Relative Cost-Effectiveness of Electricity and Transportation Policies as a Means to Reduce CO_2 Emissions in the United States: A Multi-Model Assessment

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ABSTRACT

Two common energy policy instruments in the United States are tax incentives and technology standards. Although these instruments have been shown to be less cost-effective as a means to reduce CO_2 emissions than direct emissions pricing mechanisms, it can be challenging to compare the CO_2 emissions reduction costs of such policies across sectors, given the wide range in estimates for any given policy and inconsistencies in how such estimates are constructed across studies. This study addresses this analytical gap by simultaneously comparing the cost-effectiveness of policies across the electricity and transportation sectors using three publicly available US energy system models (EM-NEMS, ReEDS, and GCAM-USA). Four policies are explicitly compared: wind and solar tax credits, a renewable portfolio standard (RPS), a renewable fuel standard (RFS), and an electric vehicle (EV) tax credit. An economy-wide carbon tax is used as a benchmark for cost-effectiveness. Results from this study confirm prior insights about the cost-effectiveness of economy-wide carbon pricing relative to sectoral instruments but also reveal several novel insights about particular sectoral policies. Specifically, this study finds that (1) current electricity tax incentives provide uneven support for wind and solar technologies, (2) despite known inefficiencies, renewable energy policies in the electricity sector are less expensive than earlier estimates due to technology advancement and changes in market conditions, (3) within transportation, an expanded RFS with increasing advanced biofuel targets is more cost-effective than an EV tax credit extension under plausible assumptions, (4) EV incentives lead to a rebound in conventional vehicle fuel economy that further erodes cost-effectiveness, and (5) the change in policy costs over time is not known a priori, but the relative cost ordering among these policies does not depend on the timeframe of analysis. These results are largely robust to the underlying modeling framework, increasing the confidence with which they can be applied to climate policy evaluation.

Keywords: Climate policy, abatement cost, energy modeling.

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1. INTRODUCTION

Given the absence of comprehensive federal climate policy in the form of economy-wide emissions pricing, climate policy in the United States is effectively defined by a collection of energy policies and measures at the federal, state and local levels.[1] Many of these policies were not primarily motivated by CO_2 emissions reduction but rather by a desire to enhance energy security, mitigate rising energy costs, or promote other objectives.[2] Two common energy policy instruments are tax incentives and technology standards.[3] Although such instruments have been shown to be less cost-effective as a means to reduce CO_2 emissions than other policies, such as economy-wide carbon pricing (Fawcett, et al. 2014), it can be challenging to compare the costs of CO_2 emissions reductions associated with such policies across sectors. This difficulty arises because of the wide range in estimates and inconsistencies in how such estimates are constructed for any given policy.

In the power sector, a number of studies have examined the cost-effectiveness of state-level or potential national-level renewable portfolio standards (RPSs) at reducing CO_2 emissions (Young and Bistline 2018, Johnson 2014, Rausch and Mowers 2014, Fell and Linn 2013, Chen, et al. 2009, Palmer and Burtraw, 2005). Of these, a subset (Johnson 2014, Fell and Linn 2013, Palmer and Burtraw 2005) have explicitly estimated CO_2 abatement costs. Depending on the particular assumptions, these studies find that the implied cost of abatement using an RPS could range from less than \$10 per ton CO_2 to more than \$500 per ton CO_2. Differences in approach (modeling or empirical), assumed stringency, regional scope (national or state-level), and study vintage are some factors that contribute to this wide range.

Other studies have estimated the costs of directed technology support in the power sector, typically tax incentives for wind and solar deployment (Abrell, Kosch and Rausch 2019, Gillingham and Tsvetanov 2019, Callaway, Fowlie and McCormick 2018, Hughes and Podolefsky 2015, Novan 2015, Cullen 2013, Macintosh and Wilkinson 2011, Frondel, et al. 2010, Gugler, Haxhimusa and Liebensteiner 2021). In the subset of studies that report costs for the US, values range between about \$40 per ton CO_2 to several hundred dollars per ton CO_2. The same differences in approach, stringency, scope and study vintage also apply to these estimates. In addition, these studies call attention to differences in the underlying cost metric, as program costs may be higher than abatement costs when there is significant inframarginal adoption (Hughes and Podolefsky 2015).[4]

By comparing several policy instruments in the power sector, some of the studies above (Fell and Linn 2013, Palmer and Burtraw 2005) and others (Palmer, Paul, et al. 2011, Fischer and Newell 2008) provide insights about the relative cost-effectiveness of RPSs versus targeted energy tax incentives. A general finding from these studies is that an RPS is more cost-effective than a technology production subsidy, because the latter is typically less flexible and also lowers

1. For a comprehensive listing of energy efficiency and renewable energy policies and measures, see https://www.dsireusa.org/.
2. See, e.g., Congressional Research Service, "Energy Policy Act of 2005: Summary and Analysis of Enacted Provisions," 2006.
3. At the federal level, these include tax credits for various generation technologies, including renewables, carbon capture and sequestration, clean coal facilities, and nuclear, accelerated depreciation for multiple types of energy property (e.g., solar, wind, natural gas pipelines), expensing and excessing benefits for oil and gas production, tax credits for alternative vehicles, and standards for transportation fuels and vehicle tailpipe emissions, among others. At the state level, they include tax credits and rebates for alternative vehicles, and clean energy standards and renewable portfolio standards for the power sector, among others. For a list of federal tax incentives, see the Joint Committee on Taxation's, "Estimates of Federal Tax Expenditures for Fiscal Years 2019–2023," available at: https://www.jct.gov/publications.html?func=startdown&id=5238. For a summary of all federal financial interventions and subsidies in energy over time, see https://www.eia.gov/analysis/requests/subsidy/.
4. Inframarginal adoption has also been called "free-ridership" in the relevant literature.

electricity prices, which stimulates demand and increases emissions, all else equal. In addition, these studies and others (Young and Bistline 2018, Rausch and Mowers 2014) find that a fully technology-neutral approach (e.g., an electric sector CO_2 cap-and-trade system or clean energy standard) would be more cost-effective than either of the renewables-focused policies due to greater compliance flexibility.

In the transportation sector, several studies have considered mandates for non-petroleum based fuels such as renewable fuel standards (RFSs) and low-carbon fuel standards (LCFSs) (Sarica and Tyner 2013, Rubin and Leiby 2013, Huang, et al. 2013, de Gorter and Just 2010, Yeh and Sperling 2010, Holland, Hughes and Knittel 2009, Hahn and Cecot 2009, Johansson, et al. 2020), and others have considered subsidies for electric vehicles (Clinton and Steinberg 2019, Archsmith, Kendall and Rapson 2015, Berestreanu and Li 2011, Chandra, Gulatai and Kandlikar 2010). The range in policy costs for both instruments is larger than the range for power sector instruments, with the upper end reaching several thousand dollars per ton CO_2 in both transportation policies. All of the reasons mentioned above apply here, with the difference between abatement cost and program cost being particularly important for the electric vehicle (EV) subsidy, given significant inframarginal adoption (Clinton and Steinberg 2019). Although there is literature on fuel economy standards as well, the net cost of fuel economy standards depends strongly on how private cost savings (from reduced fuel use) are valued, which depends on whether intervention in the vehicle market is perceived as correcting a non-climate market failure (undervaluation of fuel savings by consumers) or as restricting consumer choices that may be individually rational.[5]

Not all studies are limited to a single energy subsector. Those that compare costs across subsectors typically rely on either meta-analysis (Gillingham and Stock 2018), to which questions about consistency apply, or modeling approaches (Fawcett, et al. 2014, Tuladhar, Mankowski and Bernstein 2014, Rausch and Karplus 2014, Karplus, et al. 2013), which have primarily focused on fuel economy standards in transportation and renewable or clean electricity standards in the power sector. A general finding from this latter group of studies (notwithstanding the caveat above) is that the cost of fuel economy standards greatly exceeds the cost of an economy-wide carbon tax for the same amount of total CO_2 reduction. The cost of standards in the electric power sector also exceeds the cost of an economy-wide carbon tax (for the same level of reduction), but by a smaller amount.

Taken as a whole, the available literature leads to several conclusions about policy cost-effectiveness. First, in part due to the reasons already mentioned, there is large variation in estimates of absolute abatement cost for any given policy instrument. On the other hand, studies that compare multiple policies using a common approach draw similar conclusions about relative cost-effectiveness, particularly regarding the link between flexibility and cost. These two insights suggest that conclusions about relative cost-effectiveness are largely robust to uncertainty in absolute policy costs. In other words, while absolute costs depend on specific assumptions about stringency, regional scope, technology cost and performance, policy cost metric, and estimation method, relative costs are more robust to these choices as long as such assumptions are harmonized between the policies being compared.

Although relative cost comparisons would be meaningful across sectors, few such comparisons are available today. Existing comparisons are characterized by a disproportionate focus on the power sector, and when policies are compared between the power and transportation

5. For the latter perspective, see Mannix and Dudley (2015). For the former, see Allcott and Sunstein (2015).

sectors, most attention has been given to fuel economy standards. This focus, while important, is also a limitation since fuel economy standards are qualitatively different from other transportation policies. As a practical matter, questions about the relative cost-effectiveness of subsidies (e.g., EV tax credits) or technology mandates (e.g., RFS) are equally relevant, but to date, this broader comparison has not been undertaken.

This study fills the gap identified above by simultaneously comparing the cost-effectiveness of several US energy policies across the electricity and transportation sectors in terms of CO_2 reduction. Specifically, it considers wind and solar tax credits, a renewable portfolio standard, a renewable fuel standard, and an electric vehicle tax credit. It relies on three well-known, publicly available US energy system models (NEMS[6], ReEDS, GCAM-USA) incorporating up-to-date information about technology cost and performance to compare policy costs and examine robustness to the choice of model. The use of more recent cost and performance information relative to prior studies is particularly relevant in light of rapid technology advancement in some sectors.

The remaining sections of this paper are organized as follows. Section 2 describes the models, scenarios and approach for estimating policy cost. Section 3 describes the results and explains key findings in terms of underlying mechanisms. Section 4 concludes with general insights, caveats and implications.

2. METHODS

2.1 Models

The models used in this study are extensively documented, publicly available US energy system models that have been used in numerous climate and energy policy analyses. EM-NEMS is an OnLocation, Inc. version of the National Energy Modeling System (NEMS) developed and maintained by the US Energy Information Administration (EIA). EM-NEMS is a modular modeling framework that represents all energy supply, conversion and end use sectors in the United States with regional disaggregation and significant technology detail. The version used in this study is based on the Annual Energy Outlook (AEO) 2019 version with updates to technology assumptions described later in this section.[7] The Renewable Energy Deployment System (ReEDS) is an electricity capacity expansion model of the contiguous United States developed and maintained by the National Renewable Energy Laboratory (NREL). ReEDS has greater spatial disaggregation than many other capacity expansion models of comparable scope, which is important for representing renewable resources and the competition between variable renewable energy (VRE) and other sources at a regional grid level (Mai, et al. 2018).[8] GCAM-USA is based on the Global Change Assessment Model (GCAM) developed and maintained by the Joint Global Change Research Institute (JGCRI).[9] GCAM-USA represents all energy supply, conversion and end use sectors at the state level, but with less technology detail in some sectors than EM-NEMS.

6. NEMS refers to the National Energy Modeling System developed and maintained by the US Energy Information Administration (EIA): https://www.eia.gov/outlooks/aeo/nems/documentation/. In what follows, we will use the term EM-NEMS to refer to the version of the model used in this study to distinguish it from EIA's version.
7. EIA's Annual Energy Outlook (AEO) 2019 is available here: https://www.eia.gov/outlooks/archive/aeo19/.
8. For ReEDS documentation see: https://www.nrel.gov/analysis/reeds/.
9. For GCAM documentation see: https://jgcri.github.io/gcam-doc/.

The scope of each model is different, and each model represents technology choice differently. GCAM-USA is a more granular, US version of the global GCAM integrated assessment model, which represents the coupling between energy, land and climate systems. GCAM is recursive-dynamic and uses a multinomial logit to represent technology choice in all sectors. EM-NEMS is a model of the US energy system that consists of independent modules for different energy sub-sectors that are linked such that supplies and demands are balanced across all sectors. Technology choice in the electricity and liquid fuel production sectors is determined by forward-looking optimization, whereas technology choice in the transportation sector uses a multinomial logit. ReEDS is a recursive-dynamic capacity expansion model of the US electricity system with technology choice determined by optimization.

In the power sector, all models compete electricity technology options based on cost. EM-NEMS and ReEDS explicitly solve the electricity capacity expansion problem, satisfying demand for generation as well as planning and operating reserves in all time periods given capital, operating and fuel costs for various technologies, including transmission. These models implicitly capture the costs of balancing generation and load, the cost of providing adequate operating and planning reserves, and the cost of additional transmission capacity where necessary.[10] By contrast, GCAM-USA competes technologies in a more stylized way, using a logit formulation, based on differences in the levelized cost of electricity (LCOE). In this framework, an additional cost is added to the LCOE of VRE technologies that increases with penetration and reflects the declining value of VRE.[11]

In the transportation sector, both EM-NEMS and GCAM-USA explicitly compete options for fuels production and technologies that satisfy service demands in key end uses, such as passenger and commercial transportation. In both EM-NEMS and GCAM-USA, the cost of producing alternative liquid fuels is represented using non-energy (primarily capital) costs and a feedstock cost (based on a supply curve for each feedstock), with an assumed conversion efficiency that indicates the amount of feedstock required to produce a given amount of fuel. In passenger transportation, which is most relevant for understanding the EV tax credit extension, both EM-NEMS and GCAM explicitly represent vehicle stock turnover. Sales of new vehicles are determined endogenously and balance the demand for new vehicles that arises from increasing service demand (vehicle miles traveled) and retirement of the existing vehicle stock.[12] Within a given size class, the share of new vehicles allocated to a given type – conventional internal combustion engine vehicles (ICEVs), hybrid electric vehicles (HEVs), and battery electric vehicles (BEVs, also referred to as EVs here), among others – is determined via competition using a logit approach that accounts for differences in total cost (the sum of capital, fuel and operating costs) among vehicle types as well as other factors.[13]

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10. Neither model represents flexible end use demands, so the load shape is either exogenous (ReEDS) or determined by the mix of end use technologies deployed in a given scenario (EM-NEMS).

11. An additional difference between the models is the extent to which they incorporate foresight about the future in solving for a given time period. GCAM-USA and the version of ReEDS used in this study are recursive-dynamic, whereas the Electricity Market Module (EMM) of EM-NEMS includes foresight about future prices when determining the capacity expansion solution for the next period. This process is then repeated for all future periods.

12. In EM-NEMS, sales of new vehicles are a function of price and personal income. Since sales are not directly tied to the vehicle stock or vehicle miles traveled (VMT), the number of miles driven per vehicle is also endogenous.

13. Vehicle attributes such as range, fuel availability, home refueling capability, model availability, acceleration, and luggage space are explicitly included in the multinomial logit used to project LDV sales by type in EM-NEMS, whereas such attributes are not considered explicitly in GCAM-USA. In addition, EM-NEMS and GCAM-USA represent the cost of charging infrastructure differently. In GCAM, a per-vehicle cost of charging infrastructure is added to the levelized cost of passenger service, whereas in EM-NEMS the cost of charging infrastructure is not explicit.

The three models used in this study were selected for several reasons. First, all models are national in scope and have been used extensively in US policy analysis. Second, all models have been extensively documented and have versions that are publicly available. Third, differences in model structure and resolution provide an opportunity to evaluate robustness of policy cost outcomes to such differences. To the extent that results are qualitatively similar, greater confidence can be attached to the findings used in decision-making. Fourth, since power sector capacity expansion models are often used to evaluate VRE deployment, utilizing a spatially-explicit capacity expansion model (ReEDS) allows us to further evaluate robustness for the power sector policies examined in this study.

2.2 Scenarios

To estimate the implications of a given policy extension or expansion, it is necessary to first construct a Reference Case against which policy-driven deviations can be assessed. In this study, the Reference Case represents all existing policies and regulations, as well as their planned modifications or phase-outs. Specifically, the Reference Case includes the phase-out of the existing wind Production Tax Credit (PTC), the step-down of the solar Investment Tax Credit (ITC) (from 30% to 10% for utility-scale solar), a phase-out of the existing EV tax incentive (approximating the per-manufacturer ceiling on the number of eligible vehicles), and a continuation (but not expansion) of the federal Renewable Fuel Standard (RFS) and state-level Renewable Portfolio Standards (RPSs) already enacted.

Starting from this Reference Case, each of the dimensions can be adjusted independently to isolate the impacts of a particular policy action. In the case of wind and solar tax incentives, the extension case extends the existing tax credits at their full value through 2050 (the production tax credit of 2.3 cents per kWh for onshore wind and the investment tax credit of 30% for solar).[14] Similarly the EV tax credit extension extends the full applicable subsidy based on battery size up to $7,500 per vehicle to all new electric vehicle purchases (although this subsidy does not apply to HEVs without plugs).

In the Reference Case, the RFS volume requirements are assumed to remain roughly constant over time, with about 18 billion gallons of total biofuels required and about 75% of the total coming from corn ethanol.[15] In the expanded RFS case, total biofuel volumes are increased to approximately 34 billion gallons in 2050, with most of the increase assumed to come from advanced biofuels.[16]

Evaluating an expanded RPS is more challenging because current RPS programs are implemented at the state level, with many differences in design and stringency among them. For the purpose of constructing an expanded scenario, it is important to note that the increasing

14. Distributed PV is specified exogenously in ReEDS.

15. EPA is required to evaluate and appropriately adjust the statutory volumes each year. Based on historical experience, EIA assumes in the AEO 2019 Reference Case that these adjusted volumes remain roughly flat, which is the assumption adopted in the Reference Case here. Note that these volumes are slightly lower than those set by EPA to reflect biogas that is not included in the modeling. For annual EPA volume requirements, see: https://www.epa.gov/renewable-fuel-standard-program/renewable-fuel-annual-standards.

16. The RFS2 Program consists of a total renewable fuel volume requirement as well as several sub-requirements for cellulosic biofuel, biomass-based diesel and advanced biofuel. Therefore, to adhere to the overall policy structure, the expanded RFS case in EM-NEMS separately expands each of the specific volume requirements, starting from current levels. In GCAM-USA, only the total volume requirement and the advanced biofuel volume requirement are represented explicitly, meaning that the specific mix of advanced biofuels may differ from the mix achieved in EM-NEMS. For more details on the RFS2, see: https://www.epa.gov/renewable-fuel-standard-program/regulations-and-volume-standards-renewable-fuel-standards.

stringency of existing state-level RPSs is reflected in the Reference Case. Therefore, the expanded RPS case envisions a domestic policy environment in which at least some US states increase stringency beyond what they have already enacted. To avoid having to make judgments about which states enact which particular changes, the expanded RPS case is implemented by layering a single national RPS with unrestricted interstate trading on top of existing state RPSs.[17] The national RPS increases the share of renewable sources in national electricity generation from about 40% in the Reference Case to roughly 50% in the expanded case by 2050.[18]

In addition to the four cases discussed above, several economy-wide carbon tax cases were evaluated in order to construct the efficient frontier discussed in Section 3.[19] Specifically, four cases were run with carbon taxes starting at \$5, \$10, \$20 and \$40 per ton CO_2 in 2022 and rising at 5% per year in real terms. These trajectories were selected in order to understand how cost varies with stringency and to provide several points that would enable construction of the economic "efficient frontier" described later. In all carbon tax scenarios, the treatment of other policies follows the Reference Case.[20] All of these scenarios are summarized in Table 1.

In all scenarios, relevant technology assumptions were harmonized across models to the extent possible. For renewable technology cost and performance assumptions in the electricity sector, the NREL Annual Technology Baseline (ATB) 2018 assumptions were utilized.[21] Natural gas prices are based on EIA's AEO 2019 High Oil and Gas Resource and Technology Side Case assumptions, which yield delivered prices to the power sector between \$3.50 and \$4 per MMBtu over the projection period.[22] World oil prices are based on the same High Oil and Gas Resource and Technology Side Case assumptions in EM-NEMS. Oil prices in GCAM were adjusted to be broadly consistent with those in EM-NEMS (differences are less than 10% in all years between 2020 and 2050). For biofuel production cost assumptions, the consistent cost basis contained in version 5.2 of GCAM-USA was utilized.[23] For electric light-duty vehicle cost and performance assumptions, information from the moderate advancement case developed as part of the NREL Electrification Futures Study was utilized.[24] In each of these areas, technology costs are expected to decline over the projection period due to technological advancement.[25] However, for costs that are imported from other sources, there is no endogenous learning-by-doing in these scenarios. Native model assumptions were used in areas less likely to affect the outcomes of this study. Key cost and performance assumptions are reported in Tables S1-S3 in the Supplemental Material.

17. In GCAM-USA, state RPSs are not modeled explicitly, but the national renewable shares in both the Reference Case and the Expanded RPS Case roughly match the shares in the respective EM-NEMS cases.

18. For comparison, the renewable share in 2050 is close to 40% in the AEO 2020, which includes the latest 100% renewable and zero-carbon energy targets enacted by New Mexico, Washington, Nevada, New York and Maine. The national approach likely underestimates policy cost because a hypothetical national RPS would be more flexible than a combination of state-level RPSs achieving the same emissions outcome, unless all state-level policies were defined identically and regional trading were assumed to be unrestricted. Note also that existing hydropower and distributed PV are excluded from crediting in the expanded RPS scenario, but the approximate renewable shares are reported including existing hydro.

19. Since ReEDS only represents electricity, the same tax pathways were run as power sector carbon taxes in ReEDS.

20. One exception is that biofuel volumes in GCAM-USA are unconstrained in the carbon tax scenarios, whereas they are specified to remain at roughly current levels in the Reference Case.

21. See https://atb.nrel.gov/.

22. These prices are comparable to those in the AEO 2021 Reference Case.

23. For a discussion of the biofuel production cost assumptions and underlying sources, see Muratori et al (2017).

24. See https://www.nrel.gov/analysis/electrification-futures.html.

25. For example, in the NREL ATB 2018, the LCOE for onshore wind (TRG 3, mid case) declines by 22% between 2016 and 2030 and the LCOE for utility-scale solar PV (Kansas City, mid case) declines by 66% between 2016 and 2030.

TABLE 1

Summary of scenarios evaluated in this study. All four sectoral policy scenarios, as well as the Reference Case and four carbon tax pathways, were run in EM-NEMS and GCAM-USA. ReEDS did not evaluate the transportation policies and evaluated a power sector carbon tax in lieu of an economy-wide carbon tax.

		Electricity Sector		Transportation Sector					
		Extend Wind and Solar Tax Credits	**Expand RPS nationally**	**Expand RFS for advanced biofuels**	**Extend EV Tax Credit**	**Apply Economy-wide Carbon Tax**	**EM-NEMS**	**GCAM-USA**	**ReEDS**
	Reference Case	—	—	—	—	—	Yes	Yes	Yes
Electricity Policies	**Wind and Solar Tax Credit Extension Case**	Yes	—	—	—	—	Yes	Yes	Yes
	RPS Expansion Case	—	Yes	—	—	—	Yes	Yes	Yes
Transportation Policies	**RFS Expansion Case**	—	—	Yes	—	—	Yes	Yes	—
	EV Tax Credit Extension Case	—	—	—	Yes	—	Yes	Yes	—
	Carbon Tax Cases	—	—	—	—	Yes	Yes	Yes	Power Only

2.3 Policy cost metric

Although each of the models reports costs and CO_2 emissions, which together enable an estimate of CO_2 cost-effectiveness, there are important practical and conceptual details to consider when constructing such a metric. The most policy-relevant metric is welfare cost. In a partial equilibrium context, total surplus change, estimated as the change in producer and consumer surplus, is a useful proxy for welfare cost (Mignone, Alfstad, et al. 2012). Furthermore, when overall demand changes are small, as they are for the extended and expanded policy cases, the change in system cost reasonably approximates total surplus change.

Importantly, the change in system cost reflects the real resource cost of the policy, excluding transfers, which do not affect net societal resources, but rather represent a shift in resources between different groups. In practical terms, the real resource costs include capital, fuel and operating expenses in the electricity and fuel production sectors, as well as vehicle purchases in the transportation sector (fuel purchases for transportation are captured by the costs in the electricity and fuel production sectors). On the other hand, subsidy payments under the tax credit extension cases are transfers, which can be excluded when estimating resource costs.[26]

Under more comprehensive or stringent policies, such as the carbon tax cases considered in this study, the assumption of small demand changes may not be valid. As energy prices rise, the reduction in the demand for energy can be significant. As an alternative to estimating surplus changes across multiple markets, we estimate the cost of a carbon tax as the area under the marginal abatement supply curve, which in any given year, is defined by the carbon price and the realized abatement. Since the marginal abatement supply curve is typically convex, estimating the average cost assuming the curve is linear is effectively an upper bound on the cost of the carbon tax. Although both metrics focus conceptually on societal resource costs, the first approach (system cost method) excludes surpluses under the demand curve, whereas the second approach (area under the marginal abatement supply curve) includes them. However, this difference does not introduce significant inconsistencies when comparing policy costs as long as surpluses under the demand curve are small for policies whose costs are estimated using the first method.[27]

An additional complexity in developing a cost-effectiveness metric is the time dimension. The impact of each of the policies is projected through 2050 in each of the models. Because the policies are assumed to be in force over an extended period and because costs in a given year may not be reflective of the policy impact as a whole, a cumulative measure of cost is appropriate.[28] Such cumulative costs can be discounted at different rates depending on the application.[29] In this study, cumulative undiscounted costs are normalized by the cumulative

26. Similarly, revenues from a carbon tax, or other changes in government revenues under any of the policies (e.g., changes in fuel tax revenues) would be considered a transfer rather than a component of resource cost.

27. The approach described here that relies on two different cost metrics is the most practical among the available alternatives. Since an economy-wide carbon tax affects all energy markets, separately estimating total surplus changes in each market without double counting is challenging. The abatement cost method is a simpler way to estimate the same costs, although it is only a viable option for the carbon tax cases.

28. Policy costs are shown separately for two different time periods between 2020 and 2050 in the Supplemental Material.

29. If different positive and negative components of cost are realized at different times, then it is possible for the choice of discount rate to affect the relative cost ordering of the policies. For the policies considered here, the cost ordering is generally not sensitive to the discount rate for rates between 0 and 7%. One exception is the ordering between the RPS expansion and the wind and solar tax credit extension cases in EM-NEMS. However, although the order changes when the discount rate is increased from 0 to 7%, the costs of these two policies estimated in EM-NEMS are very similar to one another regardless of the discount rate.

economy-wide emissions reduction to provide a measure of the average cost-effectiveness over the projection period.

3. RESULTS AND DISCUSSION

3.1 Electricity sector policies

Generation in the Reference Cases in all models is shown in Figure S1 in the Supplemental Material. The models consistently project an increase in generation from natural gas and renewable sources and a decrease in generation from coal and nuclear, driven by declining VRE costs and persistently low natural gas prices. The differences observed in nuclear retirements in the Reference Cases are due to differences in underlying modeling assumptions. EM-NEMS includes only economic retirements (in addition to those already announced). GCAM-USA and ReEDS include both economic and lifetime-based retirements (in addition to those already announced), but GCAM-USA assumes a 60-year lifetime whereas ReEDS assumes a combination of 60 and 80-year lifetimes.

Figure 1 shows the response in each of the models to the wind and solar tax credit extension and the RPS expansion. There are several notable features of this response. First, the models consistently project that the tax credit extension would primarily lead to an increase in wind deployment (panels a-c). This occurs because, even though both the wind and solar tax credits are extended, the wind PTC is effectively larger than the solar ITC when they are compared on a levelized basis (Frazier, Marcy and Cole 2019). As solar capital costs have declined, so too has the value of the solar ITC, which is simply a share of the total investment cost. Second, the tax credit extension displaces a mix of coal, natural gas, and nuclear generation. Generally, the policy will deploy the subsidized technology at the expense of the next most costly option or set of options, which vary to some extent by region.[30] Furthermore, as the subsidy lowers electricity prices, some additional existing nuclear generation cannot recover going-forward fixed costs and chooses to retire in those models in which retirements are most responsive to the underlying economics (EM-NEMS and ReEDS in panels a and b, respectively).

The response to the RPS expansion is similar to the response to the tax credit extension in the sense that wind and solar deployment increases, displacing coal, natural gas and nuclear generation (panels d-f). In this case, the direction of the electricity price change is not known a priori (Fischer, 2010), but in our scenarios it tends to increase relative to the Reference Case. At the same time, nuclear generation is not eligible to receive renewable energy credits (RECs), and it is therefore subject to an additional cost as the generation fleet as a whole must satisfy the RPS constraint. This is one reason why the result for nuclear in this case resembles the nuclear result in the tax credit extension case.[31]

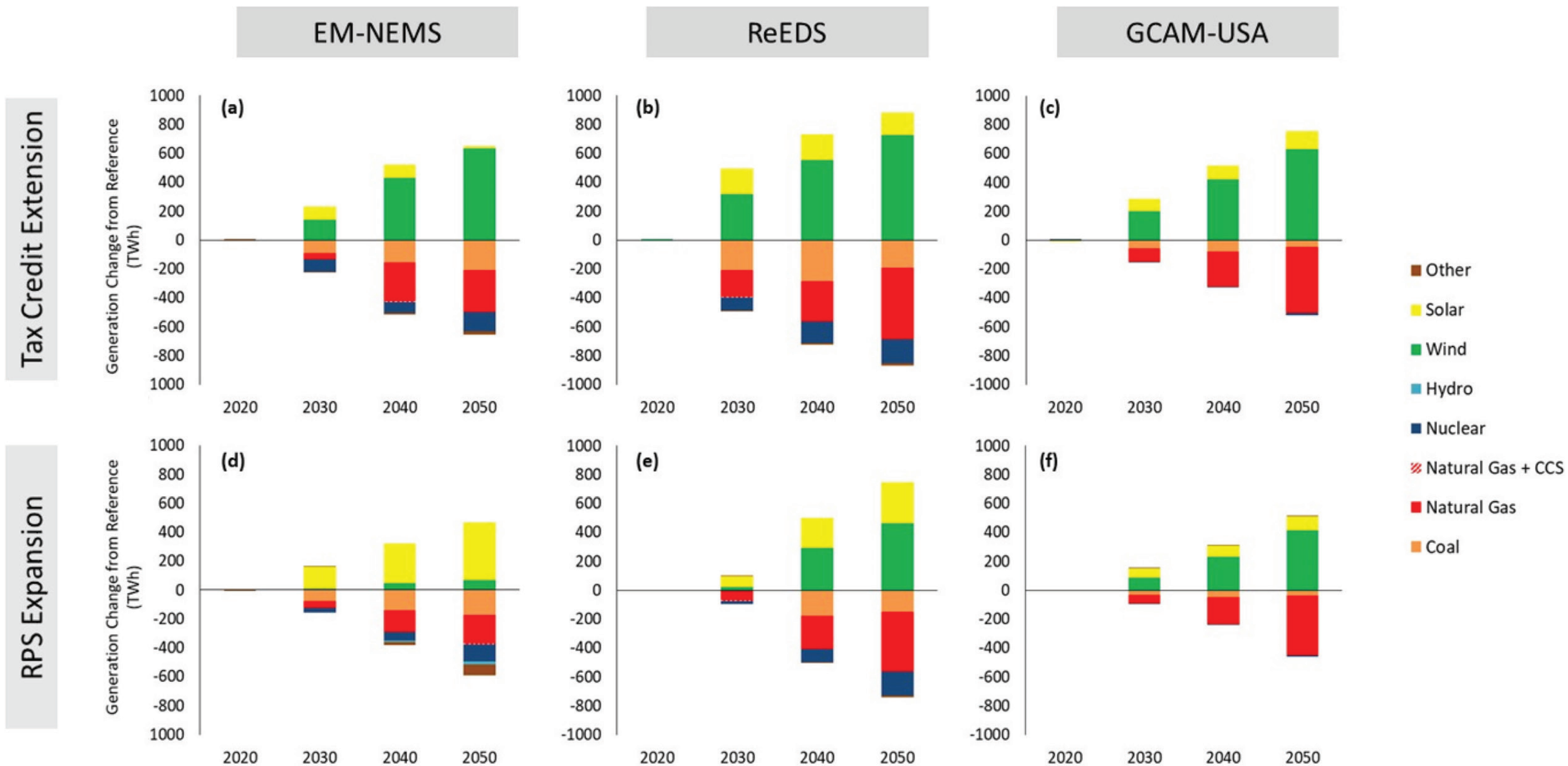
A more notable difference between the RPS and tax credit extension cases is the greater variation between models in wind and solar deployment in the RPS case. Overall, average costs for new wind and solar installations are comparable, which implies that differences in how regional or other factors are represented can tip the balance in favor of one source over the other. For example, ReEDS has greater regional disaggregation, uncovering more opportunities for

30. In this context, cost refers to total going-forward cost, not LCOE.

31. Six states have now implemented clean energy standards that, in addition to renewable technologies, treat nuclear and other non-renewable low- or zero-emitting options as eligible technologies. Such clean energy standards avoid the disincentive for nuclear and other eligible technologies.

FIGURE 1

Change in generation in response to the extension of wind and solar tax credits (panels a-c) and the RPS expansion (panels d-f). EM-NEMS results are shown in panels (a) and (d), ReEDS results are shown in panels (b) and (e), and GCAM-USA results are shown in panels (c) and (f). Differences are expressed with respect to each model's own Reference Case (see Figure S1). All generation is from the electric utility sector, with the exception of solar, which includes distributed solar PV in the residential and commercial sectors. The "other" category includes geothermal, biomass and storage losses.



low cost wind deployment. EM-NEMS, on the other hand, dispatches the system at greater temporal resolution to estimate storage expansion, potentially uncovering more arbitrage opportunities for diurnal storage, thereby lowering the effective cost of integrating solar PV. Regardless of the mechanisms at work, an important insight from these results is that the RPS enables more direct competition between wind and solar, whereas the tax incentives, at least as codified in existing federal law, incentivize one technology over the other.

For the purpose of understanding policy cost-effectiveness, it is useful to consider the qualitative features of the responses that would differ from those of a carbon tax. These features can be divided into those related to the technologies that deploy and those related to the technologies that are displaced relative to the Reference Case. On the deployment side, although wind and solar are likely to be competitive under a technology-neutral policy, other options, such as natural gas with or without carbon capture and storage (CCS) and preservation of existing nuclear are also likely to be competitive in some regions, depending on the level of the carbon price (Mignone, Showalter, et al. 2017, Logan, et al. 2013, Paltsev, et al. 2011). On the displacement side, a key aspect of the tax incentive extension and RPS expansion is the fact that lower and zero-CO_2 emission sources, such as natural gas and nuclear, are displaced along with the highest-emitting source, namely coal (Palmer and Burtraw 2005). As a result, the amount of CO_2 emissions reduction per unit generation displaced is lower than it would be under a technology-neutral emissions reduction policy that preferentially displaced higher-emitting sources. The need for less substitution of generation to achieve a given level of CO_2 emissions reduction is one reason why a technology-neutral approach is typically more cost-effective than instruments focused on deploying specific technologies without explicit regard for CO_2 emissions reduction.[32]

3.2 Transportation sector policies

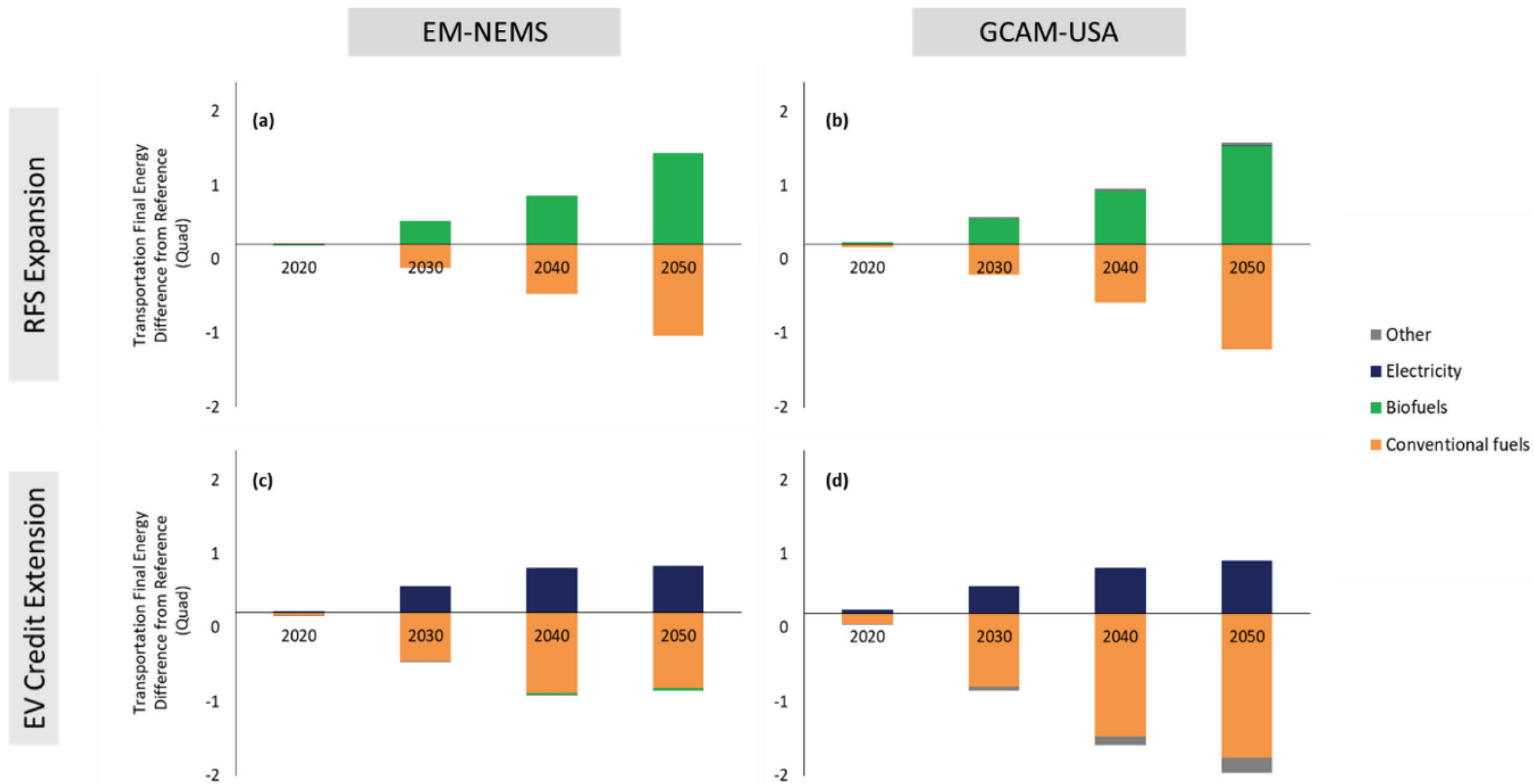
Transportation final energy in the Reference Cases is shown in Figure S2 in the Supplemental Material. Demand for transportation final energy is relatively flat, reflecting the offsetting effects of service demand increases, driven by increasing economic activity, and fuel economy increases, driven by a combination of technology improvement and increasing regulatory stringency. Transportation final energy demand continues to be supplied primarily by conventional liquid fuels in the Reference Cases.

Figure 2 shows the response in each of the models to the RFS expansion and the extension of the EV tax credit. At the level of disaggregation shown in this figure, both EM-NEMS and GCAM-USA respond similarly to the RFS expansion, which mandates an increasing level of biofuels deployment each year, displacing conventional liquid fuels. The mix of biofuels is largely driven by the assumptions regarding the volume requirements for cellulosic biofuel and biomass-based diesel. The amount of corn ethanol makes up the difference between the advanced biofuel requirement and the total requirement (the corn ethanol requirement is roughly the same between the Reference Case and the RFS expansion case, because the increase in the RFS expansion is mostly from advanced biofuels). Since biomass-to-liquids (BTL) qualifies to receive cellulosic credit under the RFS, EM-NEMS tends to satisfy the cellulosic requirement

32. The cost-effectiveness of power sector policies can also be eroded if there is significant emissions leakage as electricity or natural gas prices fall, causing an effective rebound in the use of such energy elsewhere, for example in buildings or industry. These effects are not particularly noteworthy in the cases considered here, given the assumed level of stringency of the sectoral policies. However, leakage effects will be captured by the policy cost metric when normalized by all energy system emissions abatement (any emissions leakage would reduce total abatement).

FIGURE 2

Change in transportation final energy in response to the RFS expansion (panels a and b) and extension of the EV tax credit (panels c and d). EM-NEMS results are shown in panels (a) and (c), and GCAM-USA results are shown in panels (b) and (d). Differences are expressed with respect to each model's own Reference Case (see Figure S2). The "other" category includes natural gas and hydrogen.



using BTL rather than with cellulosic ethanol, which mitigates the complication of blending larger amounts of ethanol into the motor gasoline pool.

In the case of the EV tax credit extension, both models deploy more electric vehicles for passenger transportation, primarily displacing conventional vehicles (ICEVs) that use liquid fuels (panels c and d). Importantly, although the total stock of vehicles is largely unchanged relative to the Reference Case, the increase in electricity is considerably smaller than the decrease in liquid fuels. This is largely due to the greater fuel economy of electric vehicles relative to conventional vehicles – for the same amount of vehicle miles traveled, an electric vehicle consumes less energy.

However, if differences in fuel economy were the only factor, the reduction in liquid fuels would be even greater than what is observed in Figure 2 (panels c and d), suggesting an additional mechanism at work. In both models, since the EV subsidy displaces hybrid electric vehicles that are ineligible for the subsidy, it lowers the fuel economy of the conventional fleet as a whole, which includes hybrids. Additionally, in EM-NEMS, the fuel economy of conventional vehicles does not increase as rapidly in the EV extension case as it does in the Reference Case, because the fleet-wide fuel economy standard is easier to satisfy as the share of more efficient vehicles (in this case, EVs) in the fleet increases. All else equal, these fuel economy responses increase policy costs in both models (relative to what would be anticipated without this effect) because a smaller amount of liquid fuels is displaced for a given increase in electric vehicle adoption.[33]

3.3 Comparing policy abatement costs across sectors

As discussed in Section 2, information about resource costs and CO_2 emissions is sufficient to estimate a policy abatement cost in dollars per ton CO_2. However, as discussed in Section 1, relative costs are more robust than absolute costs, suggesting the value of having a relevant benchmark for cost-effectiveness. Furthermore, because the amount of emissions reduction varies by policy instrument and by model, it is useful to have a benchmark that is parameterized by the amount of CO_2 abated. To create such a benchmark, we estimate the abatement costs of several carbon tax pathways using the approach discussed in Section 2, and then using the set of points defined by the emissions reduction and abatement cost for each carbon tax case, we interpolate between them to estimate an "efficient frontier" that provides a floor on abatement cost for any given level of emissions reduction. There is significant uncertainty in the amount of abatement associated with any particular carbon tax pathway (McFarland, et al. 2018); our goal here is not to assess the stringency of outcomes but to evaluate relative cost-effectiveness for any given level of stringency.

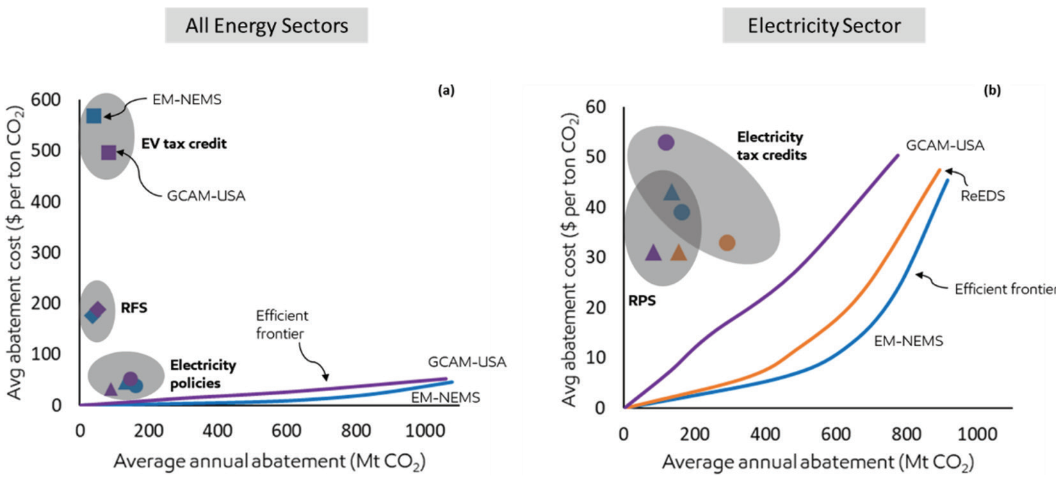
Figure 3 shows the abatement cost versus average annual abatement for each of the sectoral policies, along with the efficient frontier calculated as discussed above. In panel (a), the average annual CO_2 abatement shown on the x-axis is the reduction in total energy CO_2 emissions converted to an average annual value by dividing the cumulative abatement by 30 years. This provides a measure of the average annual emissions reduction relative to current annual energy CO_2 emissions, which is approximately 5,000 million metric tons CO_2. In panel (b), the CO_2 abatement shown on the x-axis is the reduction in electricity sector CO_2 emissions converted to an average annual value in the same way.[34] This is most relevant for understanding the power

33. For related discussion, see: https://media.rff.org/documents/RFF-BCK-McConnellTurrentine-Hybrids.pdf.

34. Electricity sector CO_2 emissions include (uncaptured) emissions from fuels combusted in the electricity sector, excluding

FIGURE 3

Average abatement cost versus average annual abatement for the four policies discussed in this paper compared to the efficient frontier. Average abatement costs are undiscounted cumulative costs through 2050 divided by cumulative CO_2 emissions reductions over the same period. The efficient frontier is defined by interpolating between four discrete points, each corresponding to one of the several carbon tax pathways discussed in the text. In panel (a), average annual abatement refers to the reduction in total energy CO_2 emissions, whereas in panel (b), it refers to electricity CO_2 emissions. For an electricity policy, the difference in placement along the x-axis between the two panels is thus a measure of emissions leakage. The abatement cost of any given policy (placement along the y-axis) is identical between the two panels for any point that appears in both panels. Note the order of magnitude difference in vertical scales between the two panels.



sector policies and facilitates comparison with the ReEDS model, which only reports costs and emissions for the electricity sector.

Several key insights follow from Figure 3. First, although some policies are closer to the efficient frontier and others are farther away, the distance between each of the policies and the efficient frontier is significant in all cases, suggesting that the CO_2 emissions reduction achieved under each sectoral policy could be realized at lower cost using a more flexible policy instrument. Second, the electricity policy instruments are significantly more cost-effective (closer to the frontier) than the transportation policy instruments, partly a result of the fact that wind, solar and battery costs have recently declined and are assumed to decline further in the future.[35] Third, the two electricity policies are closer to one another than are the two transportation policies in terms of cost-effectiveness. Fourth, the RFS is more cost-effective than the EV tax credit extension. Fifth, on several of the points above, there is reasonable agreement between models, suggesting that such findings are largely robust to the choice of modeling framework.

These results can be further explained by considering the underlying drivers of policy cost, including the technology assumptions. In the case of the electricity policies, although there is significant regional variation, the average achieved LCOEs of both wind and solar, assuming

emissions associated with producing or transporting fuels. Life cycle emissions from non-emitting sources are also excluded.

35. This forward-looking view of technology may partially explain differences with empirical approaches that estimate higher abatement costs for similar policies. For example, see: https://epic.uchicago.edu/research/do-renewable-portfolio-standards-deliver/.

unsubsidized costs, are expected to reach parity with natural gas combined cycle (NGCC) over the projection period. All else equal, this would imply no change in system cost for direct switching between natural gas and VRE generation, and therefore no cost of CO_2 abatement for this switch.[36] However, an average LCOE comparison does not fully reflect the system cost implications of a switch between two generation sources (Hirth, Ueckerdt and Edenhofer 2015). Notably, the need to balance generation in all time periods and to satisfy reserve requirements leads to changes in the way that the system operates or expands under different generation mixes, which may include changes in the deployment of flexible generation, reserve capacity, energy storage, or transmission.

In the case of transportation policies, the two policies affect choices in different sub-sectors. The RFS expansion affects the economics of fuels production, whereas the EV tax credit extension affects the economics of consumer purchasing decisions, so there is no a priori reason to expect abatement costs of these two policies to be similar. In fuels production, each dollar per gallon difference in the cost of producing fuels would lead to an abatement cost above \$100 per ton CO_2, assuming that the alternative fuel is emissions-free and displaces conventional (oil-based) liquid fuels. This analysis does not consider the full life-cycle emissions of biofuels, which is outside the scope of this paper.[37] However, the abatement costs can be scaled to account for different assumptions about such emissions. For example, if the biofuels deployed in the RFS case were assumed to be half as carbon-intensive as conventional fuels, then the effective abatement cost would double, although in this example, the resulting cost would still be lower than the cost of the EV tax credit extension.

In consumer vehicle choices, the cost of the vehicle is often a determining factor, along with other vehicle attributes. Although the cost of purchased electricity and conventional fuel savings are relevant to the cost metric used in this study, these are partially offsetting, even more so because of the rebound in fuel economy discussed earlier. Furthermore, although the cost of an EV-100 is assumed to approach parity with a conventional vehicle relatively quickly, observed preferences to date suggest that vehicles with higher ranges – with higher cost premiums – will continue to be demanded in the US market. For each \$10k in incremental capital cost, the implied abatement cost would be approximately \$300 per ton CO_2 without accounting for the emissions from purchased electricity or from the rebound in fuel economy, which would both drive the abatement cost higher.

Using the results from each model, abatement costs can be analyzed for different time periods. In Table S4, abatement costs are shown separately for the early part of the projection period (2020–2035) and the later part (2036–2050). Although technology costs decline over time in all sectors (see Tables S1-S3), other factors may also affect abatement cost such that the change in abatement cost over time is not known a priori. For example, as emissions decline in particular sectors, low-emission technologies that deploy as a result of policy will begin to

36. As modeled, the RPS expansion and tax credit extension policies lead to several changes in technology deployment; the assumption in this example of direct substitution between VRE and NGCC is a simplification of the more complex modeled response.

37. In EM-NEMS and GCAM-USA, biomass is assumed to provide the energy needed for producing advanced biofuels, meaning that there are effectively no refinery process CO_2 emissions associated with these pathways. Land use change (LUC) CO_2 emissions and non-CO_2 emissions are not included in this analysis. However, other studies have concluded that the LUC change emissions from the production of second-generation biomass feedstocks (e.g., switchgrass, miscanthus) would be considerably smaller than those from first-generation sources (e.g., corn, soy) and could be negative if perennial energy crops displace land with lower carbon density (Field, et al. 2020). For further discussion of the life cycle implications of biofuels in the regulatory context, see EPA's Regulatory Impact Analysis of the RFS2: https://www.epa.gov/renewable-fuel-standard-program/renewable-fuel-standard-rfs2-final-rule-additional-resources.

displace less emissions-intensive incumbent technologies, leading to less abatement per unit deployment. This effect can be observed in the power sector, for which some of the models show increasing abatement costs over time despite declining technology costs. In contrast, the cost of the EV tax credit extension is projected to decline in both EM-NEMS and GCAM-USA, because some of the factors that lead to higher early abatement costs (fuel economy rebound, offsetting emissions from the power sector) become less significant over time. Finally, it is important to note that the cost ordering among the four sectoral policies does not change in either sub-period relative to the ordering observed for the entire projection period.

4. CONCLUSIONS AND POLICY IMPLICATIONS

By examining the CO_2 cost-effectiveness of several existing US electricity and transportation policy instruments, as well as an economy-wide carbon tax, results from this study confirm and extend findings from prior studies and reveal several additional policy-relevant insights. Specifically, results from this study confirm that sectoral policies are less cost-effective as a means to reduce CO_2 than an economy-wide carbon tax and that transportation policies are less cost-effective than electricity policies (Fawcett, et al. 2014, Tuladhar, Mankowski and Bernstein 2014, Rausch and Karplus 2014, Karplus, et al. 2013). In addition, it is notable that the sectoral instruments considered, to the extent that they extend or modestly expand existing polices with national scope, do not achieve annual CO_2 reductions greater than ~200 Mt CO_2 per year on average over the projection period. This suggests that more expansive policy would be required to achieve CO_2 reductions consistent with stated national policy goals.

Our results also provide several insights about existing sectoral policies that are relevant as refinements and modifications to such policies are considered. First, we find that the previously enacted wind and solar tax credits strongly favor wind over solar, because the solar ITC applies to capital costs, which have decreased significantly in recent years. Second, despite known inefficiencies, renewable energy policies in the electricity sector are less costly than earlier estimates due to recent and expected future technology advancement. Third, in transport, we find that expanding advanced biofuel targets in the RFS by the amounts assumed here would be more cost-effective than extending the EV tax credit under plausible assumptions (discussed above). Fourth, we find a significant rebound in fuel economy under the EV tax credit extension, such that there is a smaller increase in fuel economy of conventional vehicles when the LDV fleet electrifies (for reasons discussed above). This effect tends to further increase the cost of the EV tax credit extension, all else equal. Finally, we find that the change in policy cost over time varies by policy and model, although the cost ordering among polices does not change when different timeframes are considered.

An important additional contribution of this study is the ability to analyze robustness by comparing results across three different models and the explanation of abatement cost results in terms of underlying energy system responses. Although abatement costs will vary with stringency, the amount of emissions reduction does not vary widely between the sectoral policies as modeled, so the ordering of cost-effectiveness among policies reflects differences in the qualitative features of the instruments more than differences in stringency. As discussed further below, an important policy question highlighted – but not resolved – by this study is whether and under what conditions policies with higher estimated abatement cost, reflecting deployment of less mature technologies, could be effective when viewed through the lens of technology policy, rather than through the lens of CO_2 emissions mitigation.

While this study builds on prior work in key areas, its scope has been constrained for practical reasons. First, some policy instruments have been placed out of scope for this study, including fuel economy standards, other energy efficiency standards, clean energy standards in the power sector, and other technology subsidies. Energy efficiency and fuel economy standards have not been considered because of the challenge in interpreting model results when there is disagreement about the rationale for policy intervention, as discussed earlier. However, both fuel economy standards and clean energy standards have been included in prior studies examining relative cost-effectiveness (Fawcett, et al. 2014, Tuladhar, Mankowski and Bernstein 2014, Rausch and Karplus 2014, Rausch and Mowers 2014, Karplus, et al. 2013). More generally, with the exception of the carbon taxes used to generate the efficient frontier, we have restricted our scope to existing policy instruments that could reasonably be extended or expanded in the near term, and have not attempted to compare prospective policies that currently are not in force at a national scale. Comparing alternative prospective policies that could lead to CO_2 reductions consistent with stated mitigation goals remains an important area for research.

Second, this study considers only the cost-effectiveness implications and not the distributional consequences of policy. It has been noted elsewhere that incentives for both renewable and non-renewable energy and alternative vehicles can stimulate inframarginal adoption (Metcalf 2009) and are often regressive (Metcalf 2019). Interaction between federal and state policies can also have distributional consequences. For example, as RPSs increase demand for renewable energy in certain states, more federal dollars (from renewable energy tax credits) are directed to those states (Metcalf 2009). Transfers between consumers and inframarginal producers are also common under supply-side policies (Mignone, Alfstad, et al. 2012), including many of the policies examined here. However, in the case of a carbon tax, the full distributional impact would depend on the details of revenue recycling, making it an explicit element of policy design rather than an unintended consequence (Caron, et al. 2018).

Third, this study considers cost-effectiveness only with respect to CO_2 emissions reduction, not with respect to other possible policy objectives, such as broader environmental protection, job creation, energy security, or technology innovation and diffusion, which have been discussed elsewhere (Johansson and Kristrom 2019, Wiser, et al. 2017, Barbose, et al. 2016, Borenstein 2012, Schmalensee 2012, Lyon and Yin 2010, Hahn and Cecot 2009, Jaffe, Newell and Stavins 2005). While other environmental externalities could provide a rationale for policy intervention, the same question about cost-effectiveness arises in relation to these other environmental issues.[38] With regard to job creation, state policy may have distributional consequences if such policies change the composition or location of employment, but they are unlikely to change the aggregate level of employment except under particular circumstances (Barbose, et al. 2016, Rivers 2013, Schmalensee 2012). With regard to energy security, such benefits have typically been found to be small relative to the costs for transportation policies, which are the policies for which such justifications have typically been offered (Hahn and Cecot 2009).[39]

With regard to technology innovation and diffusion, policies that do not appear cost-effective when viewed as a means to internalize the CO_2 externality could be more so when viewed as a means to correct other market failures (e.g., knowledge and adoption externalities) that inhibit technology innovation and diffusion (Jaffe, Newell and Stavins 2005). Put differently,

38. For a related discussion, see https://www.hamiltonproject.org/assets/files/PP_Williams_LO_FINAL.pdf.
39. See also EPA's Regulatory Impact Analysis of the RFS2 cited earlier.

policies whose current CO_2 abatement costs are high because the underlying technologies are immature or not widely deployed may be more cost-effective as a means to drive down the cost of technology or supporting infrastructure (Gillingham and Stock 2018). A challenge in designing such technology polices is ensuring that they are appropriately targeted (Borenstein 2012). A comprehensive approach to policy evaluation would therefore consider the strength of arguments for market failure in a particular area and evaluate policy options with regard to their effectiveness in addressing well-founded market failures.

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References

Abrell, J., M. Kosch, and S. Rausch. 2019. "Carbon abatement with renewables: Evaluating wind and solar subsidies in Germany and Spain." *Journal of Public Economics* 169: 172–202. https://doi.org/10.1016/j.jpubeco.2018.11.007.

Archsmith, J., A. Kendall, and D. Rapson. 2015. "From cradle to junkyard: Assessing the life cycle greenhouse gas benfits of electric vehicles." *Research in Transportation Economics* 52: 72–90. https://doi.org/10.1016/j.retrec.2015.10.007.

Barbose, G., R. Wiser, J. Heeter, T. Mai, L. Bird, M. Bolinger, A. Carpenter, et al. 2016. "A retrospective analysis of benefits and impacts of U.S. renewable portfolio standards." *Energy Policy* 96: 645–660. https://doi.org/10.1016/j.enpol.2016.06.035.

Berestreanu, A., and S. Li. 2011. "Gasoline prices, government support, and the demand for hybrid vehicles in the United States." *International Economic Review* 52: 161–182. https://doi.org/10.1111/j.1468-2354.2010.00623.x.

Borenstein, S. 2012. "The private and public economics of renewable electricity generation." *Journal of Economic Perspectives* 26: 67–92. https://doi.org/10.1257/jep.26.1.67.

Brown, D., and D. Sappington. 2017. "Designing compensation for distributed solar generation: Is net metering ever optimal?" *The Energy Journal*38 (3): 1–32. https://doi.org/10.5547/01956574.38.3.dbro.

Callaway, D. S., M. Fowlie, and G. McCormick. 2018. "Location, Location, Location: The variable value of renewable energy and demand-side efficiency resources." *Journal of the Association of Environmental and Resource Economists* 5: 39–75. https://doi.org/10.1086/694179.

Caron, J., J. Cole, R. Goettle, C. Onda, J. Mcfarland, and J. Woollacott. 2018. "Distributional implications of a national CO_2 tax in the U.S. across income classes and regions: A multi-model overview." *Climate Change Economics* 9. https://doi.org/10.1142/S2010007818400043.

Chandra, A., S. Gulatai, and M. Kandlikar. 2010. "Green drivers or free riders? An analysis of tax rebates for hybrid vehicles." *Journal of Environmental Economics and Management* 60: 78–93. https://doi.org/10.1016/j.jeem.2010.04.003.

Chen, C., R. Wiser, A. Mills, and M. Bolinger. 2009. "Weighing the costs and benefits of state renewables portfolio standards in the United States: A comparative analysis of state-level policy impact projections." *Renewable & Sustainable Energy Reviews* 13: 552–566. https://doi.org/10.1016/j.rser.2008.01.005.

Clinton, B. C., and D. C. Steinberg. 2019. "Providing the spark: Impact of financial incentives on battery electric vehicle adoption." *Journal of Environmental Economics and Management* 98. https://doi.org/10.1016/j.jeem.2019.102255.

Cullen, J. 2013. "Measuring the environmental benefits of wind-generated electricity." *American Economic Journal: Economic Policy* 5: 107–133. https://doi.org/10.1257/pol.5.4.107.

Darling, Seth B., Fengqi You, Thomas Veselka, and Alfonso Velosa. 2011. "Assumptions and the levelized cost of energy for photovoltaics." *Energy & Environmental Science* 4 (9): 3133–3139. https://doi.org/10.1039/c0ee00698j.

de Gorter, H., and D. R. Just. 2010. "The social costs and benefits of biofuels: The intersection of environmental, energy and agricultural policy." *Applied Economic Perspectives and Policy* 32: 4–32. https://doi.org/10.1093/aepp/ppp010.

Durmaz, Tunç, Aude Pommeret, and Ian Ridley. 2017 .024. "Willingness to Pay for Solar Panels and Smart Grids." *FEEM WORKING PAPERS "NOTE DI LAVORO" SERIES.* https://doi.org/10.2139/ssrn.2983006.

Fawcett, A. A., L. E. Clarke, S. Rasuch, and J. P. Weyant. 2014. "Overview of EMF 24 Policy Scenarios." *The Energy Journal* 35: 33–60. https://doi.org/10.5547/01956574.35.SI1.3.

Fell, H., and J. Linn. 2013. "Renewable electricity policies, heterogeneity, and cost-effectiveness." *Journal of Environmental Economics and Management* 66: 688–707. https://doi.org/10.1016/j.jeem.2013.03.004.

Fischer, C. 2010. "Renewable Portfolio Standards: When do they lower energy prices?" *The Energy Journal* 31: 101–120. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol31-No1-5.

Fischer, C., and R. G. Newell. 2008. "Environmental and technology policies for climate mitigation." *Journal of Environmental Economics and Management* 55: 142–162. https://doi.org/10.1016/j.jeem.2007.11.001.

Frazier, A. W., C Marcy, and W. Cole. 2019. "Wind and solar PV deployment after tax credits expire: A view from the standard scenarios and the annual energy outlook." *The Electricity Journal* 32. doi:https://doi.org/10.1016/j.tej.2019.106637. https://doi.org/10.1016/j.tej.2019.106637.

Frondel, M., N. Fritter, C. M. Schmidt, and C. Vance. 2010. "Economic impacts from the promotion of renewable energy technologies: The Geman experience." *Energy Policy* 38: 4048–4056. https://doi.org/10.1016/j.enpol.2010.03.029.

Gillingham, K, and J. H. Stock. 2018. "The cost of reducing greenhouse gas emissions." *Journal of Economic Perspectives* 32 (4): 53–72. https://doi.org/10.1257/jep.32.4.53.

Gillingham, K., and T. Tsvetanov. 2019. "Hurldes and steps: Estimating demand for solar photovoltaics." *Quantitative Economics* 10: 275–310. https://doi.org/10.3982/QE919.

Gugler, K., A. Haxhimusa, and M. Liebensteiner. 2021. "Effectiveness of climate policies: Carbon pricing vs. subsidizing renewables." *Journal of Environmental Economics and Management* 106. doi:https://doi.org/10.1016/j.jeem.2020.102405. https://doi.org/10.1016/j.jeem.2020.102405.

Hahn, R., and C. Cecot. 2009. "The benefits and cost of ethanol: an evaluation of the government's analysis." *Journal of Regulatory Economics* 35: 275–295. https://doi.org/10.1007/s11149-008-9080-1.

Hirth, L., F. Ueckerdt, and O. Edenhofer. 2015. "Integrtation costs revisited - An economic framework for wind and solar variability." *Renewable Energy* 74: 925–939. https://doi.org/10.1016/j.renene.2014.08.065.

Holland, S. P., J. E. Hughes, and C. R. Knittel. 2009. "Greenhouse gas reductions ander low carbon fuel standards." *American Economic Journal: Economic Policy* 1: 106–146. https://doi.org/10.1257/pol.1.1.106.

Huang, H., M. Khanna, H. Onal, and X. Chen. 2013. "Stacking low carbon policies on the renewable fuels standard: Economic and greenhouse gas implications." *Energy Policy* 56: 5–15. https://doi.org/10.1016/j.enpol.2012.06.002.

Hughes, J. E., and M. Podolefsky. 2015. "Getting green with solar subsidies: Evidence from the California Solar Initiative." *Journal of the Association of Environmental and Resource Economists* 2: 235–275. https://doi.org/10.1086/681131.

Jaffe, A. B., R. G. Newell, and R. N. Stavins. 2005. "A tale of two market failures: Technology and environmental policy." *Ecological Economics*54: 164–174. https://doi.org/10.1016/j.ecolecon.2004.12.027.

Johansson, P., and B. Kristrom. 2019. "Welfare evaluation of subsidies to renewable energy in general equilibrium: Theory and application." *Energy Economics* 83: 144–155. https://doi.org/10.1016/j.eneco.2019.06.024.

Johansson, R., S. Meyer, J. Whisance, W. Thompson, and D. Debnath. 2020. "Greenhouse gas emission reduction and cost from the United States biofuels mandate." *Renewable and Sustainable Energy Reviews* 119. https://doi.org/10.1016/j.rser.2019.109513.

Johnson, E. P. 2014. "The cost of carbon dioxide abatement from state renewable portfolio standards." *Resource and Energy Economics* 36: 332–350. https://doi.org/10.1016/j.reseneeco.2014.01.001.

Joskow, Paul L. 2011. "Comparing the costs of intermittent and dispatchable electricity generating technologies." *The American Economic Review*101 (3): 238–241. https://doi.org/10.1257/aer.101.3.238.

Karplus, V. J., S. Paltsev, M Babiker, and J. M. Reilly. 2013. "Should a vehicle fuel economy standard be combined with an economy-wide greenhouse gas emissions constraint? Implications for energy and climate policy in the United States." *Energy Economics* 36: 322–333. https://doi.org/10.1016/j.eneco.2012.09.001 .

Logan, J., A. Lopez, T. Mai, C. Davidson, M. Bazilian, and D. Arent. 2013. "Natural gas scenarios in the U.S. power sector." *Energy Economics*40: 183–195. https://doi.org/10.1016/j.eneco.2013.06.008.

Lyon, T. P., and H. Yin. 2010. "Why do states adopt renewbale portfolio standards? An empirical investigation." *The Energy Journal* 31: 133–157. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol31-No3-7.

Macintosh, A., and D. Wilkinson. 2011. "Searching for public benefits in solar subsidies: A case study on the Australian government's residential photovoltaic rebate program." *Energy Policy* 39: 3199–3209. https://doi.org/10.1016/j.enpol.2011.03.007.

Mai, T., J. Bistline, Y. Sun, W. Cole, C. Marcy, C. Namovicz, and D. Young. 2018. "The role of input assumptions and model structures in projections of variable renewable energy." *Energy Economics* 76: 313–324. https://doi.org/10.1016/j.eneco.2018.10.019.

McFarland, J. R., A. A. Fawcett, A. C. Morris, J. M. Reilly, and P. J. Wilcoxen. 2018. "Overview of the EMF 32 study on U.S. carbon tax scenarios." *Climate Chnage Economics* 9. https://doi.org/10.1142/S201000781840002X.

Metcalf, G. E. 2009. "Tax policies for low-carbon technologies." *National Tax Journal* 62: 519–533. https://doi.org/10.3386/w15054.

Metcalf, G. E. 2019. "The distributional impacts of U.S. energy policy." *Energy Policy* 129: 926–929. https://doi.org/10.1016/j.enpol.2019.01.076.

Mignone, B. K., S. Showalter, F. Wood, H. McJeon, and D. Steinberg. 2017. "Sensitivity of natural gas deployment in the US power sector to future carbon policy expectations." *Energy Policy* 110: 518–524. https://doi.org/10.1016/j.enpol.2017.08.012.

Mignone, B. K., T. Alfstad, A. Bergman, K. Dubin, R. Duke, P. Friley, A. Martinez, et al. 2012. "Cost-effectiveness and economic incidence of a clean energy standard." *Economics of Energy and Environmental Policy* 1: 59–86. https://doi.org/10.5547/2160-5890.1.3.5.

MITei. 2016. "Utility of the Future: An MIT Energy Initiative response to an industry in transition."

Muratori, M., H. Kheshgi, B. Mignone, L. Clarke, H. McJeon, and J. Edmonds. 2017. "Carbon capture and storage across fuels and sectors in energy system transformation pathways." *International Journal of Greenhouse Gas Control* 56: 34–41. https://doi.org/10.1016/j.ijggc.2016.11.026.

Novan, K. 2015. "Valuing the wind: Renewable energy policies and air pollution avoided." *American Economic Journal: Economic Policy* 7: 291–326. https://doi.org/10.1257/pol.20130268.

Palmer, K., A. Paul, M. Woerman, and D. C. Steinberg. 2011. "Federal policies for renewable electricity: Impacts and interactions." *Energy Policy*39: 3975–3991. https://doi.org/10.1016/j.enpol.2011.01.035.

Palmer, K., and D. Burtraw. 2005. "Cost-effectiveness of renewable electricity policies." *Energy Economics* 27: 873–894. https://doi.org/10.1016/j.eneco.2005.09.007.

Paltsev, S., H. Jacoby, J. M. Reilly, Q. Ejaz, J. Morris, F. O'Sullivan, S. Rausch, N. Winchester, and O. Kragha. 2011. "The future of U.S. natural gas productio, use, and trade." *Energy Policy* 39: 5309–5321. https://doi.org/10.1016/j.enpol.2011.05.033.

Rausch, S., and M Mowers. 2014. "Distributional and efficiency impacts of clean and renewable energy standards for electricity." *Resource and Energy Economics* 36: 556–585. https://doi.org/10.1016/j.reseneeco.2013.09.001.

Rausch, S., and V. J. Karplus. 2014. "Markets versus regulation: The efficiency and distributional impacts of U.S. climate policy proposals." *The Energy Journal* 35: 199–227. https://doi.org/10.5547/01956574.35.SI1.11.

Ridley, Ian, Justin Bere, Alan Clarke, Yair Schwartz, and Andrew Farr. 2014. "The side by side in use monitored performance of two passive and low carbon Welsh houses." *Energy and Buildings* 82: 13–26. https://doi.org/10.1016/j.enbuild.2014.06.038.

Rivers, N. 2013. "Renewable energy and unemployment: A general equilibrium analysis." *Resource and Energy Economics* 35: 467–485. https://doi.org/10.1016/j.reseneeco.2013.04.004.

Rubin, J., and P. N. Leiby. 2013. "Tradable credits system design and cost savings for a national low carbon fuel standard for road transport." *Energy Policy* 56: 16–28. https://doi.org/10.1016/j.enpol.2012.05.031.

Sarica, K., and W. E. Tyner. 2013. "Alternative policy impacts on US GHG emissions and energy security: A hybrid modeling approach." *Energy Economics* 40: 40–50. https://doi.org/10.1016/j.eneco.2013.06.003.

Schmalensee, R. 2012. "Evaluating policies to increase electricity generation from renewable energy." *Review of Environmental Economics and Policy* 6: 45–64. https://doi.org/10.1093/reep/rer020.

Tuladhar, S. D., S. Mankowski, and P. Bernstein. 2014. "Interaction effects of market-based and command-and-control policies." *The Energy Journal* 35: 61–88. https://doi.org/10.5547/01956574.35.SI1.4.
Wiser, R., T. Mai, D. Millstein, G. Barbose, L. Bird, J. Heeter, D. Keyser, V. Krishnan, and J. Macknick. 2017. "Assessing the costs and benefits of US renewable portfolio standards." *Environmental Research Letters* 12. https://doi.org/10.1088/1748-9326/aa87bd.
Yeh, S., and D. Sperling. 2010. "Low carbon fuel standards: Implementation scenarios and challenges." *Energy Policy* 38: 6955–6965. https://doi.org/10.1016/j.enpol.2010.07.012.
Young, D., and J. Bistline. 2018. "The costs and value of renewable portfolio standards in meeting decarbonization goals." *Energy Economics* 73: 337–351. https://doi.org/10.1016/j.eneco.2018.04.017.