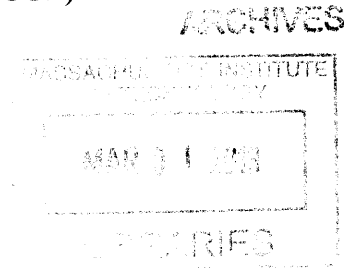# The Economics of US Greenhouse Gas Emissions Reduction Policy:
Assessing Distributional Effects Across Households and the 50 United States Using a Recursive Dynamic Computable General Equilibrium (CGE) Model

by

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The Economics of US Greenhouse Gas Emissions Reduction Policy:
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Submitted to the Department of Urban Studies and Planning on October 15, 2012 in Partial Fulfillment of the Requirements for the Degree of Master of Science in Urban Studies and Planning

Abstract

The political economy of US climate policy has revolved around state- and district- level distributional economics, and to a lesser extent household-level distribution questions. Many politicians and analysts have suggested that state- and district-level climate policy costs (and their distribution) are a function of local carbon intensity and commensurate electricity price sensitivity. However, other studies have suggested that what is most important in determining costs is the means by which revenues from a price on carbon are allocated. This is one of the first studies to analyze these questions simultaneously across all 50 United States, household income classes and a timeframe that reflects most recent policy proposals (2015 – 2050). I use a recursive dynamic computable general equilibrium (CGE) model to estimate the economic effects of a US "cap-and-dividend" policy, by simulating the implementation of the Carbon Limits and Energy for America's Renewal (CLEAR) Act, a bill proposed by Senators Cantwell (D-WA) and Collins (R-ME) in 2009. I find that while carbon intensity and electricity prices are indeed important in determining compliance costs in some states, they are only part of the story. My results suggest that revenue allocation mechanisms and new investment trends related to the switch to low-carbon infrastructure are more influential than incumbent carbon intensity or electricity price impacts in determining the distribution of state-level policy costs. These findings suggest that the current debate in the United States legislature over climate policy, and the constellation of both supporters and dissenters, is based upon an incomplete set of assumptions that must be revisited. Finally, please note that this study does not claim to comprehensively model the CLEAR Act, nor does it incorporate a number of important data and assumptions, including: the latest data on natural gas resources and prices, the price effects on coal of EPA greenhouse gas and mercury regulations, the most recent trends in renewable energy pricing.

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1. Introduction

Efforts to establish nationwide greenhouse gas reduction policies in the United States have failed largely due to disagreement over the scale of economic burden that such policies might create, and over who would bear the brunt of this burden. For example, among coal-rich states there has been concern that economic costs would fall unequally on their shoulders, while less carbon intensive states would be relatively unhindered. Others (e.g. Orszag (2007) and Greenstein (2007)) have cautioned that economic impacts could disproportionately hit low-income households, which annually spend a larger percentage of total income on non-luxury goods, such as home energy and transportation—both of which are predicted to rise in price due to an emissions abatement policy. While a number of studies have explored these questions, few have done so in a way that reflects the full political economy of US climate policy—namely at the level of states and congressional districts and across the 30-40 year timeline characteristic of most climate policy proposals. This paper adds some of this detail to the discussion, by modeling the distributional economics of a recent climate policy proposal across the 50 states and from 2006 to 2050.

The debate over climate policy in the US Congress extends at least as far back as the late 1970s, when the first hearings on the topic were held in the House of Representatives (Kamarck 2010). In the early years, there was little disagreement over the science or economics of climate change, partly because at that time Congress was only considering modest policy actions, such as funding research (Keller 2009). Trenchant debate over the economic costs and benefits of policies to reduce greenhouse gas emissions did not begin until the 1990s. In 1997, the Byrd-Hagel "Sense of the Senate" Resolution opposing the ratification of the Kyoto Protocol stated that "emission reductions could result in serious harm to the United States economy, including significant job loss, trade disadvantages, increased energy and consumer costs, or any combination thereof" (Selin and VanDeveer 2011). The resolution went on to proclaim that the Senate should not be a signatory to any agreement that "would result in serious harm to the economy of the United States," and that any proposed emissions reduction agreement or policy "should also be accompanied by an analysis of the detailed financial costs and other impacts on the economy of the United States" (105th Congress, Senate Res. 98). These declarations announced the deep concern of the US Congress about the economic impacts of a policy to reduce domestic greenhouse gas emissions; they also underscored the need for a clearer understanding of such impacts.

Concern over the economics of a policy to reduce greenhouse gas emissions in the US also includes a question of distributional effects, or the ways in which economic output or welfare is allocated among different parts of the economy. The primary domain of distributional economics refers to individuals or households across income classes. A central focus of this discourse is to determine whether a policy is

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progressive or regressive—whether the policy disproportionately benefits (progressive) or burdens (regressive) low-income groups, who are the least able to cope with additional economic costs. For example, in 2007, the House Budget Committee held a hearing entitled *Counting the Change: Accounting for the Fiscal Impacts of Controlling Carbon Emissions*, which focused on this question in great detail. Testimony from individuals such as Robert Greenstein explained that "[t]he policies needed to reduce greenhouse gas emissions would, by themselves, result in regressive changes in energy prices. But they also can generate substantial revenue that could be used to offset those regressive impacts" (Greenstein 2007). As Greenstein's statement concisely acknowledges, there is a relatively well-understood remedy for undesirable distributional impacts in the context of climate policy—the requirement that emissions permits be auctioned to generate revenue (which can also be accomplished by a carbon tax), and that these revenues be used to counteract regressivity. This continues to be an important concern in debates about the formulation of climate policy in the United States.

Another crucial sphere of the distributional economics of US climate policy deals with the allocation of welfare across the 50 United States. Palmer et al (2012) estimate that the economic burden of a carbon tax would indeed fluctuate significantly across the regions of the country. They explain that the largest increase in electricity prices would be felt by the "most coal-intensive regions . . . [b]ecause coal is more CO_2-intensive than other generation fuels" (Palmer et al 2012). Numerous studies have shown that this difference in CO_2-intesity has important political significance for climate legislation. For example, Holland et al (2011) show a strong correlation between congressional voting patterns and the extent to which a member's home district benefits economically from alternative vehicle CO_2 emissions reduction policies. Cragg et al (2012) find a similar correlation between congressional voting patterns and the per-capita greenhouse gas emissions of a congressional member's jurisdiction. Using historical voting results from both the House and the Senate and controlling for representatives' ideology, Cragg et al show that members from districts or states with high per-capita carbon emissions are less likely to vote for policies to reduce greenhouse gas emissions or promote clean energy. Alternatively, they find that members from districts or states with low per-capita carbon emissions have on average supported legislative efforts to cut emissions. They are explicit about the connection between per-capita CO_2 levels and the level of "regulatory compliance costs." Indeed they use CO_2 levels as a proxy for the "price" each region would pay for the enactment of a climate policy (with, of course, higher concentrations of CO_2 correlated with higher costs). Cragg et al connect these findings with the longstanding political economic theory that both "price" and "self-interest" are key determinants of voting behavior (Peltzman 1984). These results suggests that congressional representatives see their local carbon intensity as a determinant of whether and to what extent their constituents will benefit or pay for a climate policy. My research attempts to shed

light on these distributional questions by modeling both household and state distributional impacts of a proposed policy to reduce US greenhouse gas emissions.

2. Review of Literature on the Distributional Effects of US Climate Policy

A number of studies have approached these questions of incidence and efficiency, advancing the policy dialogue in Washington. Below is a brief summary of some of the studies undertaken thus far.

Metcalf (1999) and Dinan and Rogers (2002) address questions of economic efficiency and distributional progressivity associated with the implementation of a group of environmental taxes (Metcalf) and a CO_2 allowance scheme (Dinan and Rogers). Both studies make the important point that the allocation of revenues generated from a given policy (either from a tax on carbon or the sale of carbon emissions allowances) largely determines whether such policies are regressive or progressive, finding that carbon pricing alone is regressive. However, both studies show that such policies become progressive when they incorporate revenue allocation schemes that either reduce existing taxes (e.g. payroll taxes or income taxes) or provide flat rate lump-sum rebates to households. Both studies include detail on household income classes (deciles in Metcalf and quintiles in Dinan and Rogers) and both investigate a range of revenue allocation schemes, however there is no temporal or regional characterization.

Metcalf (2008 and 2007), Burtraw et al (2009) and Rausch et al (2009) present similar findings; namely, that significant progressivity can be achieved with carbon-pricing policies that either reduce other taxes, provide a lump-sum transfer or expand the Earned Income Tax Credit (EITC) program. These studies add regional detail of the United States, however the granularity is limited—Metcalf (2008 and 2007) utilize a 9-region format, while Burtraw et al (2009) and Rausch et al (2009) aggregate individual states into 11 and 12 regions respectively. This allows for some comparison of the policy-induced changes in household income across broad regions; however the impact on individual states is not elucidated. Metcalf (2008 and 2007) and Burtraw et al (2009) show minimal geographic variation in economic impacts on the average household—although Burtraw et al (2009) does show notable differences between regions for low-income households—while Rausch et al (2009) show significant variation among regions. Specifically, the Rausch results indicate that Midwestern and Southern areas will bear the highest economic costs of a carbon-pricing policy, which the authors attribute to more carbon intensive energy consumption and production patterns in those states. All four of these studies utilize "static" methods to estimate policy impacts—they model a single year, they do not show the progression of economic effects over time.

Hassett et al (2009) analyze household welfare impact associated with the implementation of a CO_2 tax. They add a temporal dimension (1987, 1997 and 2003) to the regional (9 regions) and class (deciles) detail of the above studies. They find that the direct impact of a CO_2 tax is regressive, while indirect effects are more proportional—suggesting that a carbon tax is "far less regressive than is generally assumed" (Hassett et al 2009), even without progressive revenue allocation measures such as reducing payroll taxes or offering a lump-sum return. The same study finds that any regressivity is reduced when lifetime income is used as the measure of welfare in place of annual income. Finally, they show little variation in welfare impacts across regions, and that whatever variation does occur diminishes over time.

Rausch et al (2010) look at the distributional impacts of a number of recent CO_2 reduction policy proposals in the United States (including the American Clean Energy and Security Act (ACES) of 2009 and the Carbon Limits and Energy for America's Renewal (CLEAR) Act).[1] The authors employ a computable general equilibrium model of the US economy with the same core structure used by Rausch et al (2009) (including the 12-region geographic aggregation). The main change from their earlier work is the incorporation of a *recursive dynamic* component to the model, which allows the authors to include significantly more temporal detail (2006 – 2050, in five year increments after 2010). The study produces similar distributional results to the studies mentioned above, i.e., that all policies with progressive allocation schemes come out as progressive overall. The study shows that negative welfare impacts (as measured by a change in household income) increase over time, as the carbon price increases due to a stricter limit on the quantity of emissions allowed in the economy. The authors show only minimal differences in welfare impacts among regions, and that these relative differences persist over time. That said, there is one major outlier, which experiences much larger welfare changes than other regions. Interestingly, this outlier is one of the few single-state regions, Alaska. The authors—with laudable transparency—point out that Alaska's extreme result is indicative of possible state-by-state differences that are muted by the aggregation of multiple states into single regions. For example, the "Mountain" region groups together eight states surrounding the Rocky Mountains. This group includes Idaho, which generated about 94 percent of its electricity in 2006 from carbon-neutral hydro and wind resources, and Wyoming, which derived roughly the same percentage (95 percent) of its total 2006 electricity from carbon intensive coal. Together, these two extreme cases effectively neutralize each other. This is a stark example of the obscuring affects that can occur with regional aggregation.

Palmer et al (2012) adds more regional detail than previous studies, but with slightly less temporal detail (2010 – 2035 in five year increments) than the Rausch et al (2010) study. Palmer et al analyze the

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[1] Please see Section 4 for a brief description of ACES and CLEAR.

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variability of revenue generation from a carbon tax, as part of the federal deficit reduction discussion. The authors note that a large share of revenues from such a tax would necessarily come from the electricity sector. This presents regional distributional challenges, since the 50 states are very diverse in terms of electricity generation mix and since this diversity will create variation in how incidence is distributed. As mentioned above, the study shows that states with carbon intensive electricity (e.g. in the Midwest) will pay more than states with relatively low-carbon sources (the Northeast and West Coast). The goal of this study is not to provide a detailed distributional analysis, and therefore it does not account for factors such as revenue recycling—which is somewhat a function of looking at a carbon tax as a deficit reduction measure. While the study provides richer geographic granularity than previous studies, it uses the electricity market modules created by the Energy Information Administration's Annual Energy Outlook, which does not map neatly to state borders.

Boyce and Riddle (2009) estimate the economic impacts of the "cap-and-dividend" policy framework characterized by the Cantwell-Collins CLEAR Act. The authors fully disaggregate the US to its 50 constituent parts and analyze household distributional impacts at both national and state levels. They show, as above, the regressivity of carbon pricing alone, and a progressive turnaround with the inclusion of a the lump-sum rebate or "dividend" mechanism. Indeed, they find the policy as a whole to be strongly progressive at both state and national levels, due to the fact that a uniform dividend (the same dollar amount is given to all households, regardless of income) is of greater value to low-income households than upper-income groups as a percentage of annual income. The authors find this balancing effect to be so strong that low-income households gain more in dividends than they loose in higher energy prices, experiencing a positive net impact. The study shows this same distributional principle, which occurs most prominently at the household level, playing-out at the state level—where poor states disproportionately suffer from the stand-alone carbon price (regressivity) and gain from the dividend mechanism.[2] Finally, the authors find that differences in policy-induced welfare impacts are much greater across income groups than across states—showing minimal variation from state to state. Like many of the above papers, this study uses a static analysis—meaning, it only views policy results for a single year (2003).

These many studies addressing the distributional impacts of a range of policies to reduce US greenhouse gas emissions form the foundation for this thesis. Of equal importance are the studies that have helped to elucidate the political economy of CO_2 regulation in the United States—namely, that the state and district

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[2] NB: Theses pains and gains are also a function of the carbon intensity of each state, and so there is not an equally lucid picture of this trend as in the case of households—which are analyzed either within the same state or across the national energy mix.

level economic impacts of such policy will have great, if not primary, significance in shaping the results of future legislative efforts (Holland et al 2011; Cragg et al 2012). This paper builds on these efforts, by modeling the impacts of a US cap-and-dividend policy, the CLEAR Act, at the level of the 50 states and across the full time dimension of most policy proposals – from 2015 to the year 2050.

3. Model Background and Assumptions

The basis for this study is a recursive dynamic computable general equilibrium (CGE) model of the United States economy designed specifically to study climate and energy policies. The model is based on the MIT United States Regional Energy Policy (USREP) model, as described in Rausch et al (2010). The explanation that follows closely mirrors Rausch et al (2010)—at times drawing text directly from that study as well as Rausch et al (2009)—while also providing additional background and outlining key differences between the two models. In addition to the description below, please refer to the appendix of Rausch et al (2009) for greater detail on key equations and technical assumptions used in this model.

General equilibrium theory was first developed by the French economist Leon Walras in the 1870s and formalized in the 1950s most notably by Kenneth Arrow and Gerard Debreu (Shoven and Whalley 1984). It is the study of how equilibrium occurs in *all markets* of an economy simultaneously, in contrast to much of microeconomics, which studies a subset of markets or a single market in isolation (i.e. partial-equilibrium analysis) (Perloff 2008). General equilibrium formulations include multiple rational agents—such as firms and consumers—which interact through the market according to optimizing behavior. For example, firms seek to optimize (maximize) profits, producing goods and services, while households aim to optimize (maximize) their welfare or utility against a budget constraint. Firms purchase intermediate inputs (such as technology or fuel) from other firms, as well as primary factors of production (such as capital and labor) from households. Households receive income from these trades and from government transfers like entitlement programs. In-turn, households spend a portion of this income on goods and services in the market. The government collects tax revenue on these activities, which is cycled back through the economy. The many interactions of these market agents are primarily mediated by prices. Therefore equilibrium is a function of a set of market-clearing prices—where supply is in perfect balance with demand. (Perloff 2008; Markusen 2002; Rausch et al 2010).

Walrasian general equilibrium theory offers a powerful—but abstract—picture of the economy, with only limited application to policy problems like the complex "internalization" process of pricing carbon in the US. The development of "applied" or "computable" general equilibrium analysis is the answer to this limitation—it is the extension of general equilibrium theory to detailed mathematical models that

incorporate empirical data and production and demand parameters representative of real economies (Shoven and Whalley 1984). As Shoven and Whalley point out, such parameterized models provide "an ideal framework for appraising the effects of policy changes on resource allocation and for assessing who gains and loses . . . providing fresh insights into long-standing policy controversies" (Shoven and Whalley 1984). Computable general equilibrium models have been effective at simulating the economic efficiency and distributional impacts of a range of policy issues, including taxation and tariff regimes, international trade dynamics, and energy policy.

As mentioned above, the model used in this study is a computable general equilibrium (CGE) model, of the sort described by Shoven and Whalley. The model is built on the MIT USREP model, which itself borrows a great deal of structure from the MIT Emissions Prediction and Policy Analysis (EPPA) model (Paltsev et al 2005). USREP employs many of the principles described above with regard to the market dynamics of the general equilibrium framework. An important addition to what is mentioned above is the fact that general equilibrium theory and modeling assumes full employment. This is of course a distortion of the economy as we know it, especially in our current times.

USREP was originally a static model, as are many CGE models. This means that it was initially capable of only solving for one time period (which is still very useful in studying the differences between a business-as-usual economy and an economy under by the policies in question). In Rausch et al (2010) a *recursive dynamic* component was added to USREP, which allowed the simulation of general equilibrium dynamics over time, in five-year increments. USREP also includes regional and household income detail, where the 50 United States are aggregated into 12 regional groups and household income groups are divided into nine categories. Finally, USREP is capable of providing significant production-side detail— reflecting the economic activity of major industries and sectors.

The model used in the current study includes all USREP components mentioned above, with two key differences. First, while the current model includes the sectoral detail of USREP, this detail is not used in the final analysis presented here. Second, and most importantly, instead of representing only 12 regions, the full detail of the 50 United States is modeled here, allowing for a closer study of the dynamics and differences among states, and rendering information at a level that is commensurate with the political economy of US climate policy.

The model used in this study is based on state-level economic data from the IMPLAN dataset (Minnesota IMPLAN Group 2008), which includes all economic activity among firms, households and the

government for the base year 2006. This is combined with regional tax data from the NBER tax simulator, TAXSIM, to create a detailed picture of the US economy. Base year primary energy consumption estimates and electricity generation mix profiles from the US Energy Information Administration's (EIA) State Energy Data System (SEDS) are merged with the above economic data to provide granular estimates of energy use profiles and greenhouse gas emissions for each state. This is further augmented by the incorporation of regional data on raw fossil fuel reserves from the US Geological Survey and the Department of Energy. Please note that this study does not incorporate the latest data on natural gas resources and resulting prices, the price effects on coal of EPA greenhouse gas and mercury regulations, nor the most recent trends in renewable energy pricing. As such, the specific levels (welfare impacts, emissions reductions, etc.) should be taken with a grain of salt, with greater attention given to the economic dynamics (e.g. correlations between emissions reductions, electricity price change, investment trends and welfare change) revealed by the model.

Electricity production in the model includes generation from coal, natural gas, oil, hydro, biomass, and an "other renewable energy" category that includes wind, solar and geothermal resources. The generation mix for each state is endogenously shaped over time by a combination of resource depletion and the economics of substitutes, the latter of which becomes highly deterministic as a price on carbon is enacted. Business-as-usual energy use for fossil fuels and for nuclear and hydro electricity by state is calibrated to EIA's Annual Energy Outlook (AEO) 2009 reference case, which means that the impacts of both the Energy Independence and Security Act (EISA) of 2007 and the American Reinvestment and Recovery Act (ARRA) of 2009 are included. Furthermore, the business-as-usual quantity of non-hydro renewables in each state's electricity fuel mix is calibrated through 2035 to the EIA's AEO 2012 reference case assumptions, with AEO growth rates from 2010 to 2035 extrapolated to 2050.

One of the more unique components of the model is a set of state-specific supply curves calculated for wind and biomass resources, the two most rapidly growing sources of renewable energy in the model. These supply curves are essentially a combination of (1) mark-ups (the y-intercept) from the price of coal and (2) CES elasticity parameters that determine the slope of the curve. Wind supply curves are calculated in a sub-model, which utilizes high-resolution wind data from the National Renewable Energy Laboratory (NREL) and levelized cost of energy assumptions presented in Morris (2009). NREL's TrueWinds model is also used to estimate capacity factors by state, which depend on the quality (intermittency, velocity, etc.) of wind resources in each state. Biomass supply curves are constructed for each state using data provided by Oakridge National Laboratory (2009). Finally, the model also includes

non-price-induced improvements in energy efficiency, with a conservative estimate of 1 percent efficiency improvement per year for all sectors.

Energy goods, other than electricity, are traded freely between regions, reflecting the "high degree of integration of intra-U.S. markets for natural gas, crude and refined oil, and coal" (Rausch et al 2010). Electricity is also traded freely as a homogenous good, however only within each of six regional electricity pools—there is no trade of electricity across regions (nationally).[3] The six electricity pools are structured to roughly reflect the existing geography of US independent system operators (ISOs) and the three major NERC interconnections. Non-energy goods are traded openly across regions as imperfect substitutes, as stipulated by the Armington assumption (Armington 1969), which states that "home and foreign goods are differentiated purely because of their origin of production" (Blonigen and Wilson 1999). In other words there is a slight bias towards in-state produced goods, where goods from out of state are imperfect substitutes for similar goods produced locally. Armington assumptions also determine the model's structure for the international trade of goods.

Firms' production functions are modeled assuming constant-returns-to-scale and using nested constant-elasticity-of-substitution (CES) functions. The use of CES functions, which are central to this and most CGE models, means that for a given production process (e.g. the production of nuclear electricity) there is a constant change in the proportion of production inputs (such as capital and labor) due to a percentage change in the marginal rate of technical substitution (Perloff 2011; Wikipedia). Constant elasticity of substitution, as mentioned below, is also assumed when modeling consumer utility functions, where the percentage change in the ratio of substitute goods (e.g. food and electricity) is constant relative to a percentage change in the marginal rate of substitution.

Technical change is a main driver of economic growth in the model, as well as an increase in labor productivity. Labor productivity growth rates by state are set according to AEO 2009 GDP growth through 2030. Beyond 2030, population and labor productivity growth rates are estimated using a logistic function that assumes convergence by 2100. The 2100 levels for annual labor productivity growth are two percent, while the population growth rate is zero.

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[3] This assumption would become obsolete if investment in super-grid infrastructure were pursued in the US, enabling for example the transmission of electricity from areas like the wind-rich Midwest to the energy-hungry areas like the Northeast.

The model assumes that capital is mobile across both industries and states, and foreign capital flows are fixed. The pervasive malleability of domestic capital is analogous to a long-run perspective. In each state, total capital is calculated as investment net of depreciation according to the "standard perpetual inventory assumption" (Rausch et al 2010). Investment sectors for each state produce an amount of investment goods (such as loans) that matches an endogenously calculated sum of household savings (from all household types), given base year (2006) data about investment demand. Ownership of capital in the form of state resources (e.g. natural resources such as coal or oil deposits) is distributed nationally in proportion to capital income. This is in contrast to a previously explored assumption (Rausch et al 2009) that state resources are owned locally (by households living within the given state). This latter approach was discarded due to the recognition that ownership of most large companies is widely distributed geographically (especially energy companies, which have significant impact in estimating policy compliance costs in this model, and so must be given special credence in the decision-making process of which of the two above assumptions to use).

While capital is mobile across both states and industries, labor is only mobile across industries (immobile across states). The labor supply curve is shaped by the household choice between leisure and labor. Compensated and uncompensated labor supply elasticities are calibrated according to the method in Ballard (2000). It is assumed for all income groups that the uncompensated labor supply elasticity is 0.1, while the compensated labor supply elasticity is 0.3. (Rausch et al 2010).

Like USREP, there are nine household income classes in the model used for this study, as displayed in Table 1 below. In addition to displaying the household income levels for each category, Table 1, shows the percentage of the total US population (in 2006) that fits within each category. For every state, the number of households per income group and overall population are estimated using data from the US Census (2009) through 2030. Beyond 2030, population growth rates in each state are applied uniformly across all income groups. How households earn income and the goods on which this income is spent varies by state. Household savings are an integral part of the consumer utility function, which makes the "consumption-investment decision endogenous" (Rausch et al 2010). The model employs an approach laid out by Bovenberg, Goulder and Gurney (2005), where household capital invested in the production of market goods and services is separated from capital that is invested back into the household (residential capital). The model assumes that income from the former is subject to taxation, while the later is not, and the model affords households the flexibility to shift their investments accordingly.

Table 1. Model Income Classes and Population

Income Class	Annual Income	Percent of US Population	Percent of US Population (cumulative)
hhl	Less than $10,000	7.3%	7.3%
hh10	$10,000 to $15,000	4.4%	11.7%
hh15	$15,000 to $25,000	9.5%	21.2%
hh25	$25,000 to $30,000	9.8%	31.0%
hh30	$30,000 to $50,000	14.3%	45.3%
hh50	$50,000 to $75,000	19.9%	65.2%
hh75	$75,000 to $100,000	13.5%	78.7%
hh100	$100,000 to $150,000	12.8%	91.5%
hh150	$150,000 plus	8.5%	100.0%

Finally, tax rates are differentiated by region and industry sector, and include both federal and state tax regimes. Tax revenues for each state are distributed proportional to current levels. Varying state tax levels and the current distribution of Federal tax revenue among the states is incorporated within these assumptions. The "intent here [is] to keep a focus on the implications of CO_2 pricing and revenue distribution, and not muddy that by assuming changes in distribution of other Federal or State tax revenues" (Rausch et al 2009). The model includes ad-valorem, income and payroll taxes, with rates set according to a combination of IMPLAN data on inter-institutional taxation and NBER TAXSIM data on marginal personal income tax rates. (Rausch et al 2009).

4. Policy Framework for Analysis: The CLEAR Act

This paper explores the broader question of the economic consequences of a nation-wide limit on greenhouse gas emissions by applying the model described above to the Carbon Limits and Energy for America's Renewal (CLEAR) Act, a federal bill introduced in 2009 by Senators Maria Cantwell (D-WA) and Susan Collins (R-ME). CLEAR was proposed as an alternative to the most recent generation of cap-and-trade policies, the American Clean Energy and Security (ACES) Act (otherwise known as Waxman-Markey) (H.R. 2454) and the American Power Act (S. 1733). Both of these bills focused on a cap-and-trade program where permits would be freely allocated in early years, and where a large percentage of emissions reductions would come from international offset projects. While ACES passed the House, the overall legislative effort failed in the Senate, in no small part due to concern about the economic costs of pricing carbon and state-level distribution questions. This concern came primarily from conservative elected officials and think tanks, yet also from Democratic officials from carbon or energy intensive states like Senator Joe Manchin of West Virginia, who aired an infamous campaign ad of himself firing a rifle round through a copy of "The Cap And Trade Bill," proclaiming that "it's not good for West Virginia."

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Many environmentalists also opposed the ACES/APA combo, arguing that its permit giveaways and heavy reliance on offsets begged for regulatory evasion and gaming, ultimately risking the ability to adequately control greenhouse gases. The CLEAR Act responded to these manifold concerns, by requiring all permits to be auctioned, minimizing international offsets, and by recycling revenues (as explained below) in a progressive way that could produce net benefits for many households. CLEAR continues to be discussed on Capitol Hill with plans for re-introduction in the 113th Congress in 2013.

CLEAR utilizes a "cap-and-dividend" approach, which begins with a quantitative limit (a "cap") on fossil carbon emissions, not unlike cap-and-trade. The cap is implemented through the issuance of a limited number of CO_2 emissions permits, which are auctioned monthly by the US Treasury and where each ton of carbon dioxide introduced into the US economy must be covered by a permit. The annual number of permits declines over the lifetime of the policy, making the cap increasingly stringent.[4] CLEAR's cap addresses CO_2 only, although non-binding provisions for reducing other greenhouse gases are included in the bill as well.

The CLEAR Act proposes to auction 100% of emission permits. These auctions are estimated to generate hundreds of billions of dollars annually—a significant new revenue source for the federal government. How these revenues are used, of course, greatly determines the overall economic efficiency as well as the incidence of the policy. As will be discussed in great detail below and as is touched on above, the incidence inquiry is concerned with the question of who in society will bear the economic burden of a given policy. Of special concern is whether a policy is progressive or regressive, as discussed above. CLEAR uniquely allocates the lion's share (75 percent) of revenues to US citizens, through the form of an annual flat-rate rebate. This rebate is what is referred to as the "dividend" in the "cap-and-dividend" framework. The fact that the rebate is flat—meaning it is the same amount of money for all US citizens, regardless of their income level—makes the policy powerfully progressive, for a given sum (say $1,000) is of much greater marginal value for low-income households (in proportion to their annual income) than it is for middle- and upper-income households.

The remaining 25 percent of revenues from CLEAR Act permit auctions are allocated to a fund called the Clean Energy Reinvestment Trust (CERT) Fund. The CERT Fund is designed to provide capital for a range of programs and incentives that either drive down emissions further or help address unwanted policy impacts. For example, the CERT Fund would provide "targeted and region-specific transition assistance to workers, communities, industries and small businesses of the United States experiencing the

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[4] Please see Scenario 1 below for more detail on how the CLEAR cap declines over time.

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greatest economic dislocations," (CLEAR Act legislative text) including training programs for the new clean energy economy, compensation for the early retirement of carbon intensive facilities and assistance to energy-intensive industries facing international competition not subject to a carbon price. The Fund would also pay for adaptation efforts, clean energy and energy efficiency projects, projects that reduce greenhouse gases other than CO_2, and programs that provide special support for low-income families struggling with energy costs. The CERT Fund has the capacity to drive down emissions beyond what the cap alone would accomplish; alternately, the CERT Fund could reduce compliance costs, by offering financial support to companies transitioning away from fossil fuels towards clean energy. The many benefits of the CERT Fund are not included in the modeling exercise that follows, nor are other of the bill's components such as the Voluntary Carbon Reduction program, Manufacturing Innovation Credits, Supplemental Emission Reduction Credits, or the Regional Dividend Adjustment clause. This means that the estimated costs of the CLEAR Act will be slightly inflated in what follows. In addition, this means that the discrepancies between states will also be overestimated, because many of the programs under the CERT Fund are aimed at smoothing geographical disparities, in addition to the Regional Dividend Adjustment program. I do not claim to have represented the economics of the CLEAR Act in its entirety in this study. Rather, CLEAR provides a jumping-off point to investigate some of the dominant issues and trends in the US climate policy debate more generally.

5. Model Results

This section presents results from the CGE model described in Section 3, simulating the economic and environmental performance of the CLEAR Act. CLEAR has been selected to investigate the possible economic dynamics of a US climate policy more broadly. Section 5 begins by outlining three CLEAR Act scenarios being considered by Cantwell staff. I first analyze the CO_2 emissions reductions under each scenario, estimating annual as well as cumulative reductions. Second, I look at the aggregate national welfare impacts due to the implementation of the first scenario only. Third, I investigate distributional questions at the household level, presenting national averages by income class. Section 5 concludes with results on the distributional effects across the 50 United States, providing new perspectives on the political economy of US climate policy.

5.1 Policy Scenarios

The first of the three policy scenarios represents the emissions reduction pathway specified in the CLEAR Act, as introduced in 2009. The second and third scenarios are being considered by the Cantwell office to temper the overall economic impact of the Act and to allow for adaptation of the requirements beginning in 2030. These modifications are inspired by the recognition that, in 2030, decision makers should have

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more information about abatement costs and the pace and severity of climate change; and that this new information will allow them to make adjustments to optimize the policy. All three scenarios assume that implementation would begin in 2015, later than originally considered in the CLEAR Act.

All three scenarios are compared with a *Reference* case, which should be seen as the "business-as-usual" pathway—the world without climate policy—from 2006 to 2050. As explained in detail in Section 3, the *Reference* case is based upon 2006 economic data provided by IMPLAN and TAXSIM, as well as primary energy consumption estimates and electricity generation mix profiles from the US Energy Information Administration's (EIA) State Energy Data System (SEDS). These data are extrapolated into the future by the recursive dynamic component of the model using assumptions about growth rates for metrics such as population and productivity, along with resource depletion curves for raw fossil fuel reserves and declining cost curves for emerging technologies such as wind, solar and geothermal. Such assumptions in turn shape growth in investment and GDP. US GDP in the *Reference* case grows at an average compound annual growth rate of 2 percent per year from 2006 to 2050, and most states see similar rates. CO_2 emissions, under the *Reference* case, grow at an average compound annual growth rate of 1 percent, from 5,874 million metric tons (MMT) in 2006 to 9,210 MMT in 2050, an overall growth of 57 percent. During the period between 2006 and 2010, CO_2 emissions decline due to the beginning of the recession. By 2015, the model assumes the nation is returning to an increasing quantity of emissions from the 2010 nadir. It is important to note that the model *does not* include the latest natural gas price projections due to hydraulic fracturing, nor does it incorporate assumptions related to the recent US EPA emissions regulations on greenhouse gases and mercury (and how these will affect the economics of any new or expanded coal fired power plants). Figure 1, Figure 2, Figure 3 and Figure 4 below all show the *Reference* case plotted alongside the various policy cases.

Scenario 1 (S1)

As stated above, *Scenario 1* follows the emissions reduction pathway laid out in the introduced version of the CLEAR Act, modified by the assumption that the policy would be reintroduced in 2013. CLEAR stipulates a two-year window between its enactment and the first year of emissions regulation. This means that emissions would begin to be capped in 2015, however the number of allowances issued for that year would be set according to estimates of 2015 business-as-usual emissions levels to ease industry into the regime. The amount of allowances issued in 2015 is then held constant for two more years (through 2017). After 2017, the number of allowances is reduced by 0.25 percent per year, creating an increasingly strict cap and reducing CO_2 emissions nationwide.
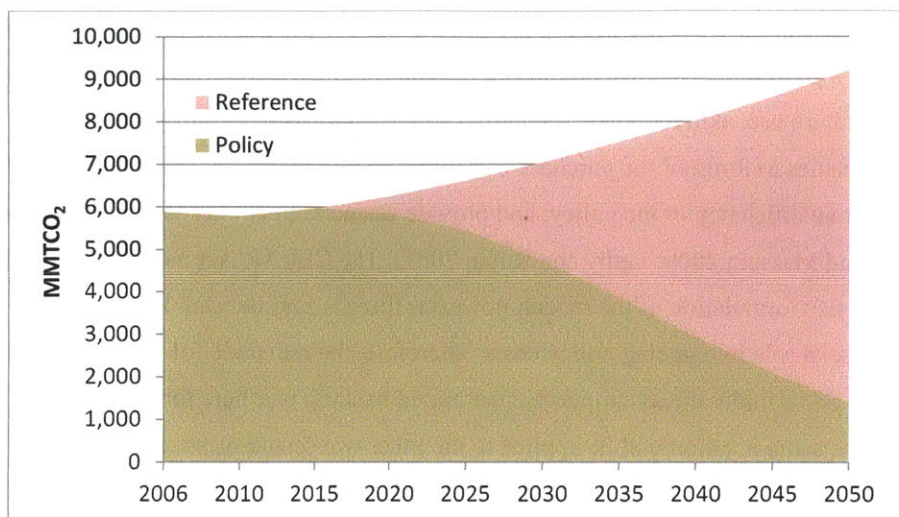
Figure 1. Scenario 1 CO_2 Emissions Trends (MMT)

Figure 1 above depicts the downward-sloping trend in emissions due to the increasingly restrictive cap ("Policy"). This trend is superimposed on the upward-sloping growth in emissions projected under the "business-as-usual" *Reference* case ("Reference"). In 2015, the estimated quantity of US CO_2 emissions is 5,964 million metric tons (MMT), which is the number of permits issued for that year (5,964 million permits, at one permit per metric ton). In 2020, the *Reference* case projects the US to emit 6,257 MMT CO_2, whereas the number of permits issued by the US Treasury in that year is cut to 5,875 million (at one permit per metric ton), a reduction of 382 MMT. This trend continues: in 2030, the *Reference* case estimate is 7,037 MMT CO_2, while only 4,738 million permits are auctioned, yielding a reduction of 2,299 MMT; in 2040, the *Reference* case projects 8,028 MMT CO_2 compared to 2,950 million permits, a cut of 5,078 MMT; and in 2050, the spread is between 9,210 MMT (*Reference*) and 1,408 million available permits, a difference of 7,802 MMT CO_2. The emissions reduction trajectory presented by *Scenario 1* achieves the following annual CO_2 reductions relative to the 2006 baseline: 19 percent reduction by 2030, 50 percent by 2040 and 76 percent by 2050, as indicated below in Table 2. Cumulatively, *Scenario 1* cuts emissions levels (from 2015-2050) to 147 billion metric tons (BMT) CO_2, relative to the *Reference* level of 266 BMT CO_2, producing nearly a 45% reduction in cumulative emissions over the 35 year period.

The emissions reduction pathway shown in Figure 1 portrays the exact emission quotas represented in the CLEAR cap, in five-year increments. The actual emissions reduction pathway may look more like Figure 2, where the effects of "banking" and "borrowing" smooth the downward slope of emissions abatement,

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while also smoothing the upward slope of CO_2 emissions permit prices (as explained in greater detail below). Banking is a provision that allows regulated companies to purchase emissions permits in advance, to be set aside for future use, akin to money secured in a bank. Borrowing is the opposite provision, which allows companies to forestall the purchase of permits, assuming future liabilities. These nuances improve the economic efficiency of the policy, and provide financial flexibility to regulated firms (Bosetti, Carraro and Massetti 2009; Leiby and Rubin 2001). The CLEAR Act includes both banking and borrowing. Within this formulation of the model, however, there is zero demand for borrowing, while banking plays a crucial role in reducing policy costs. Therefore, the remainder of this paper refers to banking only. *Scenario 1* under the assumption of unlimited banking will here forward be referred to as *Scenario 1b*, and the same notation will be applied to the other two scenarios as well.

Figure 2 projects *Scenario 1b—Scenario 1* under the assumption of *unlimited* banking. Unlimited banking here refers to a policy provision where there is no restriction on the amount of time that a banked permit can be held before being surrendered to the US Treasury to fulfill an emissions liability. Unlimited banking as represented in this model, however, does include two important constraints on the amount of banking. First, the percentage of banking allowed (relative to the CO_2 permit quota stipulated for a given year in the CLEAR Act) is constrained to 15 percent in the first year of the policy (2015) and to 20 percent for every year thereafter. For example, in 2015 the emissions cap is 5,964 million metric tons, therefore the maximum number of bankable permits is 895 million (15 percent of 5,964 million, at one permit per ton). The second constraint is that the compound annual growth rate at which the price of CO_2 emission permits rise cannot be less than 5 percent. The first constraint is based on feasibility thresholds stipulated by Cantwell legislative staff, and informal modeling of the CLEAR Act conducted by the US EPA. The second constraint is based on the assumption that no firm would invest in a financial instrument (CO_2 permit) that is rising at a rate less than the rate of interest (which has been assumed to be approximately 5 percent for the life of the policy). Welfare costs can be driven lower than those indicated below in the unlimited banking case if either of these constraints are relaxed.
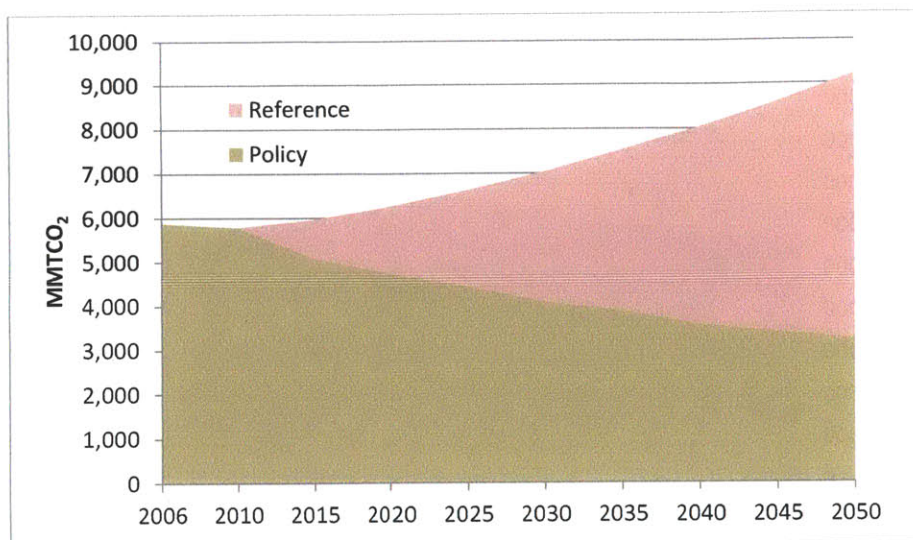
Figure 2. Scenario 1b CO_2 Emissions Trends (MMT) – Unlimited Banking

Scenario 2 (S2)

Scenario 2 takes a slightly less aggressive approach overall. It is nearly identical to *S1* until 2030, at which point the rate of declination in CO_2 allowances remains constant at 3.5 percent (the result of declining at 0.25 percent for 13 years (2018 through 2030)), instead of continuing to decrease 0.25 percent per year as in *S1*. One minor additional difference is that *S2* begins to decrease the number of emissions allowances in 2016 rather than 2017. Therefore, under both *S1* and *S2* the same number of permits are issued in 2015, however for every year thereafter they are slightly different. In 2020, the amount of permits under *S1* is 5,875 million while under *S2* there are 5,816 million. In 2030, there are 4,738 million permits under *S1* and 4,572 million under *S2*; and by 2050 there are 1,408 million permits under *S1* and 2,242 million under *S2*. *Scenario 2* is slightly more aggressive than *S1* up to 2030 (due to an earlier start in the 0.25 percent per year allowance quantity reductions), however *S1* ultimately achieves deeper emissions reductions. For example, the *S2* emissions reduction pathway (displayed in Figure 3) achieves the following annual CO_2 reductions relative to the 2006 baseline: 22 percent reduction by 2030, 45 percent by 2040 and 62 percent by 2050, as indicated below in Table 2. Cumulatively (from 2015-2050), *Scenario 2* achieves emissions levels of 151 BMT CO_2, producing nearly a 43% reduction from *Reference* case levels—only 2% less than *Scenario 1*.
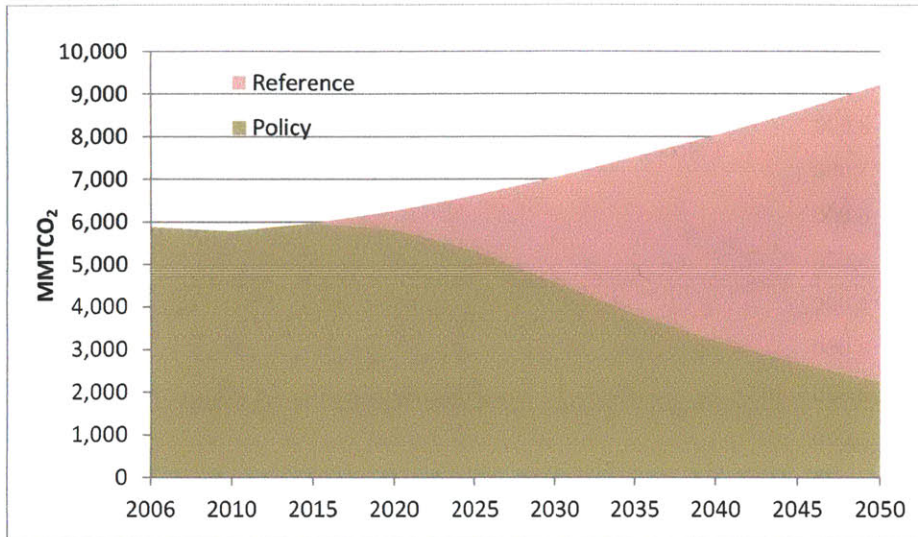
Figure 3. Scenario 2 CO_2 Emissions Trends (MMT)

Scenario 3 (S3)

Scenario 3 is the least aggressive approach, and leaves a great deal of discretion open to future decision makers. *S3* follows the pathway of *S2* until 2030, at which point the cap remains flat for the duration of the policy.[5] Figure 4 below shows the emissions reduction pathway for *S3*. From 2015 through 2030, emissions levels reflect the number of permits issued (which is the same under *S2* and *S3*). In 2030, the number of permits is 4,572 million. Under *S3*, this is the amount of permits issued in every subsequent year, indicated by the flat "Policy" slope in Figure 4. This is in contrast to *S2* where from 2030 on the number of permits continues to decline at the constant rate of 3.25 percent per year. Under Scenario 3, the maximum annual emissions reduction from the 2006 baseline is 22 percent, first achieved in 2030 (see Table 2 below). Cumulatively, *Scenario 3* reduces 35-year emissions levels (from 2015-2050) to 151 BMT CO_2, producing a 32% reduction from *Reference* case levels.

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[5] Again, as explained above, the notion here is that decision makers would have to reassess appropriate emissions reduction levels in 2030, meaning it is unlikely that the cap would stay flat after all.
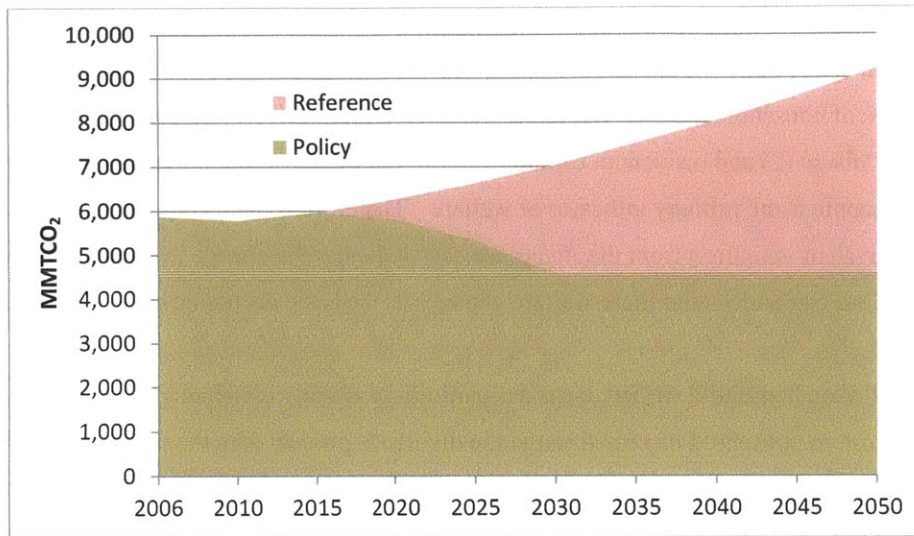
Figure 4. Scenario 3 CO_2 Emissions Trends (MMT)

Table 2. Annual CO_2 Emissions Levels Relative to 2006

	2015	2020	2025	2030	2035	2040	2045	2050
Scenario 1	2%	0%	-7%	-19%	-34%	-50%	-64%	-76%
Scenario 2	2%	-1%	-9%	-22%	-35%	-45%	-54%	-62%
Scenario 3	2%	-1%	-9%	-22%	-22%	-22%	-22%	-22%

5.2 Background on Welfare Analysis

The most basic economic outcome of the CLEAR Act is the establishment of a price on carbon. This internalizes the environmental damages associated with unabated emissions and drives up the cost of carbon intensive energy, such as coal and petroleum products, which most Americans depend on to power their modern lifestyle.[6] Recent developments in the extraction of natural gas may temper this increase in consumer energy prices, for gas is less carbon intensive than coal and increasingly less costly regardless of the price on carbon. Nonetheless, natural gas itself will have to be phased-out due to its fossil carbon content likely starting in the mid-to-late 2020s and early 2030s (as indicated by model results). Many renewable energy sources such as wind and solar are also rapidly declining in cost, however due to constraints such as intermittency it is likely that a carbon-free energy provision system (generation, storage, grid and all) will be more expensive than the current system which is based on fossil energy. Therefore, an increase in the price of energy is likely under the CLEAR Act.

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[6] Coal currently provides cheap electricity to hundreds of thousands of Americans—in 2011, 42 percent of US electricity came from coal (EIA, 2012).

As the price of energy rises, overall consumption rates will tend to decline throughout the economy. This downward trend in consumption is the result of a reduction in buying power, which effectively represents a drop in the value of household income. Using the framework established by Rausch et al (2010), consumption (1), leisure (2) and residential capital (3) represent the full value of household income in this model, and full income is the primary indicator of welfare.[7] Therefore, a percentage change in full income (measured as equivalent variation) from the *Reference* case indicates the change in welfare due to policy implementation. One can understand these welfare changes as the basic economic cost of the policy.

Under the CLEAR Act, household welfare costs are partially or entirely (depending on income class) offset by an *increase* in household income through the dividends produced by the policy (described above). There is therefore a tension between the beneficial affect of the dividend mechanism and the detrimental impact of increased costs of energy associated with the cap mechanism. These two are opposing forces in an economic tug-of-war, the result of which determines a given household's or a given state's change welfare (either positive or negative) due to the implementation of the policy.

Finally, when considering changes in welfare in the context of climate policy it would be incomplete to ignore the many welfare *benefits* of mitigating environmental damage—these benefits are, after all, the fundamental impetus for a policy to reduce greenhouse gas emissions. A special class of models called integrated assessment models[8] (IAMs) has offered an initial response to this problem by producing a metric called the social cost of carbon (SCC). The social cost of carbon estimates the "monetized damages associated with an in incremental increase in carbon emissions" (Greenstone et al 2011). This estimate includes (but is not limited to) "changes in net agricultural productivity, human health, property damages from increased flood risk, and the value of ecosystem services" (Greenstone et al 2011). By incorporating this metric into a cost-benefit analysis, every ton of CO_2 reduced has a tangible economic benefit to society and therefore improves welfare, further offsetting the costs of a policy like the CLEAR Act. While it is arguably impossible to establish a metric that perfectly reflects the many benefits of something as complex as an Earth with reduced anthropogenic climate forcing, it is arguably a step forward to approximate such benefits, such that a more thorough accounting can take place in academic

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[7] There are many other dimensions to welfare, such as public health issues associated with the social cost of carbon. These factors are not included in this study, however it is recommended that future modeling efforts do aim to incorporate them.

[8] Integrated assessment models "integrate" scientific data from Earth systems, such as the atmosphere, the oceans, terrestrial ecosystems, etc. with data on the human economic system. Examples of prominent IAMs include the MIT EPPA (Emission Prediction and Policy Analysis) model, the DICE (Dynamic Integrated Climate and Economy) model, developed by economist William Nordhaus, the PAGE (Policy Analysis of the Greenhouse Effect) model produced by Chris Hope, and the FUND (Climate Framework for Uncertainty, Negotiation and Distribution) model developed by economist Richard Tol.

and decision-making forums. Indeed, an interagency working group in the United States government established SCC values in 2010 to be applied to regulatory analyses (Greenstone et al 2011), as presented in Table 3 below.

Table 3: Social Cost of CO_2 (short ton), 2010 – 2050 (2007 dollars)[9]

Discount Rate	5%	3%	2.50%	3%
Year	Avg	Avg	Avg	95th
2010	4.7	21.4	35.1	64.9
2015	5.7	23.8	38.4	72.8
2020	6.8	26.3	41.7	80.7
2025	8.2	29.6	45.9	90.4
2030	9.7	32.8	50	100
2035	11.2	36	54.2	109.7
2040	12.7	39.2	58.4	119.3
2045	14.2	42.1	61.7	127.8
2050	15.7	44.9	65	136.2
Annualized % Change, 2010-2050	3.10%	1.90%	1.60%	1.90%

Unfortunately, incorporation of the social cost of carbon into the CGE model used for this study was not possible. Nonetheless, to provide an initial estimate of how the SCC may affect model results, I have done a post-hoc "back of the envelope" calculation. The calculation is a simple multiplication of the social cost of carbon values listed under the 3 percent (median) discount rate above by the amount of carbon reduced under each of the three scenarios. Table 4 below presents the various results for all three scenarios, under the assumption of unlimited banking.

The first column of Table 4 presents the CO_2 reductions associated with each policy, again assuming unlimited banking, which shifts emissions reductions forward in time (firms choose to reduce emissions more aggressively due to the benefits of banking, as discussed above). The emissions reduction figures in Table 4 are in the unit million metric tons (MMT). The social cost of carbon estimates presented in Table 3 have therefore been converted to metric tons from short tons (the unit of measure in Table 3). Additionally, the figures from Table 3 have been converted from USD 2007 to USD 2006, which is the unit used throughout this paper. The second column in Table 4 is the product of the total amount of CO_2 reduced for a given scenario and year and the social cost of carbon estimate. This is seen as the benefit of the policy, for it is averted social costs associated with reduced carbon emissions. The third column portrays the initial economic cost of the policy (not including the SCC benefits), which is the difference

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[9] Source: Greenstone et al (2010), Table 4.

between US GNP estimates in the *Reference* case and under the given scenario. The fourth column in Table 4 is the net of the initial policy costs and the benefits associated with reducing carbon as measured by the SCC. The final column portrays the percentage by which the incorporation of the social cost of carbon reduces the aggregate (national) policy costs.

Table 4. Back of the Envelope Estimate of the Benefits Associated with Reducing CO_2, per Social Cost of Carbon (SCC) Estimates (Assuming a 3 Percent Discount Rate)

	CO_2 Reduction (MMTCO$_2$)	SCC Benefit (Billion $2006/MMT)	Initial Policy Cost (Billion $2006)	Net Cost (Billion $2006)	Percentage Cost Reduction
Scenario 1b					
2015	895	$22.8	$66.2	$43.4	34%
2020	1,519	$42.8	$163.7	$120.9	26%
2025	2,192	$69.5	$319.7	$250.2	22%
2030	2,966	$104.2	$563.7	$459.4	18%
2035	3,646	$140.6	$834.6	$694.0	17%
2040	4,471	$187.8	$1,193.4	$1,005.6	16%
2045	5,199	$234.5	$1,585.4	$1,350.9	15%
2050	5,984	$287.9	$2,088.0	$1,800.1	14%
Scenario 2b					
2015	1,402	$35.7	$134.2	$98.4	27%
2020	1,717	$48.4	$211.7	$163.3	23%
2025	2,103	$66.7	$314.4	$247.7	21%
2030	2,609	$91.7	$461.4	$369.7	20%
2035	3,224	$124.3	$664.5	$540.2	19%
2040	4,084	$171.5	$975.8	$804.3	18%
2045	4,829	$217.8	$1,308.2	$1,090.3	17%
2050	5,632	$270.9	$1,747.7	$1,476.8	16%
Scenario 3b					
2015	728	$18.6	$49.4	$30.8	38%
2020	1,047	$29.5	$92.8	$63.3	32%
2025	1,436	$45.6	$157.5	$111.9	29%
2030	1,945	$68.4	$258.2	$189.8	26%
2035	2,456	$94.7	$381.5	$286.7	25%
2040	3,109	$130.6	$548.6	$418.0	24%
2045	3,901	$176.0	$786.8	$610.8	22%
2050	4,638	$223.1	$1,054.7	$831.6	21%

The social cost of carbon does not wholly offset the economic costs of the policy under any of the three scenarios, and the percentage cost reduction declines over time under each scenario as the economic costs of the policy outpace benefits from reducing carbon. The reader should consume this information with caution. A full accounting of the benefits associated with the social cost of carbon requires a more thorough integration within the model, and it is likely that the benefits are under-estimated in Table 4. This is a rough approximation that provides a starting point for understanding the economic benefits of reducing carbon emissions.

While the estimates above indicate that the social cost of carbon does not fully nullify policy costs, it is clear that the SCC *does* reduce policy costs. Therefore, all welfare changes presented below are skewed more negatively than they would be were the SCC included. Future efforts should aim to integrate the SCC to produce a comprehensive picture of welfare changes.

5.3 Aggregate Welfare Impacts

Figure 5 below depicts the average welfare changes of each of the three policy scenarios, under assumptions of both (a) no banking and (b) unlimited banking. Welfare change is calculated as the difference in income between the *Reference* case and the given policy scenario, divided by the original *Reference* case income level. *Scenario 1b*, which produces the greatest emissions reductions, generates a decline in average household welfare of 0.2 percent in 2030, 0.7 percent in 2040 and 1.7 percent (from the *Reference* case) in 2050. *Scenario 2b* is only slightly different from *S1*, with welfare reductions of 0.1 percent in 2030, 0.6 percent in 2040 and 1.5 percent in 2050. Finally, *Scenario 3b*, which produces the smallest emissions cuts, reduces welfare by 0 percent in 2030, 0.2 percent in 2040 and 0.6 percent in 2050. All scenarios show the beneficial impact of banking, and escalating policy costs over time (reflected in a greater percentage decrease in welfare). Additionally, under unlimited banking, the difference in welfare costs between *S1*, *S2* and *S3* is much smaller than under no banking.
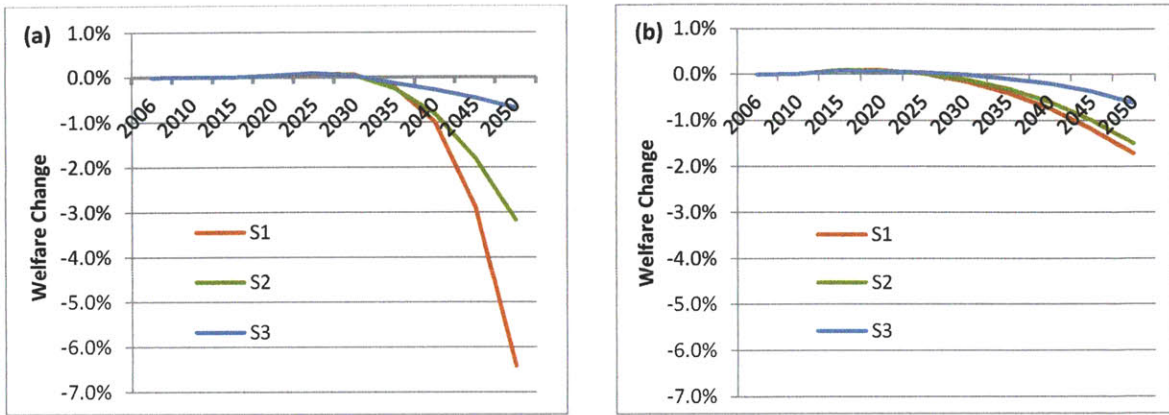
Figure 5. Welfare Changes Due to Implementation of the CLEAR Act

The welfare changes depicted above are largely a function of CO_2 emissions allowance values, or permit prices, and their propagation throughout the economy. Figure 6 below shows the radical increase in allowance values over time when banking is not permitted, and Figure 7 shows the "price-smoothing" affect of unlimited banking. It is also important to note that the CLEAR Act includes a "price collar" or a "symmetric safety valve" (Burtraw et al 2010), which protects the market from excessively high or low price shocks by stipulating both a "price floor" (minimum price) and a "price ceiling" (maximum price).
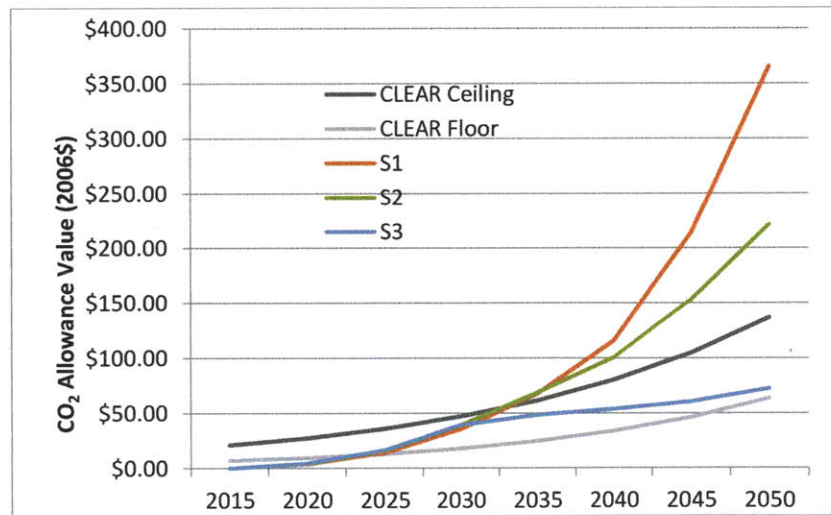

Figure 6. CO_2 Emission Allowance Values – No Banking

The existence of a price collar, however, does not negate the need for other policy measures (such as banking) that have the above-mentioned price smoothing affect (Jacoby and Ellerman 2004). For

example, when increasing prices break the ceiling, in order to keep prices down, as laid-out in the CLEAR Act, the US Treasury must issue allowances in excess of the cap quota, theoretically undermining the environmental integrity of the policy. That is, if in 2030 the number of permits to be issued is 4,738 million (which allows 4,738 MMT CO_2 into the atmosphere) but the permit price is above that stipulated by the ceiling, then more permits will have to be released into the market, releasing a commensurate amount of greenhouse gases into the atmosphere. That said, CLEAR stipulates that any revenues from these excess allowances must be allocated to the CERT Fund, which itself is dedicated to emission reduction projects. While CERT Fund projects would aim to reduce emissions commensurate with or in excess of the quantity of allowances added to the market, this one-to-one parity is uncertain and arguably unlikely.[10] Therefore, even in the context of a price collar it is important to aim for a policy formulation that keeps allowance values within the collar.
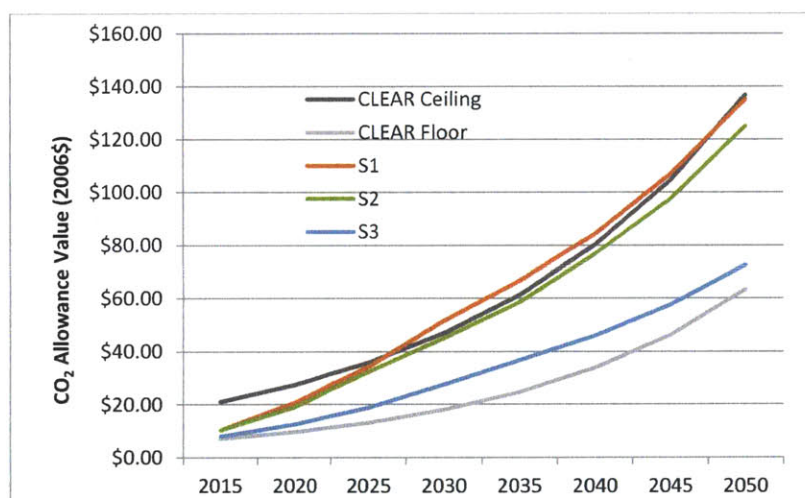

Figure 7. CO_2 Emission Allowance Values – Unlimited Banking

Another key factor determining welfare impacts is the amount of revenues recycled to citizens as dividends. The introduced version of the CLEAR Act allocates 75 percent of revenues to dividends, with the remaining 25 percent directed to the CERT Fund. Figure 8 and Table 5 below, show—for *Scenario 1b*[11] only—how welfare improves as the percentage of revenues devoted to dividends increases. For example, when 90 percent of revenues are slated for household dividends (with the remaining 10 percent allocated to the government), the policy produces an *improvement* in average household welfare through

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[10] These specific dynamics have not been simulated under this study.
[11] As noted above, Scenario 1b refers to Scenario 1 under the assumption of *unlimited banking*, while Scenario 1a refers to Scenario 1 under the assumption of *no banking*.

2035. This occurs simply because the increased value of dividends outweighs the increased costs associated with higher prices for energy, goods and services. This trend in the model is likely also partly due to the exclusion of the welfare benefits stemming from CERT Fund investments (the percentage of revenues that are not allocated to dividends). The exclusion of CERT Fund investments should under-estimate the welfare benefits of funds not allocated to dividends—which would, in turn, diminish the welfare-positive impacts of allocating more revenue to dividends. While this is likely the case, policy-makers may wish to consider increasing the portion of revenues allocated to dividends, following more comprehensive modeling that includes the CERT Fund.

Table 5. Welfare Change by Revenue Allocation Scheme (Scenario 1b only)

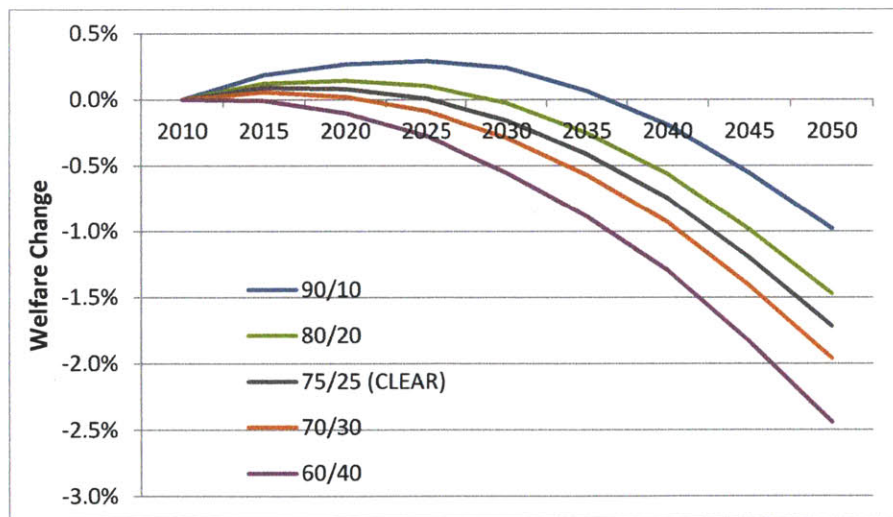| Allocation Scheme	2006	2010	2015	2020	2025	2030	2035	2040	2045	2050
90% Dividend / 10% Govt	0.0%	0.0%	0.2%	0.3%	0.3%	0.2%	0.1%	-0.2%	-0.6%	-1.0%
80% Dividend / 20% Govt	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	-0.3%	-0.6%	-1.0%	-1.5%
75% Dividend / 25% Govt	0.0%	0.0%	0.1%	0.1%	0.0%	-0.2%	-0.4%	-0.7%	-1.2%	-1.7%
70% Dividend / 30% Govt	0.0%	0.0%	0.1%	0.0%	-0.1%	-0.3%	-0.6%	-0.9%	-1.4%	-2.0%
60% Dividend / 40% Govt	0.0%	0.0%	0.0%	-0.1%	-0.3%	-0.6%	-0.9%	-1.3%	-1.8%	-2.4%

Figure 8. Welfare Change by Revenue Allocation Scheme (Scenario 1b only)[12]

[12] NB: The legend in this figure refers to the allocation breakdown, in terms of the percentage of revenues allocated to household dividends vs. government funds (e.g. 90/10 = 90% allocation to dividends and 10% allocation to government funds).

5.4 Welfare Impacts by Household

Next, we consider the distributional impacts of national welfare changes across household income classes. A primary concern is whether the policy is progressive or regressive—whether it disproportionately burdens low-income groups, who are the least able to cope with marginal hikes in energy costs. Figure 9 portrays the distributional impacts of the CLEAR Act by household income class for *Scenario 1b*, and under the revenue allocation scheme of 75 percent dividend/25 percent general government funds. Results have also been analyzed for the other two scenarios and the seven allocation schemes outlined in Figure 8 above, and the basic pattern of incidence is the same.
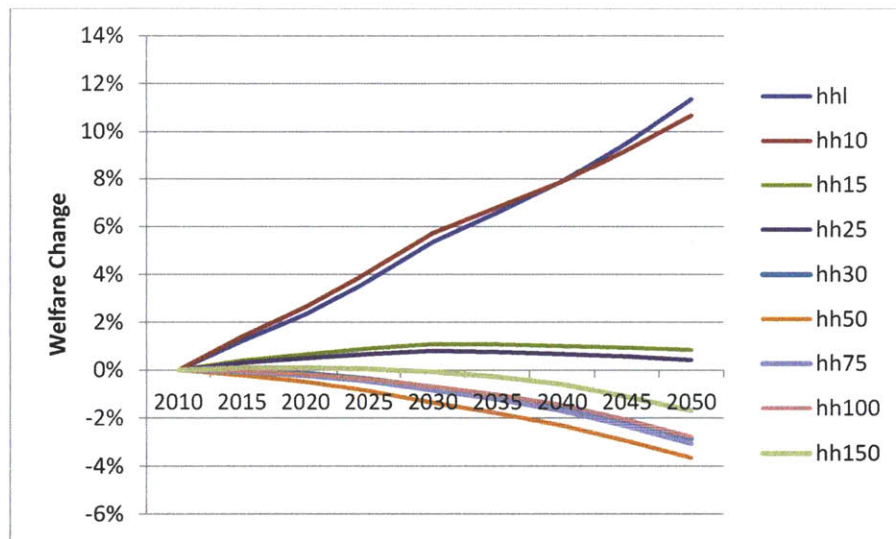

Figure 9. Welfare Change by Income Class (Scenario 1b only)

Figure 9 above clearly shows the progressive nature of the CLEAR Act. Households in the four lowest income classes, *hh1 – hh25*, are all better-off due to policy implementation (relative to the reference scenario) in every period—as increased household income from dividends outweighs the decrease in buying power associated with higher prices for energy, goods and services. This is also a reflection of the fact that the flat-rate dividend is a larger percentage of annual income for low-income households than for middle- and upper-income groups, providing greater marginal benefits.

Middle- and upper-income households experience a decline in economic welfare due to the policy, however no group experiences a decline of more than 1 percent through 2030, and only the three middle-income groups (*hh30 – hh75*) dip below that to 2 percent through 2040. Additionally, the magnitude of welfare improvements for the two lowest income groups (reaching 11 percent in 2050) is far greater than the burdens felt by middle and upper income groups (with nadirs of 2, 3 and 4 percent in 2050).

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It must be underscored that all welfare changes discussed above are simply measures of the percentage difference in welfare between the *Reference* case and the CLEAR Act's most aggressive scenario (*Scenario 1b*). That is, no change discussed above is a decline in welfare from one year to the next; it is merely a percentage change from what would have been, as assumed under the *Reference* case. To be clear, as shown in Figure 10,[13] national welfare (the sum of household income from all classes) continues to *grow* under the CLEAR Act. And this growth occurs at nearly the same rate[14] as under the *Reference* scenario, reflected in the almost identical curves in Figure 10 below.
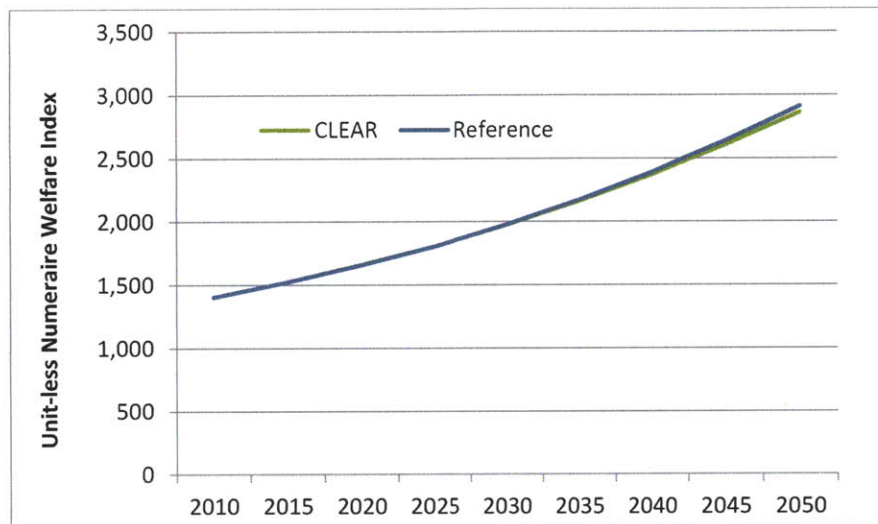

Figure 10. Real Welfare Growth with Implementation of the CLEAR Act (Scenario 1b)

Welfare also grows under the CLEAR Act for all household income groups nationally from year to year, as displayed in Figure 11. There is a definite and consistent upward slope for all household income groups in Figure 11, however the slope (or rate of growth) is greater for middle- and upper-income households.[15]

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[13] Welfare is represented here by the model's unit-less numeraire index.

[14] Both curves have approximately a 2 percent compound annual growth rate (CAGR) from 2010 to 2050.

[15] NB: The reader may wonder why middle-income households such as hh50 show a greater welfare level than upper-income households such as hh100 and hh150. This is because Figure 11 displays the total income (welfare) for each household class nationwide. Due to the fact that in the US there is a larger number of middle-income households relative to the number of high-income households, the aggregate income of middle-income households is greater, even though the income per household, of course, is less.
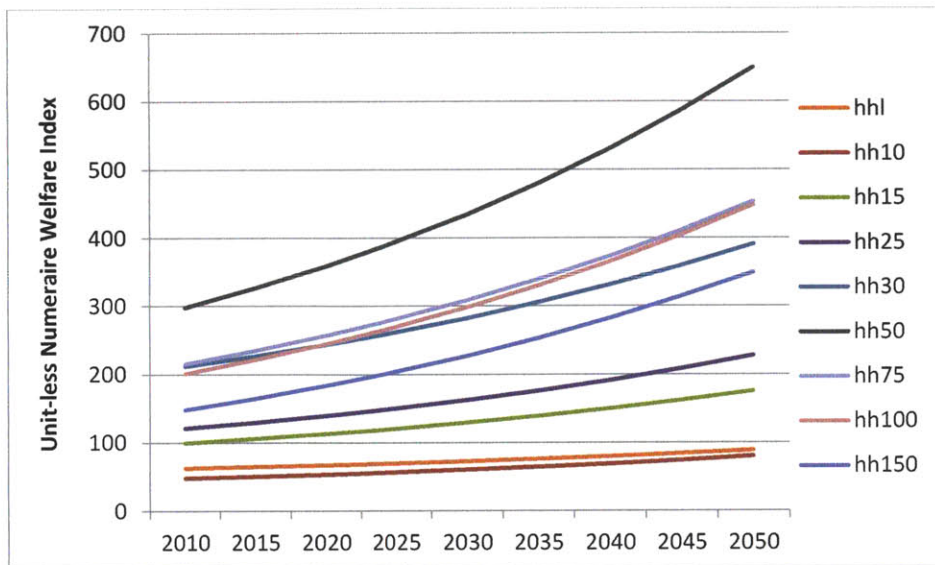
Figure 11. Real Welfare Growth by Household Income Group Under Implementation of the CLEAR Act

As outlined in Table 7, for the majority of income groups and time periods there is little change in the growth rate due to the implementation of the CLEAR Act. Deviations from this include a 0.1 to 0.3 percent improvement in the CAGR for low-income groups, and a -0.1 to -0.2 percent change in the CAGR for middle and upper income groups, as indicated in

Table 7 below. This is a further manifestation of the progressivity of the CLEAR Act, for under *Reference* case assumptions income level disparity is exacerbated by disparity in income (or welfare) growth rates: upper-income welfare growth rates are three to four times greater than that of low-income groups—see Table 6 below. This disparity in growth rates is partially offset by the implementation of the CLEAR Act. For example, the differences presented in

Table 7 represent percentage improvements in the CAGR of welfare of 42.1 and 22.9 percent for *hh1* and *hh10* respectively, while only diminishing annual growth rates for *hh100* and *hh150* by 3.2 and 1.8 percent respectively (e.g. from 2.18 percent to 2.14 percent CAGR for *hh150* and from 2.06 percent to 1.99 percent CAGR for *hh100*). That said, the disparity in growth rates persists under the implementation of the CLEAR Act, as shown by the steeper slopes for more wealthy households in Figure 11.

Table 6. Aggregate National Welfare by Income Group - Compound Annual Growth Rate (CAGR), Reference Case

Income Group	2006 -2010	2010 -2015	2015 -2020	2020 -2025	2025 -2030	2030 -2035	2035 -2040	2040 -2045	2045 -2050	2006 -2050
hhl	0.4%	0.4%	0.5%	0.5%	0.6%	0.6%	0.7%	0.7%	0.8%	0.6%
hh10	0.7%	0.8%	0.9%	0.9%	1.0%	1.1%	1.2%	1.2%	1.3%	1.0%
hh15	1.0%	1.1%	1.2%	1.3%	1.4%	1.4%	1.5%	1.6%	1.6%	1.4%
hh25	1.2%	1.3%	1.4%	1.5%	1.6%	1.6%	1.7%	1.8%	1.8%	1.5%
hh30	1.2%	1.4%	1.5%	1.5%	1.6%	1.7%	1.7%	1.8%	1.8%	1.6%
hh50	1.7%	1.9%	2.0%	2.0%	2.1%	2.1%	2.1%	2.2%	2.2%	2.0%
hh75	1.6%	1.8%	1.9%	1.9%	2.0%	2.0%	2.0%	2.1%	2.1%	1.9%
hh100	1.7%	2.0%	2.0%	2.0%	2.1%	2.1%	2.2%	2.2%	2.2%	2.1%
hh150	1.8%	2.1%	2.2%	2.1%	2.2%	2.2%	2.3%	2.3%	2.3%	2.2%
National Average	1.4%	1.6%	1.7%	1.7%	1.8%	1.9%	1.9%	2.0%	2.0%	2.0%

Table 7. Aggregate National Welfare by Income Group - Difference of Reference CAGR and Scenario 1b CAGR[16]

Income Group	2006 -2010	2010 -2015	2015 -2020	2020 -2025	2025 -2030	2030 -2035	2035 -2040	2040 -2045	2045 -2050	2006 -2050
hhl	0.0%	0.2%	0.2%	0.3%	0.3%	0.2%	0.2%	0.3%	0.3%	0.2%
hh10	0.0%	0.3%	0.2%	0.3%	0.3%	0.2%	0.2%	0.3%	0.3%	0.2%
hh15	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
hh25	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
hh30	0.0%	0.0%	0.0%	0.0%	-0.1%	-0.1%	-0.1%	-0.1%	-0.1%	-0.1%
hh50	0.0%	0.0%	-0.1%	-0.1%	-0.1%	-0.1%	-0.1%	-0.1%	-0.1%	-0.1%
hh75	0.0%	0.0%	0.0%	0.0%	-0.1%	-0.1%	-0.1%	-0.1%	-0.2%	-0.1%
hh100	0.0%	0.0%	0.0%	0.0%	-0.1%	-0.1%	-0.1%	-0.1%	-0.1%	-0.1%
hh150	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	-0.1%	-0.1%	-0.1%	0.0%
National Average	0.0%	0.0%	0.0%	0.0%	0.0%	-0.1%	-0.1%	-0.1%	-0.1%	0.0%

Finally, it is important to note—as outlined in more detail above—that all of the changes in welfare discussed above exclude any of the significant benefits arising from increased environmental stability associated with the reduction of carbon emissions and the related mitigation of negative climate change impacts. As these impacts often effect low-income groups more severely (OECD 2002), it would be

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[16] Note: the differences represented in Table 4 are a simple subtraction of Reference CAGRs from Scenario 1b CAGRs. These figures *do not* represent the percentage difference between the Reference CAGRs and the Scenario 1b CAGRs.

interesting to see a social cost of carbon metric that reflects this disparity. Inclusion of such a metric in a study like this would likely indicate an even more progressive policy at the household level.

5.5 Analysis of Welfare Impacts by State

In the climate policy debate, the question of distributional impacts does not stop at the level of household income. Rather, a greater portion of contention and concern has centered on the question of distributional impacts in the domain of the 50 United States. State-level distributional analysis begins to paint a picture of how much each state will pay under the proposed policy, which has huge political significance. Indeed, as discussed above, congressional representatives from states with high per capita carbon emissions are less likely to vote in favor of climate policy, out of concern that their states will suffer economically (Cragg et al 2012; Holland et al 2011). Congressional members from carbon intensive states such as Joe Manchin from West Virginia have spoken directly to this issue. Modeling efforts such as that conducted by Palmer et al (2012) show that, indeed, a price on carbon will cause energy prices to rise, and disproportionately so in the most carbon intensive states, such as those that get a large percentage of their electricity from coal. However, policies like the CLEAR Act, and the findings outlined below, reveal that the state-level distributional map is determined by a more complex array of factors than electricity price and incumbent carbon intensity alone. The progressive nature of the CLEAR Act, driven by the dividend mechanism, and shifts in investment behavior add a very interesting twist to the story. Relatively less wealthy states gain in surprising ways, even under doubling electricity rates and larger than average emissions reductions, and wealthy states with cleaner energy sources do worse than expected. These findings suggest that the current debate in the United States legislature over climate policy, and the constellation of both supporters and dissenters, is based upon an incomplete set of assumptions that must be revisited.

Figure 12 and Figure 13 below portray the change in aggregate state welfare[17] associated with the implementation of the CLEAR Act. Figure 12 represents these changes in an alphabetical format, whereas Figure 13 presents the results in an ordinal layout. First, it must be recognized that there is considerable spread in the welfare impacts across states. At their peak in 2050, some states experience welfare improvements of 20 to 30 percent, while others see declines of 5 to 10 percent. A slightly larger number of states gain than loose, and gains are of greater magnitude than losses (per state). However, many of the states that experience a decline in welfare are some of the most populous, such as Texas, California, New York and Florida.

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[17] Aggregate state welfare is a representation of the change in the total household income of all household classes per state. Total household income, as explained above, is the sum of consumption, leisure and residential capital.

Referring to Figure 13, it becomes surprisingly apparent that some of the most carbon intensive states in the nation experience some of the greatest welfare improvements – which means they are better off in strictly economic terms under the implementation of the CLEAR Act, without considering any environmental benefits. This is a shake-up from the usual map of climate policy incidence, where states like California, New York and New Jersey in the Northeast are usually projected to see little impact, while those in the Midwest and Mountain states are expected to feel the most pain. This is not the distributional map produced here. For example, North Dakota, which in 2006 burned carbon intensive coal for 92 percent of electricity demand and 66 percent of primary energy needs,[18] is ranked as the second-most improved state in the nation under the implementation of the CLEAR Act. Similarly, Wyoming, whose households see a welfare improvement of just under 25 percent by 2050 due to implementation of the CLEAR Act, met 94 percent of electricity needs and 64 percent of overall primary energy demands with coal in 2006.[19] Conversely, California is a relatively clean energy state, yet it is ranked sixth from the bottom in terms of welfare impacts under the CLEAR Act. These energy profiles, under the *Reference* case, do not drastically change over time. By 2050, in the *Reference* case, coal only diminishes to 75 percent of Wyoming electricity generation and 53 percent of overall primary energy requirements. While there is some reduction, this is still a large percentage of coal relative to a state like California, with 1 percent coal electricity in 2006 dropping to zero by 2050.

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[18] Energy Information Administration (EIA), State Energy Data System.
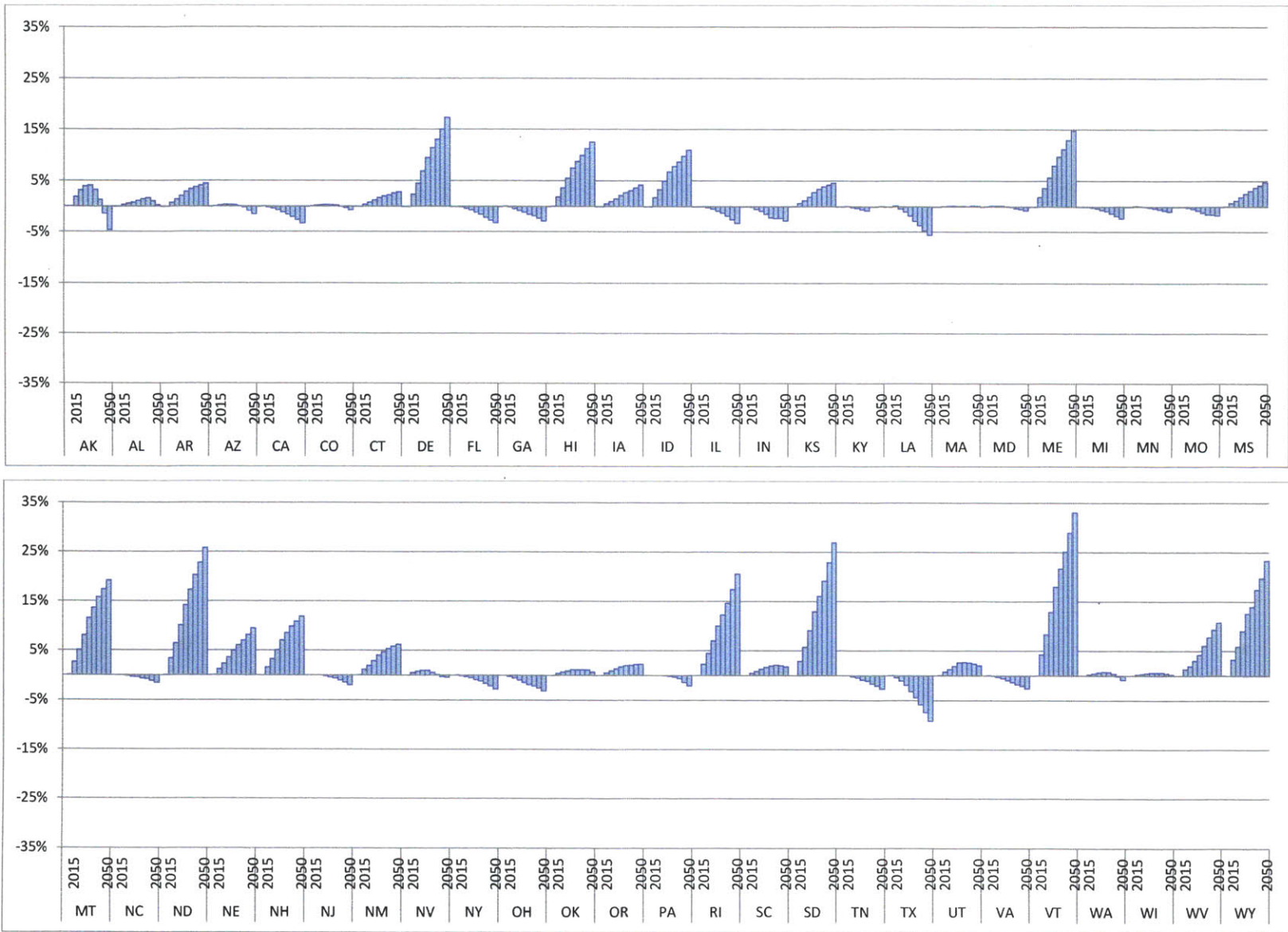[19] Ibid.

Figure 12. Welfare Change by State Due to Implementation of the CLEAR Act, Alphabetical
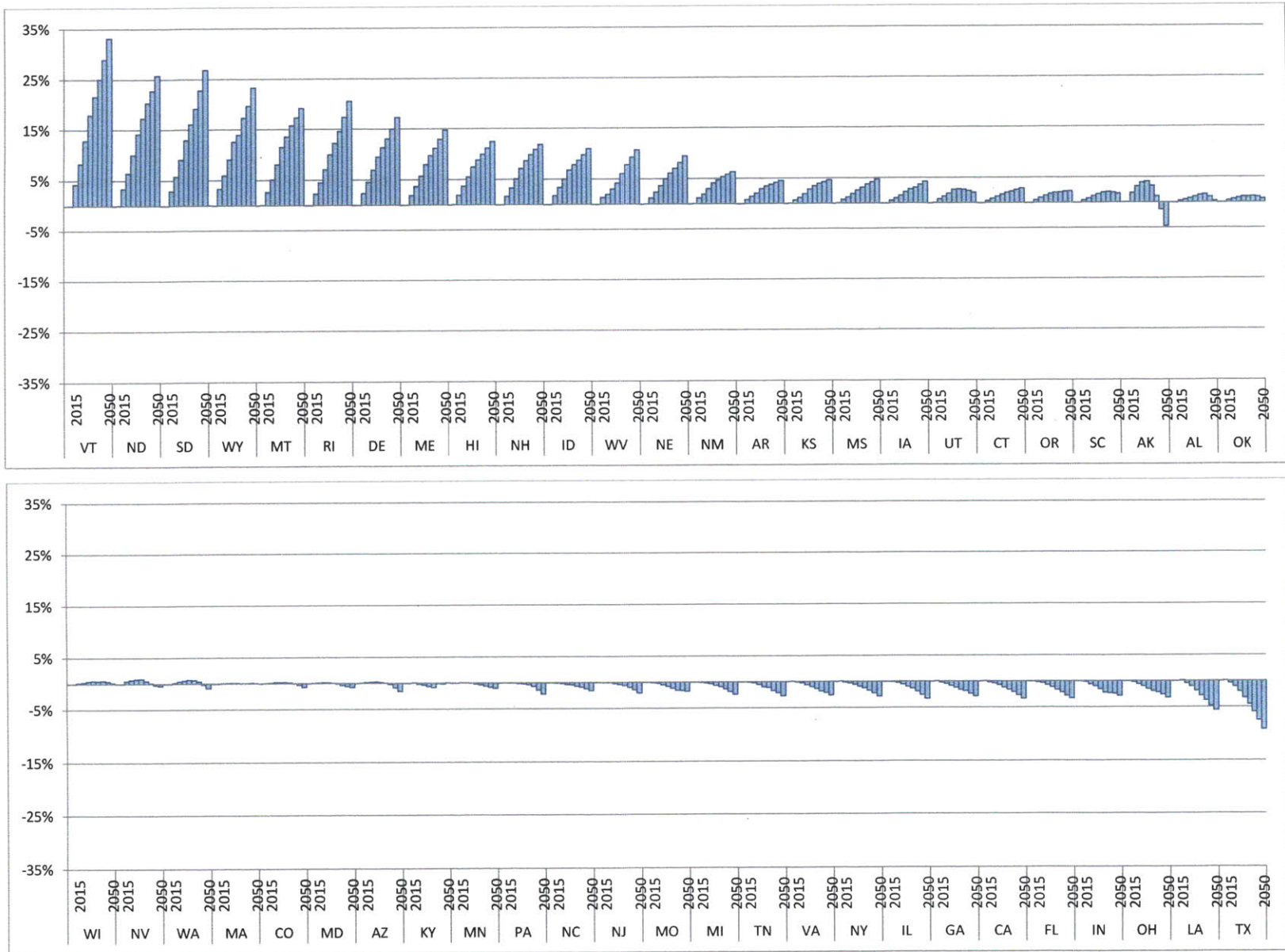
Figure 13. Welfare Change by State Due to Implementation of the CLEAR Act, Ordinal

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Figure 14 graphically represents the lack of correlation between welfare impacts and the carbon intensity of states, as indicated by a given state's percentage reduction in carbon emissions. In Figure 14, total annual CO_2 reductions by state[20] are superimposed on the ordered layout of state welfare change. One would expect states that fare best under the policy to show the smallest emissions reductions and vice-versa, for emissions reductions are a direct result of the price on carbon. Higher emissions reductions, therefore, belie greater "regulatory compliance costs" (Cragg et al 2012), as shown by Palmer et al (2012); and higher compliance costs have been considered by most to be the primary threat to welfare in the context of climate policy. Surprisingly, these results decouple a state's carbon intensity from the ultimate compliance cost it will face, pointing to the fact that other factors, such as the progressive allocation of revenues through the dividend mechanism, have potentially more influence over welfare change than incumbent state carbon intensity.

That said, looking at Figure 14, it is clear that the correlation between emissions reductions and welfare change does exist in some instances. For example, states like Vermont, Hawaii and Idaho exhibit high welfare improvements and some of the lowest CO_2 reductions. Similarly, states like Indiana and Louisiana represent the opposite trend, where high CO_2 reductions are correlated with higher welfare costs. However, numerous anomalies to this trend can be seen: in states with high emissions reductions and strong welfare improvements like North Dakota, Wyoming, and West Virginia; and in states that experience a decline in welfare despite relatively low emissions reductions, such as New Jersey, New York and California. In general, the saw tooth pattern of CO_2 reduction rates compared to the consistent trend in welfare change, shown in Figure 14, reflects the irregularity of the correlation between welfare levels and CO_2 emissions reductions.

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[20] As the percent change from *Reference* case emissions levels for the given state and year.
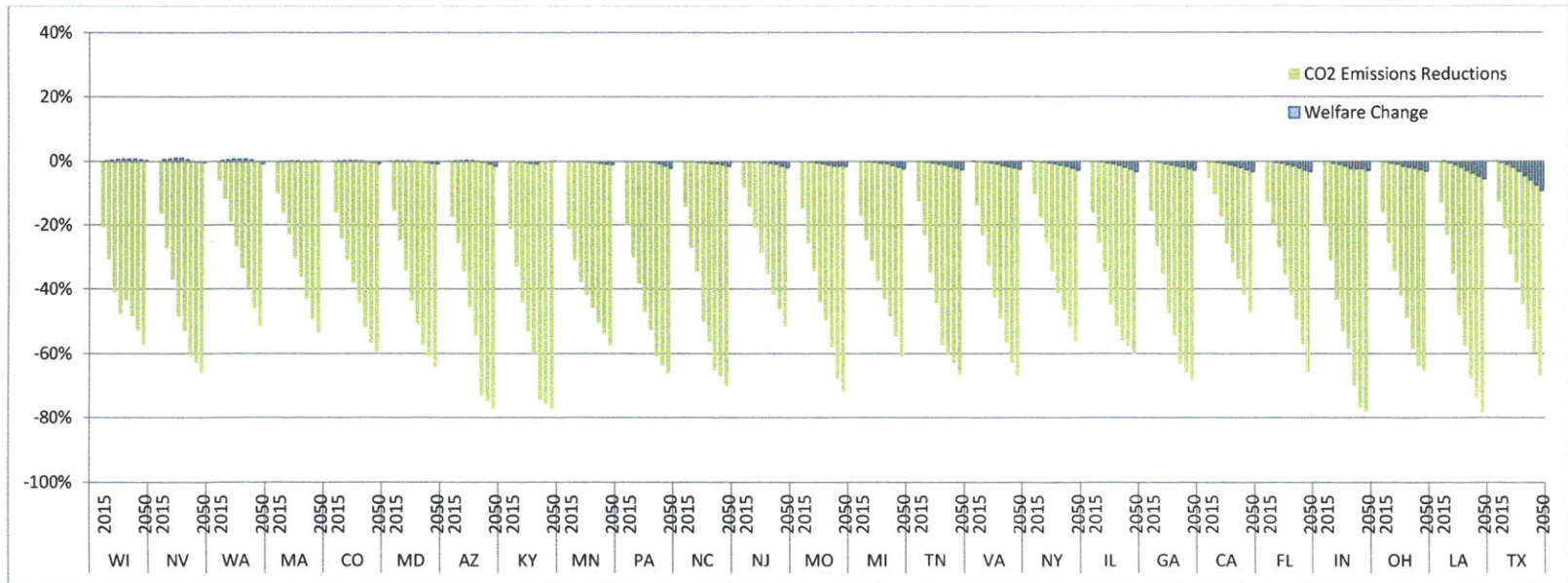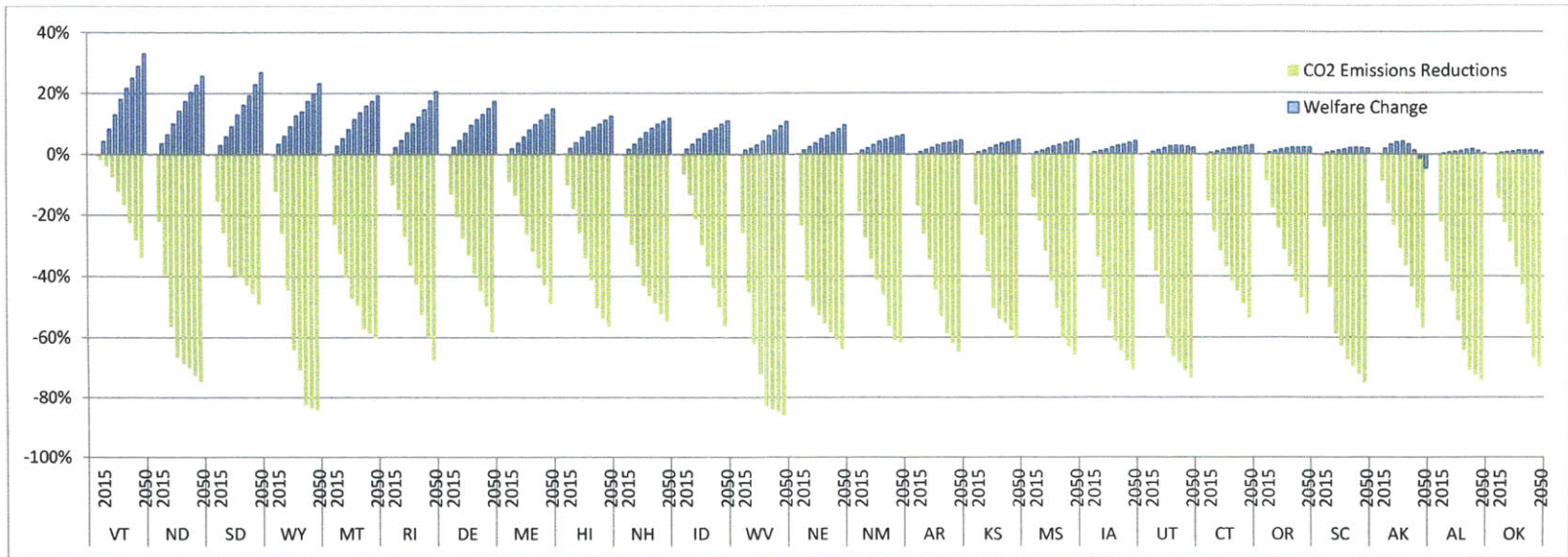
Figure 14. Ordinal Welfare Change with CO_2 Emissions Reductions by State

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Figure 15 below presents the same data as Figure 14 in a scatter plot along with a linear regression. The regression yields a slope coefficient ($\beta_{CO2\_Reduction}$) of 0.029, with a standard error of 0.016 and a p-value of 0.067—which is statistically significant at the 10 percent level. This tells us that, on average, an incremental increase in emissions reductions at the state level is correlated with an increase in the percentage change in welfare of 0.029 percentage points. In other words, these data show a counter-intuitive trend where higher emissions reductions (greater carbon intensity) by state are correlated with *net improvements* in the economic welfare of the given state. This cuts against long-held theories that carbon intensity is the primary factor determining economic welfare changes under a carbon policy. That said, the slope of 0.029 represents a very weak positive correlation. Therefore, the main point here is simply that there is not a strong negative correlation between CO_2 reductions and welfare reductions. The reader should, of course, not deduce causality from these estimates—whereby an increase in carbon intensity for a given state would be seen as the *cause* of greater welfare benefits under the policy. Per standard econometric theory, only correlation can be deduced from a sample like this one. Furthermore, what we are likely seeing is the affect of outliers like North Dakota and Wyoming, and "omitted variable bias" where factors other than CO_2 reductions are more strongly correlated with the change in welfare—and that these other correlations are the true driving force behind this positive correlation.
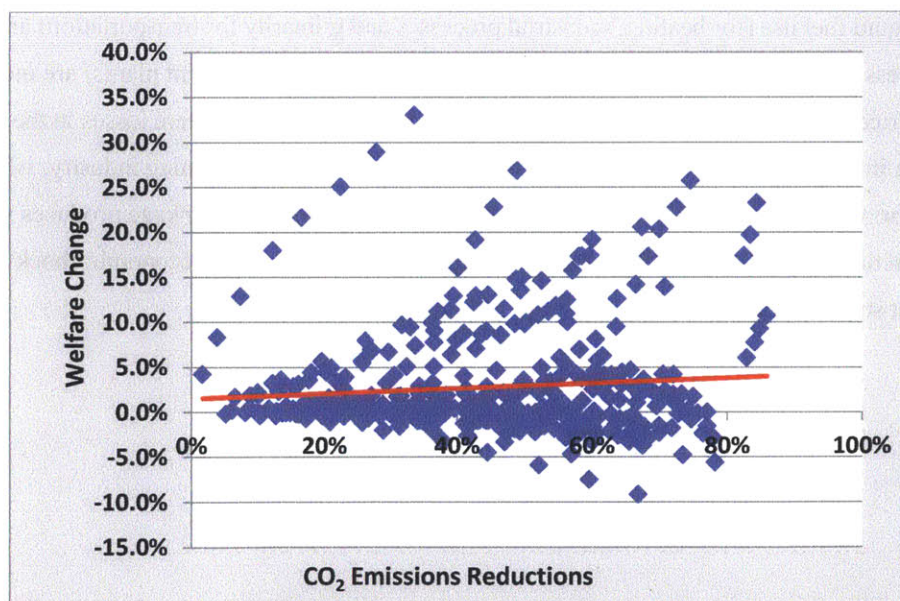

Figure 15. Correlation of CO_2 Emissions Reductions with Welfare Change by State and Year (2015-2050)

Figure 16 below adds further dimension to this inquiry, by depicting the change in the average price of retail electricity (across sectors) in conjunction with the ordinal representation of welfare change. Again, we see an irregular saw tooth pattern contrasted against the even progression of welfare change. While Figure 17 below shows an overall weak correlation between higher electricity prices and declining welfare, there are numerous clear breaks from a correlation between the price of electricity and welfare. For example, West Virginia has the third greatest increase in electricity prices (approximately an average of 102 percent over the life of the policy), and yet it experiences the twelfth highest welfare improvements of any state. Wyoming, has both the fifth greatest welfare improvements and the fifth worst (highest) hike in electricity prices. On the other end of the benefit spectrum, Louisiana experiences the second to worst (after Texas) decline in welfare, while facing the twelfth smallest increase in electricity prices—a trend that is also reflected in states like California, New York, Pennsylvania and Minnesota. These anomalies in the correlation between electricity prices and welfare takes the observations of CO_2 emissions reductions one step further, elucidating that distributional impacts across states cannot be neatly linked to fluctuations in electricity prices. These two observations together throw into question the basis of many political arguments regarding climate policy.

To be sure, electricity is only a portion of the energy consumption subject to a price on carbon. For example, all liquid fuel use (for heating, industrial processes and primarily for transportation) and industrial process emissions (like those associated with fuel refineries and cement plants) are independent of electricity prices. This perhaps explains why states like Louisiana suffer welfare losses in the midst of modest growth in electricity prices. Louisiana is home to an oil refining and mining industry, which will significantly shrink under the full implementation of the CLEAR Act. This shrinkage produces sizeable emissions reductions at the state level in Louisiana, and it also substantiates an economic shock greater than what most states experience.

Figure 16. Ordinal Welfare Change with Retail (Sectoral Average) Electricity Price Change by State

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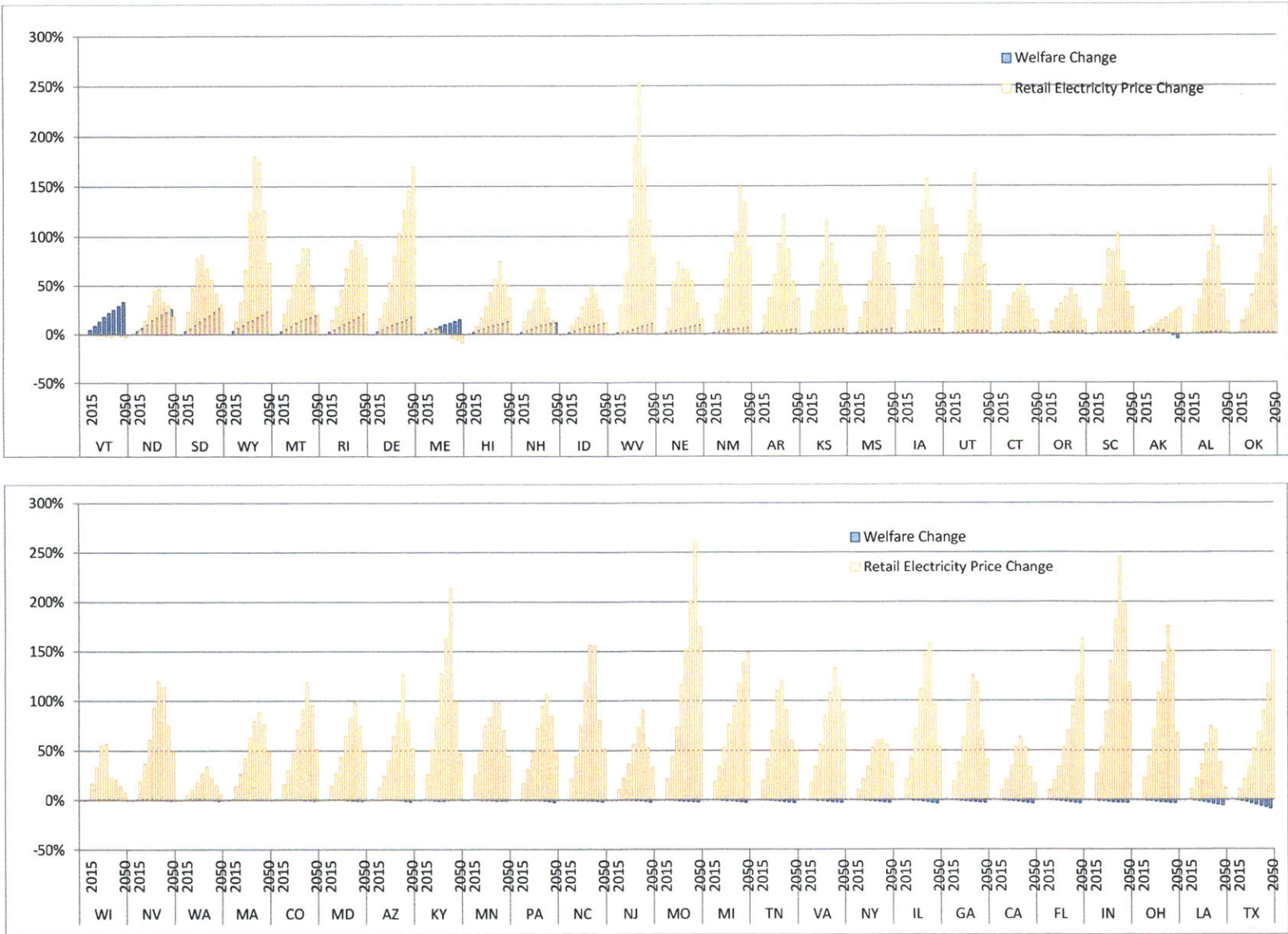
As with the CO_2 reduction dataset above, I regress the percentage change in welfare on the percentage change in electricity prices, as shown in Figure 17 below. Using the same data (by state and by year) represented in Figure 16, I estimate a slope coefficient of -0.016, with standard error 0.006 and p-value of 0.009—which is statistically significant at the 1 percent level. These results provide more of an intuitive picture than what we saw in Figure 15: here welfare declines as the percentage change in electricity price increases by state, as one would expect. Specifically, an incremental increase in the percentage change of electricity prices for a given state is correlated with a 0.016 percentage point decrease in welfare for that state. However, as with CO_2 reductions and the regression represented in Figure 15, the slope here is very small, almost zero. The takeaway again is simply that there is not a strong (negative) correlation between electricity price increase and welfare decrease. The question, then, is why is this correlation so weak?
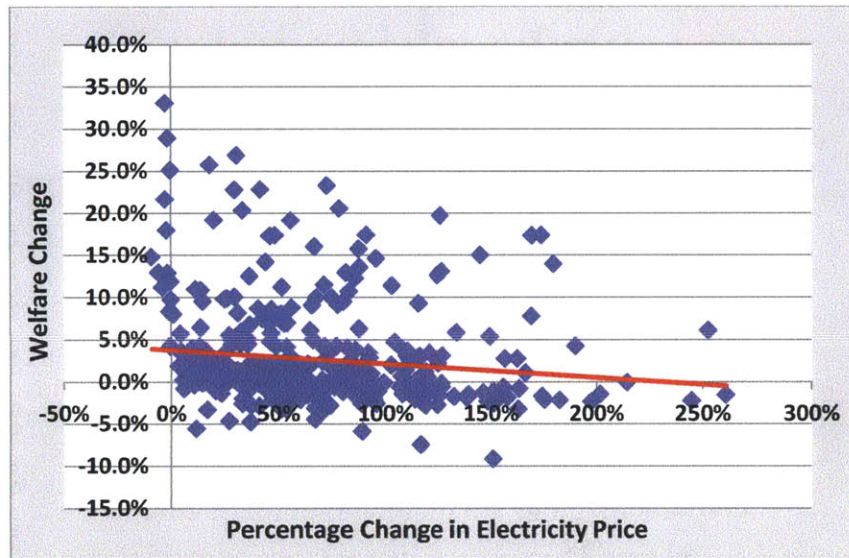

Figure 17. Correlation of Change in Electricity Prices with Welfare Change by State and Year (2015-2050)

If neither the incumbent carbon intensity of a state's economy, nor the change in electricity prices are reliable drivers of state-level distributional impacts due to the implementation of a carbon policy like the CLEAR Act, what other factors are at work? Figure 19 below displays the change in investment levels, and reveals, for the first time, a consistently positive correlation with welfare changes. Increasing investment levels may reflect a state's ability to capitalize on new infrastructure development, such as the sizeable increase in the renewable energy industry required to meet the carbon cap. For example, the *Reference* case predicts that in 2040, 12 percent of Wyoming's energy demand will come from wind, solar and geothermal electricity, while under *Scenario 1b*, 50 percent of demand will be met by these sources. On the downside, decreasing investments may reflect the shift away from fossil intensive

industries that some states (like Texas and Louisiana) have relied on as perennial drivers of the economy. This principle underscores the importance of developing the renewable energy industries that will be the source of new investment in a carbon-constrained world.

These findings are further supported by the regression in Figure 18, with a slope of 0.904, a standard error of 0.015 and a p-value of zero—which is statistically significant at the 1 percent level. These results show a strong correlation between the change in investment levels and the change in welfare due to policy implementation. Specifically, a incremental increase in investment levels is, on average, correlated with a 0.904 percentage point increase in the change in welfare. It is also worth noting that the R^2 of the regression below is 0.899, compared to 0.008 and 0.016 for the CO_2 reduction and electricity price regressions above. The higher R^2 value, which represents the closeness of fit in this regression, can also be seen as a reflection of the relatively low level of noise in this plot. This low level of noise itself reflects the consistent correlation between welfare and investment across the full array of states and time periods.
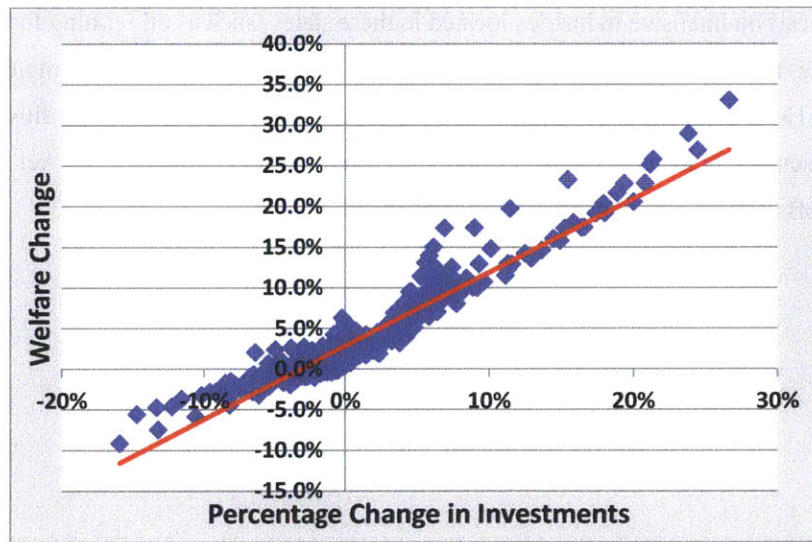

Figure 18. Correlation of Change in Investments with Welfare Change by State and Year (2015-2050)

In addition, the sheer impact of the dividend mechanism plays a part in shaping investment profiles—as increased household income leads to increased investment. One would expect this trend to be especially strong in relatively low-income states, where the influx of dividends has a greater marginal benefit. As mentioned above, there is a sort of progressivity at the state level, reflected in the fact that many of the states that do well under the policy—especially those that do well in spite of high emissions reductions and/or hikes in electricity rates—are also states with lower GDP, and larger low-income populations. This

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can be seen in Figure 20, which presents state GDP as a percentage of US GNP in conjunction with the same ordered set of state welfare changes we have seen above. There is a general correlation between states that fare well under the policy and those that have a small GDP as a percentage of GNP. For example, nine of the ten states receiving the greatest welfare improvements due to the policy are also among the bottom ten states in terms of GDP as a percent of US GNP. These nine include (in order from smallest GDP) Vermont, Wyoming, North Dakota, South Dakota, Delaware, Montana, Rhode Island, Maine and New Hampshire. The trend continues on the lower end of the benefit scale, where states like Texas, Florida, Virginia, Illinois, California, and New York all are among the highest GDP as a percentage of GNP as well as the bottom ten states in terms of net reductions in welfare statewide. However, a few interesting anomalies are present on the net-negative end of the welfare change spectrum. For example, New York and California present a jump in GDP as a percentage of GNP, and the fact that they are not lower on the welfare benefit scale is likely a reflection of their relatively clean and efficient energy systems. Indiana and Louisiana present a jump in the other direction—where they show lower GDP as a percentage of GNP than would be expected for states so low on the benefit scale. This is likely a reflection of the carbon intensive industries located in these states (such as oil refining for the entire nation in Louisiana) that will be disproportionately impacted in a negative way by the implementation of a price on carbon. Here, these negative impacts are so great as to not be offset by the positive dividend mechanism. As discussed in the concluding section, the current version of the CLEAR Act includes measures to help offset these regional differences if desired.
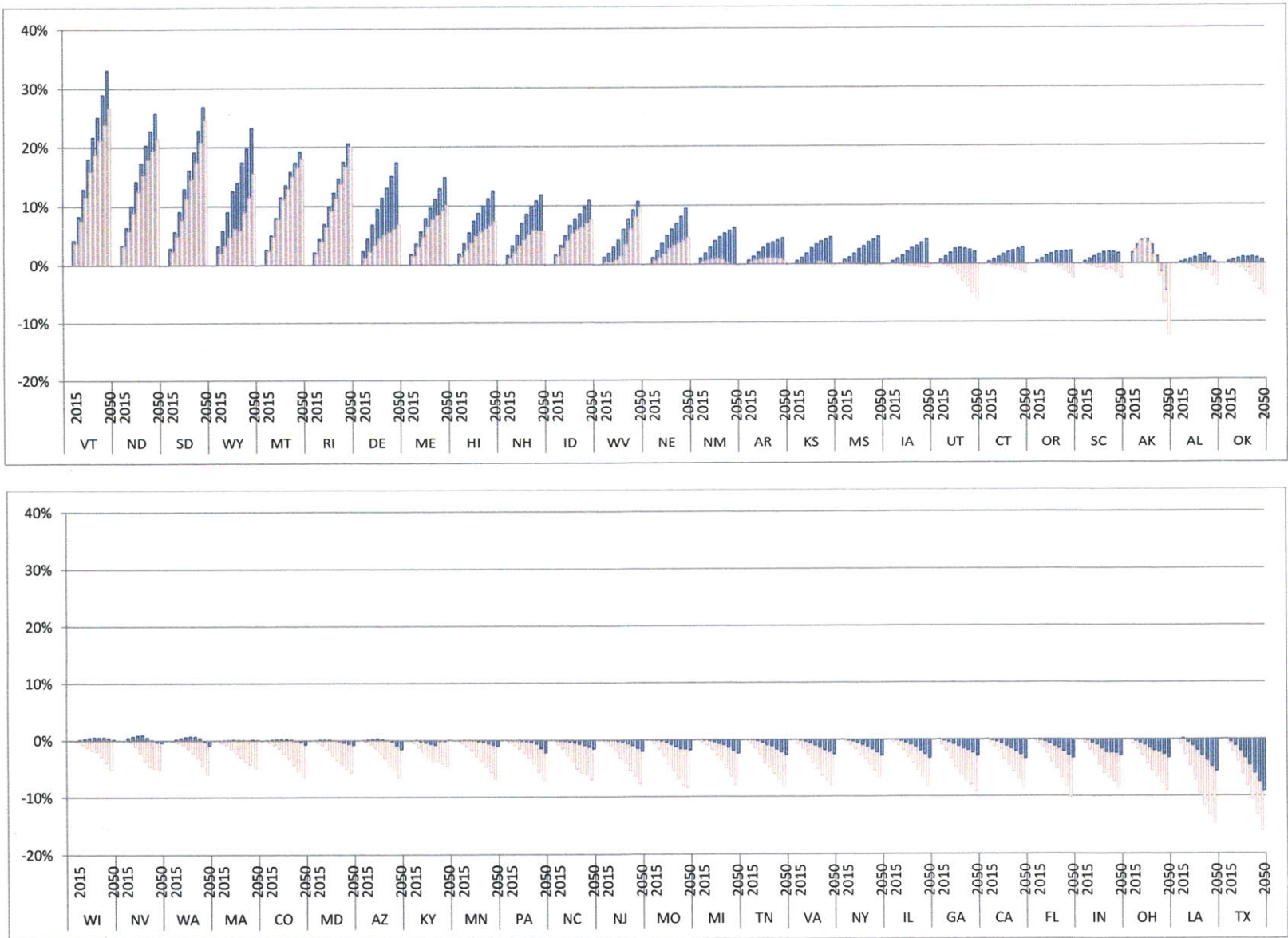
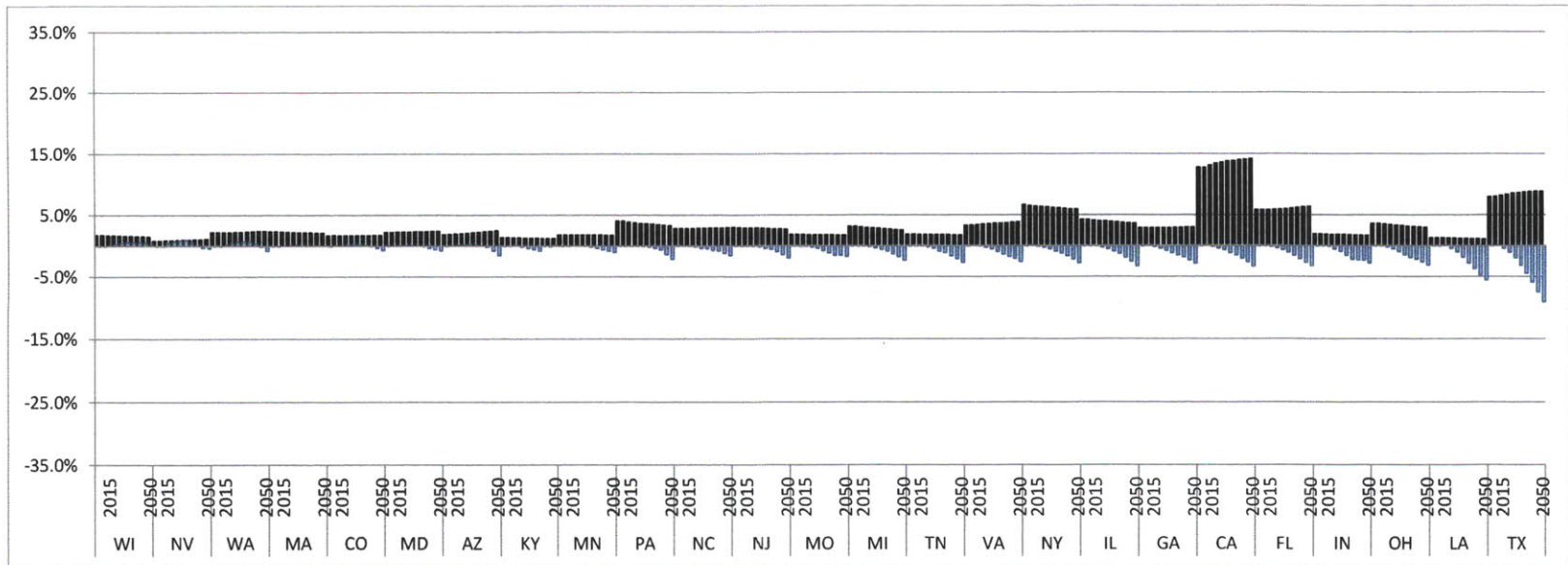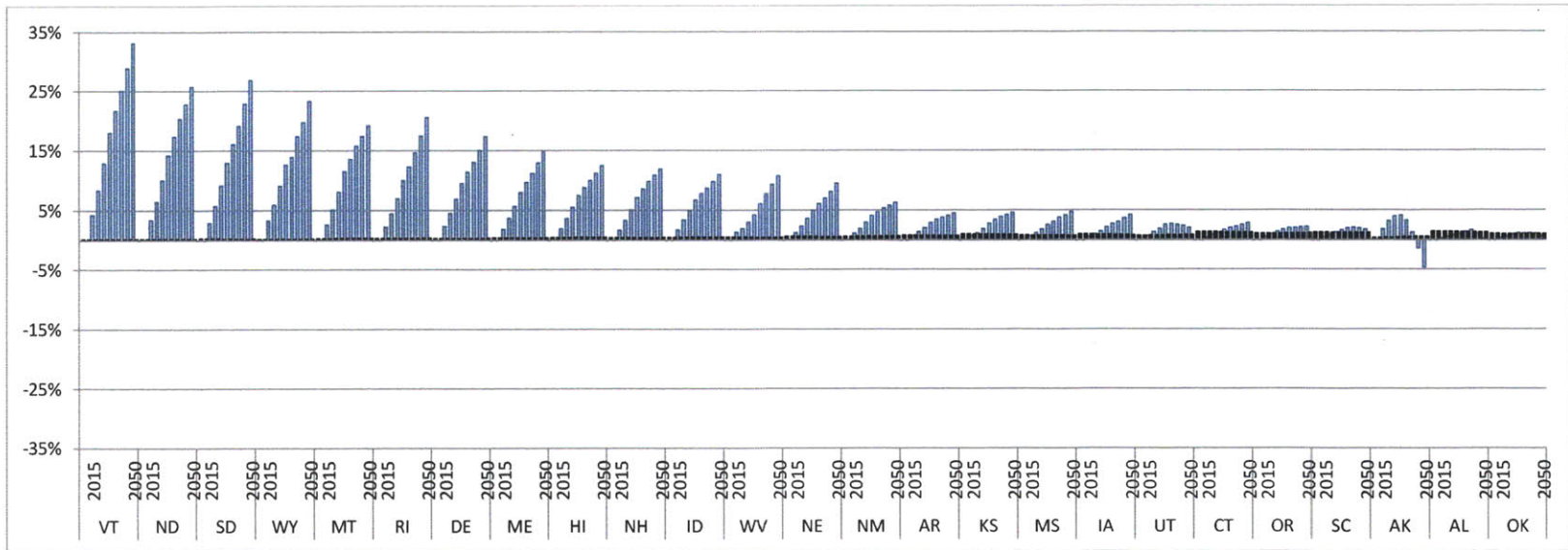**Figure 19.** Ordinal Welfare Change with Investment Change by State

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Figure 20. Ordinal Welfare Change with State GDP as a Percentage of GNP

While looking at state GDP as a percentage of US GNP may provide an initial glimpse into the relative economic strength of each state, it is not really the appropriate metric for measuring the progressive impact of the dividend mechanism. It is better to look at median household income within each state, as the progressivity of the dividend is a function of the marginal benefit it creates—which is greater for low-income households. A state with low GDP as a percentage of GNP may simply have a small population (as many of those on the lower end of the welfare change scale do), however household income levels could be quite high, which diminishes the marginal benefit of the flat-rate dividends. To address this, Table 8 below presents 2006 median household income (in 2006 dollars) by state, from the US Census Bureau's 2006 American Community Survey (ACS). Table 8 also presents the percentage difference between a given state's median household income and the national (US) median household income (MHI) in 2006 (also from the 2006 ACS). This percentage difference shows the state MHI relative to national MHI (as a percentage above or below the national MHI).

Table 8. Median Household Income (MHI) by State and the Percentage Difference Between State and US MHI

State	MHI ($2006)	Percent Difference Between State MHI and US MHI	State	MHI ($2006)	Percent Difference Between State MHI and US MHI
AK	$59,393	22.6%	MT	$40,627	-16.1%
AL	$38,783	-20.0%	NC	$42,625	-12.0%
AR	$36,599	-24.5%	ND	$41,919	-13.5%
AZ	$47,265	-2.4%	NE	$45,474	-6.1%
CA	$56,645	16.9%	NH	$59,683	23.2%
CO	$52,015	7.4%	NJ	$64,470	33.1%
CT	$63,422	30.9%	NM	$40,629	-16.1%
DE	$52,833	9.0%	NV	$52,998	9.4%
FL	$45,495	-6.1%	NY	$51,384	6.1%
GA	$46,832	-3.3%	OH	$44,532	-8.1%
HI	$61,160	26.2%	OK	$38,770	-20.0%
IA	$44,491	-8.2%	OR	$46,230	-4.6%
ID	$42,865	-11.5%	PA	$46,259	-4.5%
IL	$52,006	7.3%	RI	$51,814	6.9%
IN	$45,394	-6.3%	SC	$41,100	-15.2%
KS	$45,478	-6.1%	SD	$42,791	-11.7%
KY	$39,372	-18.7%	TN	$40,315	-16.8%
LA	$39,337	-18.8%	TX	$44,922	-7.3%
MA	$59,963	23.8%	UT	$51,309	5.9%
MD	$65,144	34.5%	VA	$56,277	16.2%
ME	$43,439	-10.3%	VT	$47,665	-1.6%
MI	$47,182	-2.6%	WA	$52,583	8.5%
MN	$54,023	11.5%	WI	$48,772	0.7%
MO	$42,841	-11.6%	WV	$35,059	-27.6%
MS	$34,473	-28.8%	WY	$47,423	-2.1%

Figure 21 plots the percentage difference between state MHI and US MHI, and depicts the linear regression of welfare change on this percentage difference by state and year. There is a crucial caveat that comes with this analysis: I have utilized only 2006 ACS data in calculating the percentage differences (for both state MHI and US MHI). The 2006 ACS is used here because it is also employed to calibrate the base year in the model, and because the model is not producing its own outputs of MHI in its current formulation. The implicit assumption here is that while the levels of MHI will surely change from 2006 to 2050, the percentage difference between a given state's MHI and the national MHI may not significantly vary over time. I do not propose that this will likely be the case, but present this as an initial estimate for exploring correlation between relative state MHI levels and welfare changes under the policy.

In Figure 21 below, the mid-point on the x-axis (zero percent) represents the value of US median household income. Any value to the left of this mid-point reflects a state with an MHI that is less than the US MHI, and any plot to the right of the mid-point represents a state with MHI greater than the national median. As the trendline shows, there is, on average, a negative correlation between relative median household income levels by state and the change in welfare due to policy implementation. The regression line has a slope of -0.032, a standard error of 0.019 and a p-value of 0.091—which is statistically significant at the 10 percent level. The interpretation of this is that a single percentage point increase in the difference between state and national MHI is, on average, correlated with a decline in welfare of 0.032 percentage points. In other words, states with lower median household income on average experience greater welfare benefits under the policy than states with higher median household income. This could be an indication of the progressivity of the dividend mechanism, playing out at the state level.
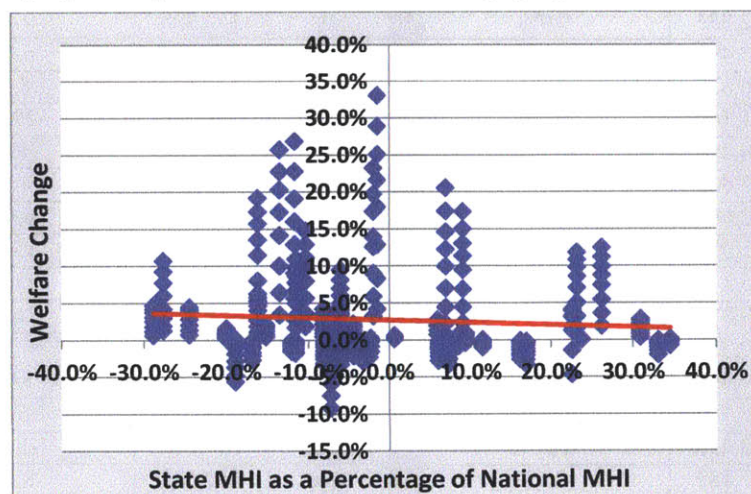

Figure 21. Correlation of Percentage Difference Between State Median Household Income (MHI) and US MHI with Welfare Change by State and Year (2015-2050)

In summary, Table 9 and Table 10 below portray for 2015 and 2050 respectively, and for each state: (a) welfare change, (b) CO_2 reductions, (c) electricity price changes, (d) changes in investment levels, (e) state GDP as a percent of US GNP, and (f) the percentage difference between state MHI and US MHI. In addition, I iteratively incorporate metrics (b) – (f) into a single welfare change regression, in an attempt to explore the omitted variable bias that is especially evident in the regressions of electricity price change and CO_2 reductions. The results of these iterations are presented in Table 11 below.

Table 9. Summary Table of (a) Welfare Change by State, with (b) CO_2 Reductions, (c) Change in Electricity Price, (d) Change in Investment Levels, (e) State GDP as a Percentage of US GNP, and (f) Percentage Difference between State and US MHI, **for the Year 2015**[21]

| State | ΔWelfare | ΔCO₂ | ΔELE | ΔINV | GDP/GNP | %MHI |
	(a)	(b)	(c)	(d)	(e)	(f)
AK	1.9%	-8.8%	3.3%	2.4%	0.4%	22.6%
AL	0.3%	-22.3%	18.1%	-0.1%	1.4%	-20.0%
AR	0.7%	-16.9%	18.8%	0.4%	0.7%	-24.5%
AZ	0.2%	-17.3%	12.6%	-0.3%	2.0%	-2.4%
CA	-0.2%	-5.2%	10.0%	-0.6%	13.2%	16.9%
CO	0.1%	-15.8%	15.7%	-0.4%	1.7%	7.4%
CT	0.4%	-15.3%	14.5%	-0.2%	1.3%	30.9%
DE	2.3%	-13.1%	16.2%	1.2%	0.3%	9.0%
FL	-0.2%	-12.7%	10.1%	-0.7%	5.8%	-6.1%
GA	-0.2%	-15.7%	18.9%	-1.0%	2.9%	-3.3%
HI	1.9%	-10.1%	8.0%	1.3%	0.4%	26.2%
IA	0.5%	-20.2%	23.4%	0.0%	0.9%	-8.2%
ID	1.7%	-6.6%	8.7%	1.5%	0.4%	-11.5%
IL	-0.1%	-16.1%	21.3%	-0.5%	4.2%	7.3%
IN	-0.1%	-20.3%	26.0%	-0.7%	1.9%	-6.3%
KS	0.6%	-16.5%	22.3%	0.0%	0.9%	-6.1%
KY	0.1%	-21.1%	25.9%	-0.5%	1.3%	-18.7%
LA	0.1%	-12.8%	10.9%	-0.9%	1.3%	-18.8%
MA	0.0%	-10.0%	13.5%	-0.5%	2.3%	23.8%
MD	0.1%	-15.6%	13.7%	-0.4%	2.3%	34.5%
ME	1.9%	-9.0%	6.1%	1.5%	0.4%	-10.3%
MI	-0.1%	-17.0%	18.3%	-0.4%	3.1%	-2.6%
MN	0.1%	-21.2%	24.9%	-0.5%	1.8%	11.5%
MO	-0.1%	-14.9%	21.3%	-0.8%	1.9%	-11.6%
MS	0.7%	-14.3%	16.0%	0.2%	0.8%	-28.8%
MT	2.6%	-23.0%	20.5%	2.4%	0.3%	-16.1%
NC	-0.1%	-14.2%	21.5%	-0.8%	2.8%	-12.0%
ND	3.4%	-21.9%	4.4%	3.3%	0.2%	-13.5%
NE	1.2%	-23.3%	26.0%	0.6%	0.6%	-6.1%
NH	1.6%	-20.7%	12.8%	1.0%	0.4%	23.2%

[21] The percentage changes depicted in this table are the result of the simulated implementation of the CLEAR Act (under Scenario 1b) in comparison to levels estimated under the business-as-usual *Reference* case.

Table 9. Summary Table of (a) Welfare Change by State, with (b) CO_2 Reductions, (c) Change in Electricity Price, (d) Change in Investment Levels, (e) State GDP as a Percentage of US GNP, and (f) Percentage Difference between State and US MHI, **for the Year 2015**[22] *(continued)*

State	ΔWelfare	ΔCO₂	ΔELE	ΔINV	GDP/GNP	%MHI
	(a)	(b)	(c)	(d)	(e)	(f)
NJ	0.0%	-8.1%	11.1%	-0.6%	3.0%	33.1%
NM	1.1%	-18.9%	19.3%	0.4%	0.6%	-16.1%
NV	0.5%	-16.3%	18.7%	0.0%	0.9%	9.4%
NY	-0.1%	-10.4%	10.5%	-0.5%	6.4%	6.1%
OH	-0.2%	-16.2%	22.0%	-0.8%	3.5%	-8.1%
OK	0.3%	-14.5%	12.8%	-0.2%	1.0%	-20.0%
OR	0.5%	-8.8%	12.3%	0.0%	1.1%	-4.6%
PA	0.0%	-20.1%	16.4%	-0.4%	3.9%	-4.5%
RI	2.2%	-10.0%	14.4%	2.0%	0.3%	6.9%
SC	0.4%	-23.8%	24.8%	-0.2%	1.2%	-15.2%
SD	2.9%	-15.3%	23.1%	2.4%	0.3%	-11.7%
TN	-0.1%	-12.6%	19.7%	-0.7%	1.8%	-16.8%
TX	-0.4%	-12.8%	10.8%	-1.0%	8.2%	-7.3%
UT	0.7%	-25.3%	26.4%	-0.1%	0.7%	5.9%
VA	-0.1%	-13.7%	17.4%	-0.8%	3.4%	16.2%
VT	4.2%	-1.7%	-0.6%	3.8%	0.2%	-1.6%
WA	0.2%	-6.1%	5.4%	-0.2%	2.2%	8.5%
WI	0.2%	-20.5%	16.8%	-0.3%	1.8%	0.7%
WV	1.3%	-25.7%	29.4%	0.5%	0.5%	-27.6%
WY	3.3%	-12.2%	13.3%	2.0%	0.2%	-2.1%

Table 10. Summary Table of (a) Welfare Change by State, with (b) CO_2 Reductions, (c) Change in Electricity Price, (d) Change in Investment Levels, (e) State GDP as a Percentage of US GNP, and (f) Percentage Difference between State and US MHI, **for the Year 2050**[23]

State	ΔWelfare	ΔCO₂	ΔELE	ΔINV	GDP/GNP	%MHI
	(a)	(b)	(c)	(d)	(e)	(f)
AK	-4.7%	-57.0%	27.1%	-12.3%	0.5%	22.6%
AL	0.2%	-74.3%	12.3%	-3.9%	1.2%	-20.0%
AR	4.5%	-64.5%	35.8%	0.5%	0.7%	-24.5%
AZ	-1.5%	-77.1%	52.3%	-6.5%	2.5%	-2.4%
CA	-3.3%	-47.1%	16.9%	-8.5%	14.1%	16.9%
CO	-0.7%	-59.4%	51.3%	-6.5%	1.7%	7.4%
CT	2.8%	-53.7%	13.5%	-1.6%	1.2%	30.9%
DE	17.3%	-58.1%	169.5%	6.9%	0.3%	9.0%
FL	-3.3%	-65.6%	163.0%	-10.2%	6.4%	-6.1%
GA	-2.9%	-68.4%	41.2%	-9.2%	3.0%	-3.3%
HI	12.5%	-56.3%	36.7%	7.4%	0.5%	26.2%
IA	4.2%	-70.6%	77.4%	-0.8%	0.8%	-8.2%

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[22] The percentage changes depicted in this table are the result of the simulated implementation of the CLEAR Act (under Scenario 1b) in comparison to levels estimated under the business-as-usual *Reference* case.
[23] The percentage changes depicted in this table are the result of the simulated implementation of the CLEAR Act (under Scenario 1b) in comparison to levels estimated under the business-as-usual *Reference* case.

Table 10. Summary Table of (a) Welfare Change by State, with (b) CO_2 Reductions, (c) Change in Electricity Price, (d) Change in Investment Levels, (e) State GDP as a Percentage of US GNP, and (f) Percentage Difference between State and US MHI, **for the Year 2050[24]** *(continued)*

State	ΔWelfare (a)	ΔCO₂ (b)	ΔELE (c)	ΔINV (d)	GDP/GNP (e)	%MHI (f)
ID	11.0%	-56.2%	11.4%	7.6%	0.5%	-11.5%
IL	-3.3%	-60.1%	53.7%	-8.1%	3.7%	7.3%
IN	-2.8%	-78.0%	118.6%	-8.5%	1.6%	-6.3%
KS	4.6%	-60.5%	28.6%	-0.5%	0.9%	-6.1%
KY	0.0%	-77.1%	47.2%	-4.6%	1.2%	-18.7%
LA	-5.6%	-78.3%	11.7%	-14.7%	1.1%	-18.8%
MA	0.1%	-53.4%	49.0%	-4.9%	2.1%	23.8%
MD	-0.8%	-64.2%	49.1%	-5.7%	2.4%	34.5%
ME	14.8%	-48.8%	-9.2%	10.1%	0.3%	-10.3%
MI	-2.3%	-60.7%	148.4%	-7.9%	2.5%	-2.6%
MN	-1.0%	-57.5%	44.5%	-6.8%	1.7%	11.5%
MO	-1.8%	-71.9%	174.3%	-8.5%	1.7%	-11.6%
MS	4.7%	-65.7%	46.4%	-0.2%	0.7%	-28.8%
MT	19.2%	-60.1%	20.1%	18.0%	0.3%	-16.1%
NC	-1.5%	-70.0%	51.2%	-7.0%	3.0%	-12.0%
ND	25.7%	-74.6%	18.2%	21.4%	0.2%	-13.5%
NE	9.5%	-63.6%	14.8%	4.6%	0.5%	-6.1%
NH	11.9%	-54.6%	-0.3%	5.7%	0.4%	23.2%
NJ	-2.0%	-51.5%	33.5%	-7.8%	2.7%	33.1%
NM	6.3%	-61.6%	88.0%	-0.2%	0.7%	-16.1%
NV	-0.4%	-66.0%	49.1%	-5.2%	1.1%	9.4%
NY	-2.8%	-56.2%	37.2%	-6.6%	5.9%	6.1%
OH	-3.2%	-65.5%	67.4%	-9.1%	3.0%	-8.1%
OK	0.7%	-69.6%	107.6%	-5.5%	0.9%	-20.0%
OR	2.2%	-52.1%	13.6%	-2.4%	1.2%	-4.6%
PA	-2.1%	-66.0%	47.6%	-7.0%	3.3%	-4.5%
RI	20.5%	-67.5%	78.7%	20.0%	0.3%	6.9%
SC	1.8%	-75.0%	26.7%	-2.5%	1.2%	-15.2%
SD	26.8%	-49.0%	30.7%	24.5%	0.3%	-11.7%
TN	-2.7%	-66.3%	49.6%	-8.4%	1.7%	-16.8%
TX	-9.2%	-66.9%	151.2%	-16.0%	8.8%	-7.3%
UT	2.0%	-73.3%	43.5%	-6.4%	0.9%	5.9%
VA	-2.6%	-67.0%	89.0%	-8.1%	3.9%	16.2%
VT	33.0%	-33.7%	-2.7%	26.6%	0.2%	-1.6%
WA	-0.8%	-51.4%	6.1%	-6.1%	2.4%	8.5%
WI	0.2%	-57.3%	7.2%	-5.1%	1.5%	0.7%
WV	10.7%	-85.9%	83.3%	9.6%	0.4%	-27.6%
WY	23.2%	-84.4%	72.8%	15.5%	0.2%	-2.1%

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[24] The percentage changes depicted in this table are the result of the simulated implementation of the CLEAR Act (under Scenario 1b) in comparison to levels estimated under the business-as-usual *Reference* case.

In Table 9 and Table 10, we see the considerable difference across states for all indices, as outlined in the preceding discussion. These differences intensify over time, which can be seen by comparing the spread of each of the four indices in 2015 (Table 9) and 2050 (Table 10). For example, the spread in welfare impacts goes from 4.6 percentage points (-0.4 percent (TX) - 4.2 percent (VT)) in 2015 to 42.2 percentage points in 2050 (-9.2 percent (TX) - 33.0 percent (VT)). While 2015 results are more closely aligned with previous studies, 2050 results differ significantly from previous work. Relevant studies include Burtraw et al (2009), Metcalf (2008 and 2007) and Boyce and Riddle (2009), all of which show minimal difference between US regions (Metcalf and Burtraw) or even between the 50 United States (Boyce and Riddle) under various policy proposals to limit greenhouse gas emissions. One reason for this difference may be that many of the previous studies apply a static model (representing a single time period) to the question of policy impacts and distributional dynamics, while this study utilizes a recursive dynamic formulation. That said, Rausch et al (2010) also utilize a dynamic model and they too find small distributional spreads across a 12-region representation of the United States. This, however, underscores the other primary reason for the difference between this study and earlier studies—that the regional grouping employed by many models cloaks between-state differences, as pointed-out in Rausch et al (2010).

Table 11. Regression of Welfare Change by State and Year (2015 – 2050) on CO_2 Emissions Reductions, Change in Electricity Prices, Change in Investment Levels and the Percent Difference btwn State and US MHI[25]

	(1)	(2)	(3)	(4)
CO_2 Emissions Reductions	0.029*	0.086**	0.074**	0.077**
	(0.016)	(0.019)	(0.004)	(0.004)
Change in Electricity Prices		-0.038**	-0.001	0.0002
		(0.008)	(0.002)	(0.002)
Change in Investment Levels			0.934**	0.943**
			(0.011)	(0.011)
Percentage Difference btwn State and National MHI				0.023**
				(0.004)
Observations	400	400	400	400
R^2	0.01	0.06	0.95	0.96

Table 11 summarizes and groups the regressions of welfare changes on the four variables regressed individually above. The first iteration (1) duplicates the regression represented in Figure 15, where welfare change is regressed on CO_2 reductions only. This shows the weakly positive correlation (on

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[25] Standard errors are listed in parentheses. ** and * denote statistical significance at 1 and 10 percent levels respectively.

average) between emissions reductions and welfare changes, indicating a counter-intuitive trend whereby welfare costs decline as emissions reductions increase by state. As discussed above, this is more likely due to an "omitted variable bias" than a true positive correlation between CO_2 reductions and welfare changes—that is, there is something else at work here. This underscores the notion articulated throughout this paper that for many states (as well as many households) the welfare-enhancing impact of the dividend mechanism and the shift of investments towards new low-carbon infrastructure outweighs the welfare-reducing influence of increased costs for goods and services due to a price on carbon.

The second iteration (2) listed in Table 11 adds the variable of electricity price changes to the first regression. This addition increases the strength and statistical significance of the CO_2 reduction correlation coefficient, which can be interpreted to mean that when we hold electricity price changes constant the (counter-intuitive) association of increased emissions reductions with increased welfare becomes stronger. This strengthening of the CO_2 reduction correlation coefficient (β_{CO2}) is partially offset in the third iteration (3) where the variable representing changes in investment levels is included. In addition to reducing β_{CO2}, the inclusion of the investment variable nearly nullifies $\beta_{electricity}$, the electricity price change correlation coefficient. This represents the removal of some of the omitted variable bias driving the results depicted in Figure 15 and Figure 17. Specifically, the strong positive correlation ($\beta_{Investment} = 0.934$) between investment levels and welfare changes had been creating an inflated picture of the correlation between welfare and CO_2 reductions and between welfare and electricity price effects. The inclusion of the percentage difference between state and national MHI, in the fourth iteration (4), sends $\beta_{electricity}$ towards zero (actually beyond zero to a very small positive number), otherwise, holding this variable constant does not significantly alter the results. Finally, while adding investment to the regression decreased the counter-intuitive correlation between CO_2 reductions and welfare, it has not reduced it to zero as one may have expected. This could mean that there are other omitted variables of importance, which further study should aim to uncover.

7. Next Steps

There are countless ways that the work undertaken in this study could be improved upon. I would like to point out a few areas of development that are particularly salient. First, as mentioned at multiple points above, the model used in this study does not include the most recent estimates on US natural gas resources and prices. My initial guess is that this exclusion (and therefore the current formulation) produces higher policy costs than what we would see under the new natural gas regime, for cheaper natural gas prices means a cheaper substitution away from carbon-intensive incumbent energy sources such as coal and oil. That said, others have argued that the inclusion of current natural gas data may make

policy costs increase, as the baseline *Reference* case would then incorporate natural gas, reducing its role as a low-hanging fruit in the bundle of substitutes under the policy case. Whether the inclusion of these new findings would shift policy costs upwards or downwards is not clear, however there is little doubt that they would have a significant impact. These data must be incorporated to gain a valid and current perspective on climate policy scenarios.

Similarly, the model does not include assumptions based on the EPA Mercury and Air Toxics Standards (MATS) for power plants, established in December 2011. The EPA MATS significantly raise the cost of building new coal-fired power plants—indeed some feel these regulations may amount to an economic moratorium on any new coal fired power plants in the United States. The inclusion of assumptions reflective of these standards within the model should lower policy costs, for the *Reference* case would hold a much smaller percentage of cheap coal, which imposes high costs of substitution under the policy scenarios. The model would also be improved by incorporating a more detailed rendition of the electricity sector, including updated price estimates for renewables. The estimates in this formulation do follow a modest cost reduction curve for emerging renewable energy technologies, following an exponential learning curve plotted and extrapolated from historical data. That said, some of these historical data sets have most recent cost estimates from the mid 2000s. This must be updated and improved.

Each of the above topics would have a direct effect on the estimates of policy induced welfare costs. The other item in this vein is the importance of including the social cost of carbon in future work, as outlined in detail in Section 5 above.

It is perhaps glaringly evident to some readers that this study has not conducted sensitivity analyses on some of the core assumptions in the model. For example, it would have been instructive to investigate the sensitivity of the model to the assumed elasticities of the CES functions that drive both production and consumption side estimates. Or as done by Boyce and Riddle (2009) and Grainger and Kolstad (2010), it could be useful to construct a more transparent representation of household consumption bundles and associated carbon intensities, considering how they differ across states and time and revealing model sensitivity to these assumptions. I apologize to the reader for not more fully unpacking the relative weight of such core assumptions, and I direct your attention to the appendix of Rausch et al (2009) for greater detail on some of these topics.

Due to the many limits of this study, I encourage the reader to focus less on specific values or levels presented herein and more on the economic dynamics—for example, the evinced progressivity of a cap-

and-dividend policy across both household income classes and states, and the observation that the revenue allocation mechanism and new investment decisions arguably have greater weight in determining the distributional economics of a US climate policy than incumbent carbon intensity or electricity price effects at the state level.

8. Conclusion

This study uses a recursive dynamic computable general equilibrium model to estimate the economic effects of US greenhouse gas emissions reduction policy. I do this by simulating the implementation of the Carbon Limits and Energy for America's Renewal (CLEAR) Act, a bill proposed by Senators Cantwell (D-WA) and Collins (R-ME) in 2009. I do not claim to have comprehensively rendered the CLEAR Act in this study, as components of the bill structure have been left out of the model (such as the many benefits stemming from the Clean Energy Reinvestment Trust (CERT) Fund and the multiple credit programs). This study estimates the performance of the CLEAR Act based upon the bill's central cap and dividend mechanisms, as a jumping-off point for the investigation of trends and issues pertinent to the US climate policy debate more broadly.

This is one of the first studies to look at the economic effects of a major US climate policy both across all 50 United States and across a timeframe that reflects most recent policy proposals (2006 – 2050). Historically, the economic effects of US climate policies have been either assessed at the regional level, obscuring state differences, or over a single time period, which does not show the full manifestation of policy impacts. The aim of the approach taken in this study is to provide information that parallels the political economy of US climate policy, such that decision-makers may better understand the dynamics of such policy and structure their positions accordingly.

The political economy of US climate policy has centered on the question of *price* as a key determinant of congressional voting patterns. By "price" I mean how much a given state or congressional district will pay—in increased costs for goods and services, and in supply-side shifts away from incumbent carbon intensive industries to clean alternatives—to achieve nation-wide emissions reduction goals. This reflects conventional political economy wisdom, which states that indeed price (and "self-interest" in reference to price) shape the vote on most issues, not only climate policy (Cragg et al 2012; Peltzman 1984). This is largely confirmed by Holland et al (2011), who show in the context of CO_2 reduction transportation policies a correlation between congressional voting behavior and how well the given members' state or district will do economically under the proposed policy. States that stand to gain economically have on

average provided support, while those that anticipate increased costs have voted against such policies. If policy compliance cost is the primary determinant of voting behavior, then our challenge is to estimate what these costs will be and what drives them. This is, in many respects, a question of distributional economics, where the analytical goal is to estimate how the distribution of national wealth or welfare may change across the 50 United States due to policy implementation.

Many have perceived climate policy costs to be a function of the carbon intensity of the home state or district. This is understandable, for the primary purpose of most climate policy is to internalize the economic costs of carbon emissions. For example, Cragg et al (2012) have used per capita carbon emissions (a measure of carbon intensity) as a proxy for "price" or how much a district or state will pay for a given policy. And, similar to Holland et al, they show a correlation between per capita carbon emissions and congressional voting patterns on climate policy, where members from carbon intensive states have on average opposed climate policies and vice-versa. This correlation suggests that federal elected officials too gauge how much the policy will cost their constituents based on their jurisdiction's carbon intensity.

As a subset to the carbon intensity discussion, there is also much attention given to the likelihood that a climate policy will raise electricity prices, and that state-to-state variability in this domain will determine the distributional cartography. Indeed, Palmer et al (2012) write that "[t]he political economy of a carbon tax will depend importantly on what happens to electricity prices locally." They have shown that indeed this variability is to be expected, and that it is largely a result of the carbon intensity of a given region's incumbent electricity sector.

What politicians must understand is that while carbon intensity and electricity prices are indeed important in determining compliance costs, they are only part of the story. The results of this study suggest that the ultimate cost and distributional dynamics of a carbon policy will be largely determined by how revenues from a price on carbon are allocated (whether they are generated by a tax or a permit system) and how this and other economic forces will shape new investment activity. I show that the beneficial economic impacts of the dividend mechanism and new investment are so great that *more than half of the 50 United States experience overall household welfare improvements (net benefits) under the policy*. This means that these states are better off—in strictly economic terms, without incorporating any of the benefits associated with reducing the social cost of carbon emissions—under the CLEAR Act than they would have been in its absence. This result throws into question much of how Washington has viewed the issue of climate policy.

In addition to showing that many states will experience net economic benefits from a price on carbon under a policy like the CLEAR Act, the model results reveal a marked lack of correlation between electricity price changes and carbon intensity on one hand and the welfare changes that represent the true "cost" of the policy on the other. Many states that are better off under the policy are highly carbon intensive and show some of the greatest retail electricity price spikes. Examples include West Virginia, North and South Dakota, Delaware and Wyoming. Conversely, many of the states that are estimated to pay the most under the policy are less carbon intensive, such as California, New York and New Jersey.

One hypothesis explaining these results is that the strongly progressive nature of a dividend-based policy outweighs the negative impacts of a price on carbon. That is, on average, relatively low-income economic agents are better-off under the policy than upper-income agents. I use the word "agent" here because this progressive trend is visible at both household and state levels. States that do best under the policy have the smallest GDPs in the country and those that face costs are among the highest. Similarly, on average across the 50 United States, low median household income is correlated with higher welfare benefits. My results also suggest that shifts in investment—away from carbon intensive industries, towards new clean technologies—are perhaps the greatest determinant of economic outcomes at the state level. The relationship between investment levels by state and revenue allocation via the dividend mechanism is not clear from my analysis, and would be a useful inquiry for further study.

In sum, these results suggest that the way revenues are allocated and how investment decisions are made will arguably be more important than incumbent carbon intensity or electricity price impacts in determining the ultimate costs and distributional economics of a climate policy in the United States. As a point of policy consideration, these distributional differences can be mediated by a provision to adjust regional dividends such that each state experiences relatively the same level of economic impact. The CLEAR Act includes such a component, and future modeling efforts would do well to estimate the dynamics of this program. As discussed in detail above, future efforts should also aim to include the social cost on carbon, estimating the benefits of reducing greenhouse gas emissions from the biosphere; after all, these benefits are the reason why this debate exists in the first place.

The reader must note some key limitations to this study. These include the fact that this study does not incorporate the most recent reserve and cost estimates for the US natural gas sector, nor the price impacts on coal-fired electricity of the EPA Mercury and Air Toxics Standards (MATS). Additionally, further work must be done to update cost estimates for the renewable energy sector. Due to the many limits of

this study, I encourage the reader to focus less on specific values or levels presented herein and more on the economic dynamics.

Finally, Cragg et al (2012) point out that the politics of climate change are only partly driven by the rational calculus of distributional economics and marginal welfare. In their study, the strongest determinant of congressional voting patterns on climate policy is not price, but ideology. Granted, much of the ideological forces at work in America revolve around economics, however it is worth asking whether a new map of incidence alone will shift the political accretions that have shaped the climate policy debate for decades. If not economic analysis, what will guide us through the dialogue that fosters the meeting of ideologies towards constructive solutions and a common good?

Acknowledgements

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