002	.002	.002	.002	.002	.002	.002	.003	.003	.004	.004	.004	.002	.003	.004	.005	.005	.005	.005
VT	0	.002	.003	.003	.003	.003	.003	0	.003	.005	.005	.005	.005	.005	0	.003	.006	.006	.007	.007	.007
WA	.002	.010	.019	.019	.019	.019	.019	.002	.013	.027	.028	.028	.028	.029	.002	.016	.034	.036	.037	.038	.038
WI	0	.002	.007	.007	.007	.007	.007	0	.003	.010	.011	.011	.011	.011	0	.003	.013	.014	.014	.015	.015
WV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WY	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	**.092**	**.341**	**.648**	**.648**	**.648**	**.648**	**.648**	**.092**	**.427**	**.849**	**.877**	**.896**	**.916**	**.935**	**.092**	**.504**	**1.05**	**1.11**	**1.17**	**1.23**	**1.22**

Coal Retirement: Coal retirement is based on economics, and all plants, regardless of their location, age, pollution level, and other factors must adhere to the economic principles.

Plant data is collected from EIA (2018 version)("Form EIA-923 Detailed Data with Previous Form Data (EIA-906/920)" n.d.) and supplemented by financial information from Bloomberg New Energy Foundation's "Half of U.S. Coal Fleet on Shaky Economic Footing:

Coal Plant Operating Margins Nationwide" research(Coglianese and Walters 2019). The Bloomberg research provides long-run margins of coal-fired power plants between 2012 and 2017, with data collected at an hourly level. This margin is calculated based on the following parameters:

- Revenue from sale of electricity at the power market
- Cost of fuel acquisition
- Cost of Operation and Maintenance (Variable Environmental related, Other Variable and Fixed)
- Cost of environmental compliance (SO2 related)

Consider an example case, On January 1st of 2012, the first unit of the AB Brown Power Plant generated 75,490 MWh of electricity and it used 35,343 tons of coal to do so. In the process it emitted 270 tons of SO2.

Power revenue per MWh at the MISO (the market where the plant sold power to) at that day was $29. So, the plant made approximately $2.19 million in power sale revenue.

For each MWh generated, the plant ran into variable operation cost of $2.8. It also must pay environmental compliance costs of $7.6. Additionally, each ton of SO2 generated has a penalty (removal costs) of approximately $0.6 per ton. These together cost the plant $783,145.

There is a fixed cost of operation for the plant at $897,350.

For each ton of coal procured, the plant has to pay around $75 in fuel costs. The fuel costs total to around $2.67 million

Therefore total revenue = $2.19 million

Total cost = $2.67 million + 0.9 million + 0.78 million = $4.35 million (approx..)

Long run margin = $2.19 million - $4.35 million = -$2.14 million (approximate)

For every coal-fired power plant, we assume the retirement rules specified in Table SM1.4. Essentially, for a given year and scenario every plant that has suffered X or more years of losses will have to retire. For example, in Medium – we assume that in 2025, plants which have suffered 5 or more years of losses will have to retire. Under the "Retire All" case, every coal plant retires. In BAU, only the present-day consistently profitable remain online after 2050. By design, every coal power plant retires in the Medium scenario by 2050, and the same happens in the High scenario by 2040.

Additionally, any power plant due to retire anyway within 2030 based on Sierra Club data("Coal Pollution In America | Beyond Coal" n.d.), regardless of their profitability status will also retire.

Table SM1.4 – Rules of Retirement for Coal-Fired Power Plants

Scenario	2025	2030	2035	2040	2045	2050
BAU	6 yr loss	5 yr loss	4 yr loss	3 yr loss	2 yr loss	1 yr loss
Medium	5 yr loss	4 yr loss	3 yr loss	2 yr loss	1 yr loss	Retire All
High	3 yr loss	2 yr loss	1 yr loss	Retire All	Retire All	Retire All

A list of coal fired-power plant capacity remaining by year, scenario and state can be found in Table SM1.5

Table SM1.5 – Remaining coal-fired power plant capacity by state and scenario. Capacity in GW. 2020 is the common starting point for every scenario. St. = State, Tot. = Total. XY under scenario names indicate year 20XY.

St.	2020	BAU						Medium						High					
		25	30	35	40	45	50	25	30	35	40	45	50	25	30	35	40	45	50
AL	6	3	3	3	3	2	0	3	3	3	2	0	0	3	2	0	0	0	0
AR	5	5	2	2	1	1	1	2	2	1	1	1	0	1	1	1	0	0	0
AZ	5	6	5	3	0	0	0	5	3	0	0	0	0	0	0	0	0	0	0
CO	5	5	5	4	3	2	2	5	4	3	2	2	0	3	2	2	0	0	0
CT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FL	8	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GA	10	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IA	5	5	3	2	2	2	1	3	2	2	2	1	0	2	2	1	0	0	0
IL	12	15	13	13	12	8	5	13	13	12	8	5	0	12	8	5	0	0	0
IN	15	13	6	3	3	3	0	6	3	3	3	0	0	3	3	0	0	0	0

KS	5	5	5	3	2	0	0	5	3	2	0	0	0	2	0	0	0	0	0
KY	13	15	6	4	2	1	1	6	4	2	1	1	0	2	1	1	0	0	0
LA	3	2	1	1	1	0	0	1	1	1	0	0	0	1	0	0	0	0	0
MA	0	1	1	1	1	1	0	1	1	1	1	0	0	1	1	0	0	0	0
MD	3	5	5	4	3	3	0	5	4	3	3	0	0	3	3	0	0	0	0
MI	10	9	4	1	1	1	1	4	1	1	1	1	0	1	1	1	0	0	0
MN	4	3	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
MO	11	11	9	5	4	3	2	9	5	4	3	2	0	4	3	2	0	0	0
MS	2	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	0
MT	2	2	2	2	2	2	2	2	2	2	2	2	0	2	2	2	0	0	0
NC	11	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ND	3	3	3	2	0	0	0	3	2	0	0	0	0	0	0	0	0	0	0
NE	4	3	3	3	3	2	1	3	3	3	2	1	0	3	2	1	0	0	0
NH	1	1	1	1	1	0	0	1	1	1	0	0	0	1	0	0	0	0	0
NJ	0	1	1	1	1	1	0	1	1	1	1	0	0	1	1	0	0	0	0
NM	3	3	2	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0

NV	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NY	1	1	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
OH	12	16	16	16	13	11	6	16	16	13	11	6	0	13	11	6	0	0	0
OK	3	5	3	1	0	0	0	3	1	0	0	0	0	0	0	0	0	0	0
OR	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
PA	13	13	13	11	9	6	3	13	11	9	6	3	0	9	6	3	0	0	0
SC	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TN	4	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TX	19	24	24	21	15	12	6	24	21	15	12	6	0	15	12	6	0	0	0
UT	3	3	3	3	3	1	0	3	3	3	1	0	0	3	1	0	0	0	0
VA	3	4	4	2	1	1	0	4	2	1	1	0	0	1	1	0	0	0	0
WA	1	1	1	1	1	0	0	1	1	1	0	0	0	1	0	0	0	0	0
WI	6	7	2	1	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0

WV	12	13	13	13	10	6	3	13	13	10	6	3	0	10	6	3	0	0	0
WY	6	7	7	3	3	3	3	7	3	3	3	3	0	3	3	3	0	0	0
Tot	**234**	**226**	**170**	**130**	**100**	**73**	**38**	**170**	**130**	**100**	**73**	**38**	**0**	**100**	**73**	**38**	**0**	**0**	**0**

Handling Nuclear Power and Gas: Baseline assumptions as per the America's Pledge Study are adopted for nuclear power. As per these, 12.7 GW of at-risk capacity stay online due to actions from New York, Illinois, Connecticut, New Jersey, and Ohio. However, an additional 8.3 GW of other at-risk capacity does retire. A further assumption is that the Georgia Vogtle Units currently under development come online in 2020- 2021, adding 2.2 GW to the total U.S. fleet("VOGTLE" n.d.). Unlike the America's Pledge study, there are no plant-by-plant retirement assumptions for the advanced scenarios, as gas plants are allowed to compete on an economic basis within the GCAM market system with other technologies.

Building and Vehicle Electrification: These were modelled at the state level however no explicit state policies were used. National assumptions from NREL's "Electrification Futures Study: Scenarios of Electric Technology Adoption and Power Consumption for the United States"(Mai et al. 2018) were used. Data was utilized for residential and commercial sectors in the case of buildings. The national level building electrification potential (in additional EJ of electricity used by buildings due to electrification in various years/by scenario and segment) is presented in Table SM1.6

Table SM1.6 Building Electrification – Changes to additional electricity used by buildings (in EJ)

Sector	**US Electrification Scenario**	2020	2025	2030	2035	2040	2045	2050
Residential	High	0.1	0.2	0.3	0.5	0.7	1.0	1.3
	Medium	0.1	0.1	0.2	0.3	0.5	0.6	0.8

	Low	0.1	0.1	0.2	0.2	0.3	0.4	0.5
Commercial	High	0.0	0.1	0.2	0.3	0.5	0.7	1.1
	Medium	0.0	0.1	0.1	0.2	0.3	0.5	0.7
	Low	0.0	0.0	0.1	0.2	0.2	0.3	0.4

For vehicle electrification, Vehicle Miles Travelled assumptions were used. It was assumed that nationally that up to 500,000 VMT would be electrified by 2050 in the BAU scenario, followed by 1 million VMT in the Medium scenario and 1.5 million VMT in the High scenario. Year-by-year national data for three scenarios are provided in Table SM1.7.

Table SM1.7 Electrification of national VMT by scenario and year

Scenario	2020	2025	2030	2035	2040	2045	2050
BAU	24,489	127,919	297,175	350,000	400,000	450,000	500,000
Medium	24,489	150,000	300,000	450,000	600,000	800,000	1,000,000
High	24,489	200,000	400,000	650,000	900,000	1,200,000	1,500,000

Technology Costs: Capital cost of generation technologies vary across the three scenarios. Costs in the three scenarios correspond to different cost scenarios in NREL's Annual Technology Baseline data for 2019(Vimmerstedt et al. 2019). The Medium cost corresponds to the Medium Scenario, the Low costs corresponds to the High scenario. ATB's high costs are essentially constant costs after 2020, which seems unrealistic. So instead 2020 cost numbers are utilized along with GCAM's cost improvement rate designed for low cost improvement scenarios(Muratori et al. 2017).

In order to match the NREL technologies to GCAM technologies, the following assumptions were used:

- 2020 cost is kept the same for all scenarios, by using the Medium ATB costs.
- Battery costs is assumed to be four times that of ATB. This is because ATB reports costs for a 4 hour battery with 15 year lifetime. We assume a 8 hour battery with 30 year lifetime, more consistent with storage requirements and project lifespan of intermittent technologies in GCAM.
- All data is assumed to be in 2017 dollars.
- AC to DC conversion factor of 0.85 assumed for PV and Rooftop PV.
- Overnight costs considered except for battery storage due to lack of data. Capex is considered for Battery.
- Onshore Wind = TRG 5 resource group costs used.
- Offshore wind cost = TRG 4 Fixed cost used. These costs correspond well with the existing GCAM costs.
- Geothermal wind cost = Hydro Flash technology cost used.
- CSP = Costs in $/kWe
- NREL does not report CSP cost without storage
- (marginal cost of storage reported in terms of $/kWh without clear indications on how much energy that system is expected to generate and over what period).
- So existing GCAM proportion of intermittent/baseload CSP costs are taken to derive CSP intermittent costs

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Supplementary Materials for Energy Strategy: Aggregate household behavior in heating and cooling control strategy and energy efficient appliance adoption

Further methodological details.

Multivariate probit model: The study uses the “triprobit” add-on of Stata(Terracol 2002) to undertake the analysis. Seventy-five draws ($\sqrt{5686} = 75.4$) are used in this study due to the recommendation of the number of draws being roughly the square root of the sample size (Cappellari and Jenkins, n.d.). The add-on also allows the use of probability weighting, and the final sample weights from the database are used for this purpose.

Triprobit estimates simulated maximum-likelihood three-equation probit models using the (Geweke-Hajivassiliou-Keane) GHK smooth recursive simulator. The mathematical process is summarized in the notes of the author of the triprobit add-on (Terracol, n.d.).

$$y_1 = 1 \text{ if } X\beta + \varepsilon_1 > 0$$

$$= 0 \text{ otherwise} \qquad (1)$$

$$y_2 = 1 \text{ if } Z\gamma + \varepsilon_2 > 0$$

$$= 0 \text{ otherwise} \qquad (2)$$

$$y_3 = 1 \text{ if } W\theta + \varepsilon_3 > 0$$

$$= 0 \text{ otherwise} \qquad (3)$$

With, $\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix}$ -> N (0, Σ)

(4)

X, Z and W are the respective vectors of independent variables associated with these binary variables; β, γ, and θ are the corresponding coefficients; and $\varepsilon1$, $\varepsilon2$, $\varepsilon3$ are the error terms. Essentially, $X\beta + \varepsilon1$, $Z\gamma + \varepsilon2$, and $W\theta + \varepsilon3$, can be considered as specifications of continuous latent variables associated with y1, y2, and y3 (assume $y^*_1 = X\beta + \varepsilon_1$, $y^*_2 = Z\gamma + \varepsilon_2$, and $y^*_3 = W\theta + \varepsilon_3$). We assume that the binary variables take on the value 1 only if the value of the underlying latent variables are positive.

<u>Latent Class Analysis:</u> LCA can be undertaken using sample weights within Stata(Pitblado 2017), however this led to convergence issues when using the dataset in the study. As a result, sample weights are not used – hence interpretation of the LCA results cannot be easily generalized to the entire population. For computational efficiency, the R package "poLCA" was used for Latent Class Analysis (Linzer and Lewis 2011). A short description of the process, following the poLCA documentation is provided below.

Assume there are J polytomous categorical variables each with K_j possible outcomes, with each variable likely to have different number of possible outcomes indexed by j. Let the individuals to which these outcomes are attributable to be indexed by i= 1,…,N. Denote

Y_{ijk} = 1 if the i-th individual gives the k-th response to the j-th variable,

= 0 otherwise. (5)

The model approximates the observed joint distributions of the categorical variables as a weighted sum of a finite number R. This R is pre-determined and is known as the number of latent classes. Assume, π_{jrk} being the class-conditional probability that an observation in class r = 1,..,R produces the k-th outcome for the j-th variable. Further define p_r as the prior probabilities of the latent class membership.

We can define probability that an individual i of class r produces a particular set of J outcomes as:

$$f(Y_i, \pi_r) = \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}} \qquad (6)$$

The probability density function can be defined as:

$$P(Y_i|\pi, p) = \sum_{r=1}^{R} \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}} \qquad (7)$$

Given estimates of p_r and π_{jrk} that can be estimated from the model, we can determine the posterior probability that each individual belongs to each class, conditional on the observed values of the categorical variables, can be calculated as:

$$\hat{P}(r_i|Y_i) = \frac{\hat{p}_r f(Y_i; \hat{\pi}_r)}{\sum_{q=1}^{R} \hat{p}_q f(Y_i; \hat{\pi}_q)} \qquad (8)$$

The latent class model parameters are estimated by maximizing the following log likelihood function.

$$lnL = \sum_{i=1}^{N} ln \sum_{r=1}^{R} p_r \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}} \qquad (9)$$

Three to five class models are evaluated and the optimal class number is chosen on the basis of goodness of fit criteria focusing on parsimony. The poLCA package calculates Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) automatically. Preferred models are those that minimize values of the BIC and/or AIC. Low AICs and BICs are represented by higher values of log-likelihood, lower number of estimated parameters and smaller number of total observations. Since across classes the number of observations are the same, most efficient fit in terms of number of classes is obtained by higher log-likelihood values and lower number of estimated parameters.

The posterior probabilities for each household being assigned to a certain class are assigned to provide a class assignment to each household, which is then used in the following step.

<u>Multinomial Logit Model</u>: Stata's mlogit command is used for the analysis of the multinomial logit regression. A summary of the theoretical description of the model is described Greene (Greene 2003).

Consider Y being a vector of categories for the dependent variable, with values ranging from Y_1 to Y_J, indexed as Y_i denoting the choice for the i^{th} individual in the dataset. If X denotes the set of explanatory variables, with x_i being the vector of explanatory variable for the i^{th} individual.

The probability of i^{th} individual picking the j^{th} choice is denoted by:

$$Prob(Y_i = j) = \frac{e^{\beta_j' x_i}}{\sum_{k=0}^{J} e^{\beta_k' x_i}} \qquad (10)$$

The model as it stands in (1) in undetermined. A convenient normalization that solves the problem is $\beta_0 = 0$. This leads to:

$$Prob(Y_i = j|x_i) = \frac{e^{\beta_j' x_i}}{1 + \sum_{k=1}^{J} e^{\beta_k' x_i}} \qquad (11)$$

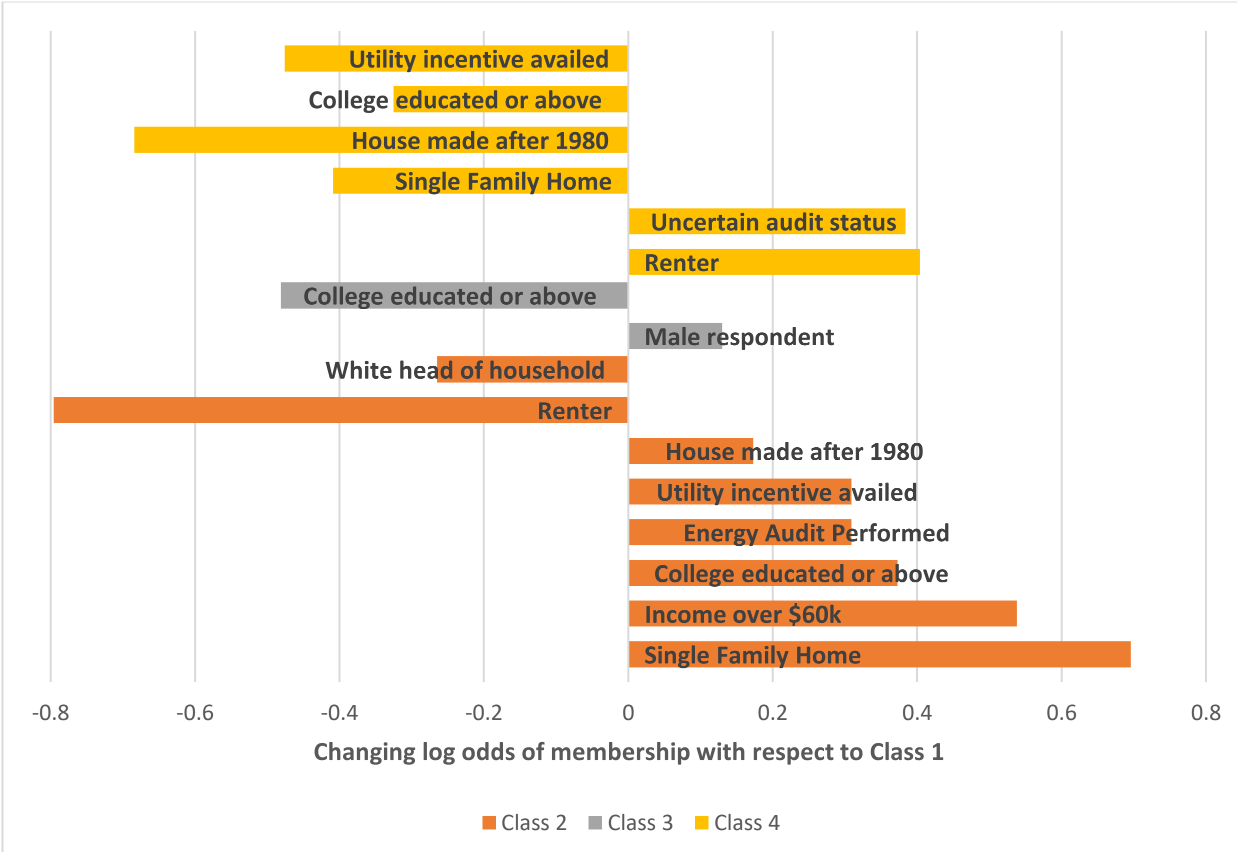
From (2), if k=0, we can calculate log-odds ratios given by

$$ln[\frac{p_{ij}}{p_{ik}}] = x_i(\beta'_j - \beta'_k) = x_i\beta'_j \qquad (12)$$

The denominator of the conditional probability equation remains unchanged, i.e. it is not affected by the choice of j. For notational convention, assume Prob (Y_i = j | x_i) can be written as p_{ij}. Therefore, taking the log on both sides, assuming Y_i = j gives us $\ln(p_{ij}) = \beta'_j x_i$. For a baseline Yi = k, the choice against which the odds of j is calculated, $\ln(p_{ik}) = \beta'_k x_i$. Therefore $\ln(p_{ij}/p_{ik}) = x_i (\beta'_j - \beta'_k) = x_i \beta'_j$ if k =0.

Visual Representation of the Multinomial Logit Model Results:

Chart SM2.1: Independent variables affecting log-odds of membership in Classes 2-4 compared to Class 1.



Regional Breakdown of classes

It is interesting to determine if there are regional factors that affect in which class households are classified. To accomplish this we compare the regional frequency tables for the entire dataset to those with the classes. Note that there are 10 regions under consideration,

1	New England
2	Middle Atlantic
3	East North Central
4	West North Central
5	South Atlantic
6	East South Central
7	West South Central
8	Mountain North
9	Mountain South
10	Pacific

Table SM2.2 Regional classification of household classes (depicted as percentage of class members from a certain region) and regional classification of the sample as a whole. Column totals add up to 100 per cent.

Classification/ Regions (↓)	**1**	**2**	**3**	**4**	**Sample**
1	5.76%	4.35%	2.66%	5.75%	4.45%
2	9.99%	10.37%	8.48%	9.93%	9.51%
3	13.45%	17.06%	16.72%	8.89%	14.70%
4	7.74%	10.14%	9.94%	5.23%	8.64%
5	16.55%	17.50%	23.69%	10.63%	18.61%
6	5.44%	2.56%	10.54%	3.14%	6.54%
7	10.93%	9.25%	11.40%	4.70%	10.20%
8	4.41%	6.35%	2.11%	5.40%	4.01%
9	4.23%	5.91%	3.77%	3.48%	4.26%
10	21.50%	16.50%	10.69%	42.86%	19.08%

Apart from a few isolated cases, region does not seem a major predictor of household classification given relatively small deviations from the sample percentages. Notable cases include slight overrepresentation of Classes 2 and 3 and under-representation of Class 4 for East North Central (Region 3); overrepresentation of Class 3 and under-representation of Class 4 for South Atlantic (Region 5); overrepresentation of Class 3 and under-representation of Class 2 and 4 for East South Central (Region 6); Class 4 is under-represented in West South Central (Region 7) but heavily overrepresented in the Pacific (Class 10).

These alone however are not strong indicators of any regional trends, and a full-fledged multilevel analysis is required to understand the regional implications, including variables that act as explanatory variables for the regions themselves such as income and weather conditions.

Another useful way of looking at this is to determine the relative rank of regions in the classifications and compare this to the total sample, i.e. if for example Pacific is the dominant region in the sample, is this the case for the household classes as well. Results are presented in Table SM2.3

Table SM2.3 Ranking of regional importance within class/sample

Classification/ Regions (↓)	**1**	**2**	**3**	**4**	**Sample**
1	7	9	9	5	8
2	5	4	7	3	5
3	3	2	2	4	3
4	6	5	6	7	6
5	2	1	1	2	2
6	8	10	5	10	7
7	4	6	3	8	4

8	9	7	10	6	10
9	10	8	8	9	9
10	1	3	4	1	1

Certain region-class combinations are more interesting than others, given that largely the sample rank is within 1 place higher or lower than the regional rank of a particular class. Class 4 stands out in most regional cases, following the trend of its percentage shares being quite different than the sample ones. This suggests that Class 4 households are not as well-behaved in terms of regional distribution compared to the sample as a whole, with regions such as New England and Middle Atlantic (Regions 1 and 2) being of higher importance to Class 4 than the entire sample, and regions such as the two South Centrals and Mountain North (Regions 6,7 and 8) being of lower importance. Class 2, the thermostat user class also has some deviations in terms of ranking comparison, most notably in the Pacific (Region 10), but also in the two South Centrals and Mountain North. Pacific being relatively unimportant compared to the sample is a trend for Class 3 as well, along with deviations in East South Central and Middle Atlantic. These regions and households that adhere to certain characteristics can be interesting points of further study in analyzing whether regional characteristics influence household behavior or not.

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Supplementary Materials for Pricing Prosumers: Can distributed solar tariffs jointly make sense for prosumers and utilities?

Data Analysis Techniques

State level data

1. Use the Tracking the Sun(Barbose et al. 2019) database to determine which states are represented: Arizona, Arkansas, California, Connecticut, Delaware, Florida, Massachusetts, Maryland, Minnesota, New Hampshire, New York, Oregon, Pennsylvania, Texas, Vermont and Wisconsin
2. Determine which states have studies on VoS through meta studies(“The Hunt for the Value of Distributed Solar” n.d.) (“Solar Cost-Benefit Studies” n.d.) and find commonalities with the TTS states: Arizona, Arkansas, California, Connecticut, Massachusetts, Maryland, Minnesota, New Hampshire, New York, Oregon, Pennsylvania, Texas and Vermont
3. Disqualify the following states:
    a. Massachusetts: Similar in structure (synthetic demand/ utility tariff/ median household data) to the New England state Connecticut. Also doesn’t have two utilities with ToU Tariff, which Connecticut does
    b. Maryland: Households don’t have Zip code data.
    c. New Hampshire: Similar to Massachusetts
    d. Vermont: Similar to Maryland
4. Admit one-utility states: Oregon (Portland General) and Texas (Austin Energy). This is because these two states have utility-specific VoS studies that are applicable to only these two utilities.

5. Pollution data: Pollution data in terms of pollution rate was obtained from eGRID database("EGRID2018 Summary Tables," n.d.). See Table SM3.1.

Table SM3.1.1: Pollution data from eGRID

State	**CO_2e**	**Annual NO_x**	**SO_2**	**PM2.5**
AR	1219.14	0.69	1.60	0.02
AZ	972.25	0.64	0.30	0.02
CA	422.03	0.38	0.04	0.01
CT	509.48	0.27	0.05	0.02
MA	733.84	0.56	0.21	0.02
MN	1003.11	0.71	0.56	0.04
NH	305.82	0.28	0.16	0.02
NY	418.68	0.23	0.09	0.01
OR	314.16	0.27	0.09	0.01
PA	788.84	0.44	0.66	0.02
TX	983.66	0.61	0.90	0.02

The EASIUR(Heo, Adams, and Gao 2016) database was the source of zip-code level pollution data. Ground data for annual pollution level was used to estimate marginal dollar value of local pollutant impact. Data is tabulated in Table SM3.1.2

Table SM3.1.2 – Marginal dollar value of pollutant impact by utility (2010$/tonne) calculated from EASIUR Model. Data is at the zip code level.

Utility	Spring	Summer	Fall	Winter	Unit	Pollutant
PPL	364000	402000	385000	437000	$/tonne	PM2.5
PPL	42600	46600	25100	27500	$/tonne	SO2
PPL	31000	15900	29300	38800	$/tonne	NOX
Portland General	443000	574000	359000	330000	$/tonne	PM2.5
Portland General	37800	37800	28000	18700	$/tonne	SO2
Portland General	15100	11000	28700	21200	$/tonne	NOX
PSEG	814000	689000	392000	491000	$/tonne	PM2.5
PSEG	94400	61200	21400	15900	$/tonne	SO2
PSEG	105000	32000	16900	24400	$/tonne	NOX
Xcel Energy	391000	430000	427000	581000	$/tonne	PM2.5
Xcel Energy	33700	31100	22200	30800	$/tonne	SO2
Xcel Energy	15000	6510	15500	42200	$/tonne	NOX
ConEd	722000	822000	611000	761000	$/tonne	PM2.5
ConEd	63300	64900	33200	18400	$/tonne	SO2
ConEd	52800	26100	56400	39900	$/tonne	NOX
Minnesota Power	127000	99200	83100	75600	$/tonne	PM2.5
Minnesota Power	70000	47300	12500	14400	$/tonne	SO2
Minnesota Power	21800	7690	3120	9030	$/tonne	NOX
United Illuminating	511000	533000	451000	525000	$/tonne	PM2.5
United Illuminating	68200	55700	31800	21700	$/tonne	SO2
United Illuminating	45900	17900	31900	35600	$/tonne	NOX

Eversource	476000	523000	448000	535000	$/tonne	PM2.5
Eversource	60000	55200	30700	22000	$/tonne	SO2
Eversource	37800	14900	29500	38000	$/tonne	NOX
Salt River	71400	77400	94600	106000	$/tonne	PM2.5
Salt River	8020	7480	12700	19800	$/tonne	SO2
Salt River	1260	455	4680	9890	$/tonne	NOX
Carroll Electric	59800	62600	96000	90400	$/tonne	PM2.5
Carroll Electric	18200	21500	16400	24600	$/tonne	SO2
Carroll Electric	2800	1450	4970	10200	$/tonne	NOX
APS	183000	207000	194000	233000	$/tonne	PM2.5
APS	11700	8300	11200	16500	$/tonne	SO2
APS	2550	1400	6880	12100	$/tonne	NOX
Entergy	86300	79000	122000	120000	$/tonne	PM2.5
Entergy	20300	18600	14000	24800	$/tonne	SO2
Entergy	3160	1300	3340	11600	$/tonne	NOX
Austin Energy	173000	170000	200000	228000	$/tonne	PM2.5
Austin Energy	17100	13400	12200	33000	$/tonne	SO2
Austin Energy	4380	949	2040	11700	$/tonne	NOX
PECO	507000	543000	510000	586000	$/tonne	PM2.5
PECO	46300	52900	27800	23300	$/tonne	SO2
PECO	34500	14900	37300	39300	$/tonne	NOX
SCE	141000	153000	161000	180000	$/tonne	PM2.5
SCE	18100	18500	15800	26400	$/tonne	SO2

SCE	6860	3300	8300	9050	$/tonne	NOX
PG&E	147000	157000	157000	168000	$/tonne	PM2.5
PG&E	21700	25200	20400	27100	$/tonne	SO2
PG&E	6510	4050	17900	24100	$/tonne	NOX

States to Zip codes

1. For each state identify the utilities with the most number of installations. The Tracking the Sun database has utility-level information that can be filtered to do this. Pick the top two utilities, exceptions being Oregon and Texas for reasons discussed previously.
2. For each utility, pick the zip code with the highest number of installations.
3. Use TMY3 data ("Index of /Datasets/Files/961/Pub/RESIDENTIAL_LOAD_DATA_E_PLUS_OUTPUT" n.d.) to generate synthetic demand data by plugging in the zip codes into HOMER Grid (Energy 2018), which automatically finds the nearest TMY3 data point and synthetic hourly demand curve for one year.
4. Check that the location for which the TMY3 demand curve was generated and the installation location zip code are indeed part of the same utility. If no, move to the next highest installation zip code and repeat Step 3. An example of this forcing us to change zip codes is for ConEd, where a Staten Island zip code was found with the highest number of installations. However, the nearest TMY3 demand data

from HOMER Grid was obtained for Newark, which had a different utility (PSEG New Jersey – not PSEG Long Island which is also analyzed in this study)

5. From the finalized zip code, use all the available installation data within that zip code to generate a median household in terms of System Size and Installation Cost.
6. Incentive data is not always available or incomplete in the database, and we assume that the prosumer obtained a 30 per cent Investment Tax Credit for the system in these cases.
7. Create PV generation data for one year on an hourly basis using NREL PVWatts("PVWatts Calculator" n.d.), by inputting the zip code and the system size information. Use the default PVWatts assumptions.
8. Assume a 0.5% degradation of output for generating 25-year data.
9. Assume demand stays flat, since we have no way of knowing how synthetic demand will change. We also assume that the same "year" chosen for the demand and the generation data repeats over and over again, so no leap years/ different holiday dates/ weather conditions have to be accounted for in order to simplify our models. This is primarily due to difficulty in estimating long-term demand changes from synthetic demand data where the underlying assumptions are difficult to replicate.
10. Generate the final list of utilities, zip codes, installation size, installation cost, synthetic demand locations, Average demand data, and Average generation data. (Table SM3.2)

Table SM3.2 List of Selected Utilities and Zip Code with Cost, Size, Demand and Generation Information

Utility	Synthetic Demand Location	Installation Size (kW)	Installation Cost ($ - post incentives)	Average Annual Demand (kWh)	Average Annual Generation (kWh)
Salt River Project	Casa Grande	6.7	22179.5	11986	12476
Eversource Energy	Hartford Brainard Field	7.52	22195.6	8891	9103
SCE	Camp Pendleton	5.04	15116.3	8088	8019
PPL Electric Utilities	Lancaster	6.97	29281.5	8919	8615
United Illuminating	West Haven Tweed	6.88	18694.2	8971	8401
Minnesota Power	Duluth	3.48	15738.1	8974	8396
APS	Phoenix Deer Valley	6.89	24299.8	12295	11147
PG&E	Beale AFB	5.74	18665.5	9637	8283
Xcel Energy	Minneapolis St Paul	5.19	18853.2	9235	6428

ConEd	JFK Queens	7.58	24022.6	12439	9352
PSEG Long Island	Islip Long Island	6.91	24235.8	12334	9001
Portland General	Portland	3.97	18019.2	7753	4131
PECO	Willow Grove	6.5	30708.6	12299	7902
Carroll Electric	Harrison	5.74	32862.5	12973	7480
Austin Energy	Austin Mueller	5.88	19745	14796	8243
Entergy	Hot Springs Mem	3.17	19315.6	13490	4011

Additional Utility Data

1. Utility tariffs are obtained from their respective websites. Residential tariffs were used. The following is a list of websites from which the tariffs were obtained. Tariffs are accurate as of November 2019:
    a. Entergy: https://www.entergy-arkansas.com/userfiles/content/price/tariffs/eal_rs.pdf (Base) and https://www.entergy-arkansas.com/userfiles/content/price/tariffs/eal_rt.pdf (ToU)
    b. Carroll Electric: https://www.cecpower.coop/rates-service-charges
    c. APS: https://www.aps.com/-/media/APS/APSCOM-PDFs/Utility/Regulatory-and-Legal/Regulatory-Plan-Details-Tariffs/Residential/Service-Plans/PremierChoice.ashx (Base) and https://www.aps.com/-/media/APS/APSCOM-PDFs/Utility/Regulatory-and-Legal/Regulatory-Plan-Details-Tariffs/Residential/Service-Plans/SaverChoice.ashx (ToU)
    d. Salt River: https://www.srpnet.com/prices/home/basic.aspx (Base) and https://www.srpnet.com/prices/home/tou.aspx (ToU)
    e. PG&E: https://www.pge.com/tariffs/assets/pdf/tariffbook/ELEC_SCHEDS_E-1.pdf (Base) and https://www.pge.com/en_US/residential/rate-plans/rate-plan-options/time-of-use-base-plan/time-of-use-plan.page (ToU, B option chosen)

f. SCE: http://www.sce.com/regulatory/tariff-books/rates-pricing-choices (Base) and http://www.sce.com/residential/rates/Time-Of-Use-Residential-Rate-Plans (ToU)

g. Eversource: https://www.eversource.com/content/docs/default-source/rates-tariffs/ct-electric/ct-electric-rates.pdf?sfvrsn=2d9afe62_30 (All Rates)

h. United Illuminating: https://www.uinet.com/wps/wcm/connect/b95cd00e-f972-4d12-a99b-88f116ed57f7/UI-Tariffs-Effective-January-1-2019.pdf?MOD=AJPERES&CACHEID=ROOTWORKSPACE-b95cd00e-f972-4d12-a99b-88f116ed57f7-mw5Ld-e (All Rates)

i. Minnesota Power: https://www.mnpower.com/CustomerService/ResidentialRates (All Rates)

j. Xcel Energy: https://www.xcelenergy.com/staticfiles/xn/Regulatory%20&%20Resource%20Planning/Minnesota/Me_Section_5.pdf (All Rates)

k. ConEd: https://www.coned.com/_external/cerates/documents/elecPSC10/electric-tariff.pdf (All Rates)

l. PSEG: https://www.psegliny.com/aboutpseglongisland/ratesandtariffs/-/media/A0FDA80A6FE44A45973922422E86BD9E.ashx (All Rates)

m. Portland General: https://www.portlandgeneral.com/residential/power-choices/basic-service (Base) and https://www.portlandgeneral.com/residential/power-choices/time-of-use (ToU)

n. PECO: https://www.peco.com/SiteCollectionDocuments/RateRResidentialService.pdf (All Rates)

o. PPL: https://www.pplelectric.com/-/media/PPLElectric/At-Your-Service/Docs/Current-Electric-Tariff/master.pdf (All Rates)

p. Austin Energy: https://austinenergy.com/ae/rates/residential-rates/residential-electric-rates-and-line-items (All Rates)

2. From the detailed tariff breakdowns, generation costs are obtained and these are used as proxy for utility energy procurement expenses.
3. Growth rate of tariff and generation costs are expected to be equivalent
4. Growth rates obtained from state level data of electricity retail price growth rate for the residential sector between 2009 and 2018 per EIA data("Electric Power Annual 2018," n.d.).
5. A full table of utilities with tariff structure and growth rate is provided at Table SM3.3 (Utility, Tariff/Cost Escalation, Season, Tier and Time-of-day definition) Tables SM3.4 (Utility, Energy Cost breakdown) and Table SM3.5 (Utility, Tariff Structure)
6. Explanation of table items: For Table SM3.3, Summer and Winter are typically defined by most utilities, and tiers and peak times will vary depending on the season. Tiered tariff (as is the case with most Base Tariff structure utilities) will generally consist of multiple tiers and each "/" indicates tier progression. If one

number is mentioned, then this is a 2-tiered tariff system, and anything excess of the specific number is considered to be the second tier. Any time that is not within the defined peak is generally considered off-peak, unless a Midpeak is defined (only for Portland General). There may be multiple peak times, in the morning and evening. Saturday, Sunday and Federal Holidays are generally off-peak 24 hours, unless clearly specified (Portland General again).

For Table SM3.4, generation costs recovered through retail prices are sometimes flat, but most often they'll vary based on the applicable season, tier, and time-of-day. Some utiltiies such as Consolidated Edison gives users the option to purchase energy from elsewhere. In these cases, the "default" generation cost is included, i.e. the generation cost the user would face if they chose not to exercise the option. NSGC for Southern California Edison stands for New System Generation Charge, which is a generation surcharge that is used by the utility to fund its generation projects. This is extremely low and is unlikely to reflect the actual energy procurement costs, but no further details are available for this utility.

For Table SM3.5, the two minimums are the minimum charge a user must pay regardless of actual generation. For base tariff, tariffs are organized into two columns for each season – the tariff for the first period, and the tariff for subsequent tiers. Like energy costs, tariffs are specified at $/kWh. The VoS tariff specified are the benchmarks obtained from literature (sources provided in Item 7 of this section). Salt River Project uses an explicit generation credit for prosumers, and that tariff is used instead of the VoS tariff from literature. This is also the case from Austin Energy, which uses an explicit VoS tariff to credit prosumers.

Table SM3.3: Utility, Escalator, Season, Time of Day and Tier Definition

Utility	Escalator	Summer (if defined, other months are Winter)	Tier Cutoff	Peak Time in Summer	Peak Time in Winter
Entergy	1%	Jun - Sep	1500	1pm-8 pm	7a - 6 pm
Carroll Electric	1%	Not defined	100	NA	NA
APS	2%	May - Oct	Upto 400/400-800/800-3000/3000+	3 pm to 8 pm	3 pm to 8 pm
Salt River Project	2%	May - Oct	2000		
PG&E	2%	Jun - Sep	18.7/24.9 per day (Summer/Winter)	3 pm to 8 pm	3 pm to 8 pm
SCE	2%	Jun - Sep	18.3/12.6 per day (Summer/Winter)	4 pm to 9 pm	4 pm to 9 pm
Eversource Energy	0%	Not defined	NA	12 pm to 8 pm	12 pm to 8 pm
United Illuminating	0%	Jun - Sep	NA	12 pm to 8 pm	12 pm to 8 pm
Xcel Energy	3%	Jun - Sep	NA	9 am to 9 pm	9 am to 9 pm
Minnesota Power	3%	Not defined	Upto 400/400-800/800-1200/1200+	NA	NA
PSEG Long Island	1%	Jun - Sep	250	2 pm to 7 pm	2 pm to 7 pm
Consolidated Edison	1%	Jun - Sep	250	10 am to 10 pm	10 am to 10 pm

Portland General Electric	2%	May - Oct	1000	10 pm to 6 am	**Summer** Peak 3 pm to 8 pm; Midpeak 6 am to 3 pm/ 8 pm to 10 pm; **Winter** Peak 6 am to 10 am and 5 pm to 8 pm; Midpeak 10 am to 5 pm and 8 am to 10 pm; **Saturday** Midpeak (All

					seasons) 6 am to 10 pm
PPL Electric Utilities	2%	Jun - Nov	NA	2 pm to 6 pm	4 pm to 8 pm
PECO	2%	Not defined	NA	NA	NA
Austin Energy	-1%	Not defined	Upto 500/500-1000/1000-1500/1500-2500/2500+	NA	NA

Table SM3.4 Utility and Energy Costs

Utility	**Energy Cost ($/kWh)**
Entergy	0.07
Carroll Electric	0.07
APS	0.067 (Summer/400 and under) 0.114 (Summer/400 to 800) 0.141 (Summer/800 to 3000) 0.154(Summer/Excess of 3000) 0.198 (Summer/Peak) 0.186(Winter/Peak) 0.064(Off-Peak)
Salt River Project	0.046 (Summer) 0.029 (Winter)

PG&E	0.118 (Basic) 0.201(Summer/ToU/Peak) 0.126(Summer/ToU/Off Peak) 0.114(Winter/ToU/Peak) 0.0998(Winter/ToU/Off Peak)
SCE	0.00697 (NSGC)
Eversource Energy	0.09414 (Basic) 0.08550(ToU/Off) 0.1205(ToU/Peak)
United Illuminating	0.1056 (Basic) 0.131 (ToU/Peak) 0.0961 (ToU/Off)
Xcel Energy	0.103(Summer) 0.088(Winter)
Minnesota Power	0.07
PSEG Long Island	0.1
Consolidated Edison	0.1
Portland General Electric	0.063(Tier 1)/0.071(Tier 2) 0.124(Peak)/0.07(Mid Peak)/0.04(Off-peak)
PPL Electric Utilities	0.076
PECO	0.061
Austin Energy	0.028/0.058/0.078/0.093/0.108 (For Tier 1 to Tier 5 of consumption)

Table SM3.5 Utility and Tariff Structure

Utility	**Basic Tariff Minimum**	**Summer First Tier Tariff**	**Summer Higher Tiered Tariffs**	**Winter First Tier Tariff**	**Winter Higher Tiered Tariff**	**TOU Minimum**	**VoS Tariff**
Entergy	8.4	0.074	0.096	0.07	0.052	13.81	0.114
Carroll Electric	29.5	0.127	0.108/0.105	0.127	0.108/0.105	NA	0.114

APS	15	0.112	0.159/0.186/ 0.199	0.109	0.109	13	0.16
Salt River Project	20	0.112	0.116	0.078	0.078		0.0281 (export credit)
PG&E	10	0.236	0.297	0.236	0.297	10	0.13
SCE	11	0.0951	0.15	0.0951	0.15	11	0.12
Eversource Energy	10	0.214	0.214	0.214	0.214	10	0.17
United Illuminating	13	0.265	0.265	0.251	0.251	13	0.17
Xcel Energy	10	0.103	0.103	0.088	0.088	10	0.11
Minnesota Power	8	0.074	0.098/0.121/ 0.147	0.074	0.098/0.121 /0.147	NA	0.11
PSEG Long Island	13	0.083	0.105	0.083	0.105	13	0.19
Consolidated Edison	16	0.111	0.128	0.111	0.111	20.5	0.3
Portland General Electric	11	0.112	0.119	0.112	0.119	11	0.056
PPL Electric Utilities	18	0.095	0.095	0.095	0.095	18	0.22
PECO	12	0.188	0.188	0.188	0.188	NA	0.2
Austin Energy	10	0.078	0.108/0.128/ 0.143/0.158	0.078	0.108/0.128 /0.143/0.158	NA	0.097

7. Value of Solar study sources – The following VoS study sources were used.

    a. Arkansas: https://drive.google.com/file/d/0BzTHARzy2TINbHViTmRsM2VCQUU/view

    b. Arizona: https://images.edocket.azcc.gov/docketpdf/0000168554.pdf

    c. California: http://drpwg.org/wp-content/uploads/2016/07/R1408013-et-al-SCE-LNBA-Working-Group-Final-Report.pdf

    d. Connecticut: https://acadiacenter.org/wp-content/uploads/2015/03/AcadiaCenter_GridVOS_Connecticut_March_2015.pdf. This is a third-party study not authorized by the regulatory commission, which now has commissioned its own study (https://enerknol.com/connecticut-opens-proceeding-to-study-value-of-solar/) undergoing analysis.

    e. Minnesota: https://ilsr.org/wp-content/uploads/2014/04/MN-Value-of-Solar-from-ILSR.pdf

    f. New York: Value of Solar obtained through location specific (zip code) analysis using the New York State Energy Research and Development Authority Value Stack calculator (https://www.nyserda.ny.gov/All-Programs/Programs/NY-Sun/Contractors/Value-of-Distributed-Energy-Resources/Solar-Value-Stack-Calculator)

    g. Oregon: https://apps.puc.state.or.us/orders/2019ords/19-023.pdf

h. Pennsylvania (also includes New Jersey in the study): https://www.nj.gov/emp/pdf/cleanrenewablepower/MSEIA-Final-Benefits-of-Solar-Report-2012-11-01(1).pdf

i. Texas: https://ilsr.org/wp-content/uploads/2013/03/Value-of-PV-to-Austin-Energy.pdf

Benefits Analysis:

Deep Dive into Prosumer Benefits: In the main text, we surmised that under any compensation system, Buy-All Sell-All (energy is bought and sold through separate transactions), Banking (excess energy is only bought at the end of multiple billing periods, not after each one, and any excess energy from one period can be used to reduce demand in the next period) and the one used in our analysis Net Generation (excess energy is bought at the end of one billing period and demand is zeroed out or reduced in every period depending on how much energy was produced in that period), Prosumer Benefit from the consumption and sales from the system will be the same IF solar compensation equals retail rate. Let's recap that analysis.

Assume there are two periods 1 and 2, with X1 and X2 being the respective demands and Y1 and Y2 being the respective generation, where Y1 > X1 and X2 > Y2.

Assume retail rate and solar compensation equals to "r".

Then under net generation the total benefit to the prosumer = (Y1-X1)*r - (X2 – Y2)* r.

Under banking, the total benefit = 0 - (X2 – Y2 – (Y1 – X1))* r = (Y1-X1)* r – (X2 – Y2)*r.

Under buy-all, sell-all, the total benefit = $(Y1+Y2)^* r - (X1+X2)^* r = (Y1 - X1)^*r - (X2 - Y2)^*r$.

This case can be extended in a scenario with "r" as the retail rate and "s" as the solar rate where $r>s$,

then under net generation benefit = $(Y1-X1)^*s - (X2-Y2)^*r$ (NG1)

Under banking, if we assume that $X1 + X2 > Y1 + Y2$, we have

Banking benefit = $0 - (X2 - Y2 - (Y1 - X1))^* r = (Y1-X1)^* r - (X2 - Y2)^*r$. (BK1)

If we assume $X1 + X2 = Y1 + Y2$, we have

Banking Benefit = 0 (BK2)

If we assume $X1 + X2 < Y1 + Y2$, we have

Banking Benefit = $0 + (Y2 + (X1 - Y1) - X2) * s$ (BK3)

Under Buy All, Sell-All, total benefit = $(Y1+Y2)^* s - (X1+X2)^*r$ (BS1)

<u>Compare NG1, BK1, BS1</u>

Since $(Y1-X1)^* r > (Y1-X1)^*s$, because $r>s$, Clearly BK1 > NG1

Note that BK1 can be re-written as: $(Y1+Y2)^*r - (X1+X2)^*r$

Since $(Y1+Y2)^*r > (Y1+Y2)^* s$, Clearly BK1> BS1

Re-arranging, NG1 we have: $(Y1^*s + Y2^*r) - (X1^*s + X2^*r)$

While BS1 can be written as: $(Y1^*s+Y2^*s) - (X1^*r+X2^*r)$

Since $Y2^*r > Y2^*s$, the first part of NG1> first part of BS1

Also since –X1*s less than -X1*r, the second part of NG1 < the second part of BS1

Therefore, NG1>BS1

<u>Compare NG1, BK2, BS1</u>

We have established NG1>BS1

By our assumptions, NG1 is positive for a valid analysis, so NG1 > BK2.

Since Y1 + Y2 = X1 + X2, let’s assume Y1 + Y2 = X1 + X2 = Z.

Then BS1 can be re-written as Z(s-r). This is clearly negative since r>s. Therefore, BK2> BS1

<u>Compare NG1, BK3, BS1</u>

We have established NG1> BS1

BK3 can be re-written as (Y2-X2)*s + (X1-Y1)*s.

We have assumed, Y1 > X1 and X2 > Y2. Hence BK3<0. So NG1>BK3.

BS1 can be re-written as, (Y2*s – X2*r)- (X1*r -Y1*s).

Since r>s, first part of BK3> first part of BS1, and since the second part is preceded by a minus sign in any case for BS1, BK3 > BS1.

Therefore we have:

BK1> NG1> BS1

NG2 > BK2 > BS1

NG3 > BK3 > BS1

Even under the first scenario, Banking may not prove to be the most beneficial strategy because utilities will typically offer to bank at a rate lower than the solar compensation usually offered(“Net Energy Metering (NEM) and Your Bill” n.d.), or have altogether eliminated this policy(“New Hampshire Utilities, Solar Companies File Rate Design Settlement Proposals” n.d.). That being said it is often not up to the user which policy they fall under, but net generation credited at a monthly basis seems to be the most popular option among the utilities.

Sensitivity Analysis

Each utility has 24 possible cases of analysis, 12 if there is no ToU tariff. These are:

Tariff (2) * Demand (3) * Discount Rate (2) * Sizing (2 = Optimal/Default).

The logic behind choosing 4 per cent and 7 per cent discount rate is explained in the main text. A list of demand scenarios for each utility is given in Table SM3.6. Table SM3.7 has a list of optimal sizes given each demand level, as well as the base sizes.

Table SM3.6 – Demand Sensitivities

Utility	**Base Demand (Average Annual kWh)**	**Low Demand (Average Annual kWh)**	**High Demand (Average Annual kWh)**
Entergy	13490	7217.371135	20415.15985
Carroll	12973	7010.393592	19233.50509

APS	12295	5776.373809	20343.11777
Salt River	11986	5626.845435	19866.26027
PG&E	9637	4661.310606	15302.90061
SCE	8088	4094.591417	8996.200741
Eversource	8891	4329.369383	13525.49078
United	8971	4367.977317	13835.14488
Minnesota	8974	4435.657409	13683.77232
Xcel	9235	4468.915866	14416.94049
ConEd	12439	6765.977968	18183.11329
PSEG	12334	6726.191019	17929.29389
Portland	7753	3999.108033	10475.0598
PECO	12299	6712.103704	17820.30128
PPL	8919	4363.820409	13837.22552
Austin	14796	7128.909192	26963.86981

Table SM3.7 – Optimal Sizes for Each Demand Sensitivity and the Base Size (all in kW)

Utility	**Base Size**	**Optimal Size for Base Demand**	**Optimal Size for Low Demand**	**Optimal Size for High Demand**
Entergy	3.17	10.04	5.37	15.19
Carroll	5.74	9.38	5.07	13.91
APS	6.89	7.16	3.36	11.85

Salt River	6.7	6.92	3.25	11.47
PG&E	5.74	6.29	3.04	9.99
SCE	5.04	4.79	2.42	5.33
Eversource	7.52	6.92	3.37	10.53
United	6.88	6.92	3.37	10.67
Minnesota	3.48	6.99	3.46	10.66
Xcel	5.19	7.02	3.40	10.96
ConEd	7.58	9.5	5.17	13.89
PSEG	6.91	8.92	4.86	12.97
Portland	3.97	7.02	3.62	9.48
PECO	6.5	9.53	5.20	13.81
PPL	6.97	6.8	3.33	10.55
Austin	5.88	9.95	4.79	18.13

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