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Marginal Abatement Cost Curves for U.S. Net-Zero Energy Systems

A Systems Approach

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Executive Summary

Traditional marginal abatement cost (MAC) curves have become the de facto starting point for comparing emission reduction measures since being popularized by McKinsey & Company more than a decade ago. However, traditional MAC methodologies are ill-suited to the task of today — analyzing the coordinated deployment of low- and zero-carbon measures required to reach net-zero energy systems by 2050. Prior methodologies have failed to assess cross-measure interactions and measure deployment across a range of marginal abatement costs, and they have relied on a comparison of measures to a counterfactual that does not reflect the dynamics of a decarbonizing energy system. This paper presents a new methodology that embraces the aspects of traditional MAC curves that make them so compelling (e.g., simplicity and accessibility) while also addressing their limitations. By utilizing the latest energy optimization models and systems-level analysis, our new approach produces a MAC curve that is more sophisticated and better suited for informing policy decisions around achieving net-zero.

Our approach models changes in the U.S. energy system between today and 2050 as marginal abatement costs increase. It produces a MAC curve that is more relevant for analyzing the trends and interactions associated with net-zero by making three critical improvements:

1. **Capturing critical interactions between measures and across sectors**, including how the order of deployment influences the cost and emissions reductions of subsequent measures. A classic example of this type of interaction is how the emissions reduction potential and marginal abatement cost of electric vehicles (EVs) depend on their adoption as well as the simultaneous deployment of clean electricity resources (i.e., emissions reductions from EVs are greater when the grid has cleaner electricity). This interdependency of measures is integrated into the analytical framework used to produce our MAC curves, resulting in more accurate estimates of measure emission reductions and cost.

2. **Using a systems-level methodology** to provide insights into the differing costs of deploying an individual measure under different contexts. The marginal abatement cost of a given measure can vary considerably depending on its level of deployment and the deployment of other measures in the energy system. For example, while solar PV might be a low or even negative cost measure in many areas of the country today, increasing its deployment will eventually require supporting resources (e.g., new transmission lines, batteries, or hydrogen electrolysis) to enable its integration — increasing its relative cost. Whereas traditional MAC curves generally depict the average cost of each measure, our approach shows how each measure could be deployed across a range of marginal abatement costs. By highlighting the importance of context and interactivity, our approach illustrates there is no single silver bullet solution for deep decarbonization and underscores the importance of coordinated measure deployment.

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3. **Expanding the array of relevant measures** to include those that only become cost-effective once there is significant deployment of other measures. For instance, electric boilers would not be included as an emissions reduction measure using a traditional MAC curve because deploying the measure today tends to increase emissions, even though it has the potential to decrease emissions if the electricity grid becomes cleaner. Since traditional MAC curves are primarily developed by assessing measures against a fossil-dominated counterfactual, they do not address how measures perform in an energy system with much lower emissions. This in turn limits what these approaches can say about when and which measures become cost-effective, as well as, how changes in the energy system drive these economics. By evaluating all measures over many marginal abatement costs, our new methodology can show the contexts in which measures like electric boilers become important, thereby offering deeper insights into the ultimate scale of measure deployment for deep decarbonization.

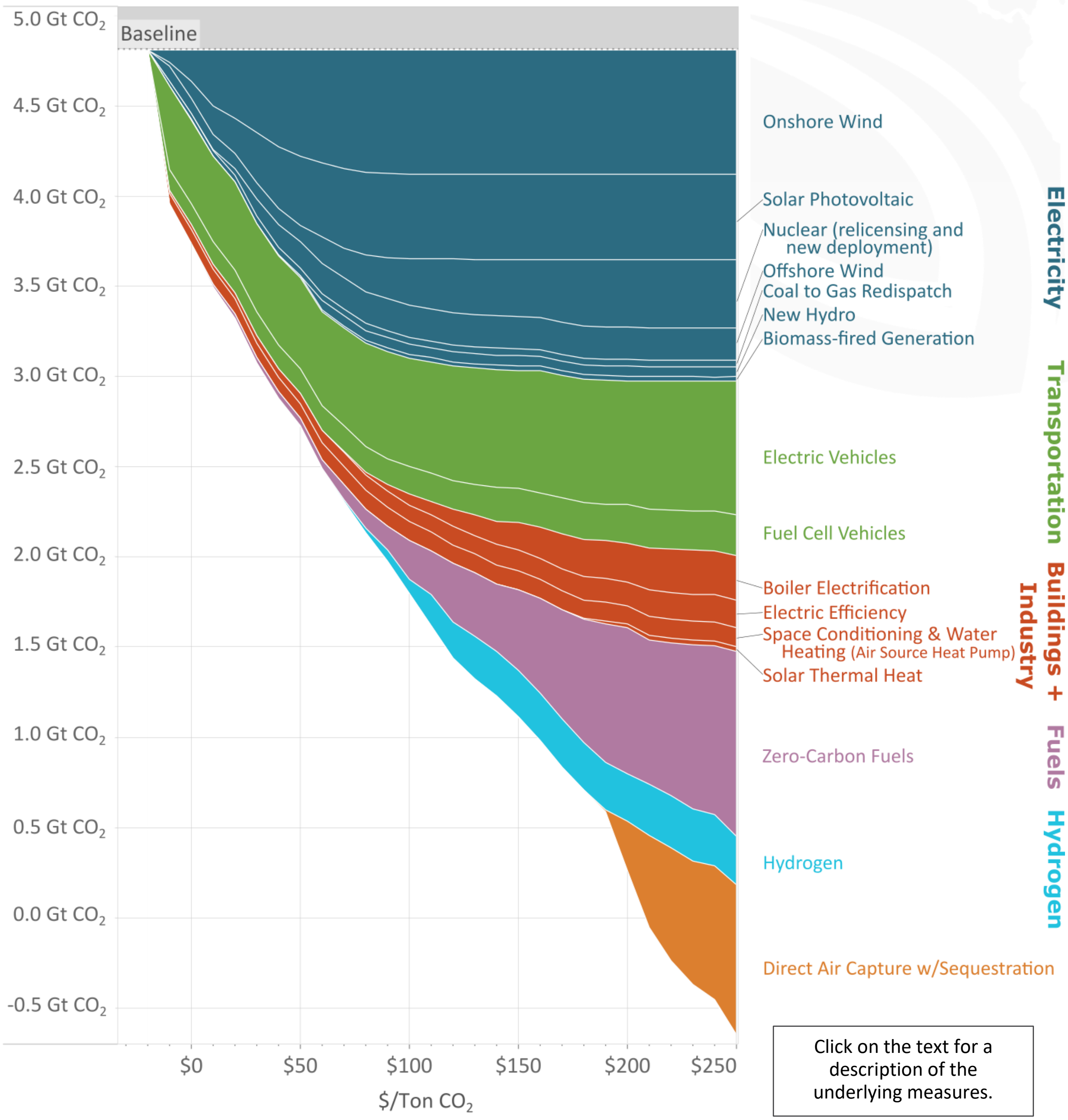
Figure 1 shows the results of our new methodology, a MAC curve of measures to reduce CO_2 emissions from the U.S. energy and industry system in 2050. The curve shows annual emission reductions from measures relative to a baseline scenario[1] as a function of marginal abatement cost. At the high end of the cost range in the figure,[2] the measures included in this analysis could, if deployed in coordination, collectively achieve net-negative CO_2 levels in line with net-negative greenhouse gas emissions across the whole economy.[3]

[1] The baseline reflects estimated measure deployment based on existing policy through the beginning of 2020.

[2] This range of marginal abatement costs fits with recent studies of achieving net-zero energy and industry CO_2 emissions for the U.S. by 2050 at modest cost, where annual energy system costs as a percentage of GDP are comparable or lower than recent energy system costs, including a paper on US Carbon-Neutral Pathways, and the Princeton University Net-Zero America study. As a specific example from the Princeton study, several scenarios achieve net-zero greenhouse gas emissions by 2050 at a modest incremental cost in the range of 1-3% of GDP. All these scenarios have 2050 marginal abatement costs in the range of $250 to above $350 per ton, with the differences driven by assumptions about the availability of key technologies.

[3] See the net-negative emission scenario in the recent US Carbon-Neutral Pathways study, where 2050 CO_2 net-emissions from industry and energy are -500 million tons.

Figure 1 – A 2050 MAC curve developed using the new approach, shows annual reductions from measures for U.S. energy and industry CO_2, where reductions are relative to 2050 emissions for a baseline scenario. Each segment represents an individual measure, and colors correspond to related groupings of measures.



This new approach offers key measure-specific insights in terms of deployment levels and emissions reductions by 2050. These are organized by ranges of marginal abatement cost:

- **Less than or equal to $0 per ton**

  Several measures are cost-effective at marginal abatement costs of $0 per ton or less — including several **electric vehicle** classes, **electric efficiency**, high-quality **solar PV** and **onshore wind** resources, and **nuclear relicensing**. Together, the measures in this range represent more than a gigaton of potential annual emission reductions by 2050. However, achieving these reductions will require addressing several non-cost barriers limiting deployment, including the slow rate of change of consumer awareness and market structures that would incentivize their deployment.

- **$0 to $60 per ton**

  In this range, an additional gigaton of annual reductions could be achieved, primarily driven by electricity measures including **solar PV**, **onshore wind**, and **offshore wind**. Among all measures in our analysis, these renewable generation measures offer the greatest opportunity for dramatic emissions reductions at a modest cost — reinforcing the policy imperative to support ongoing electricity decarbonization.

- **$60 to $90 per ton**

  As marginal abatement costs rise to $60-$90/ton, diminishing marginal returns begin to materially impact the cost-effectiveness of deployed measures. Incremental deployment of renewables continues in this range but at a much slower rate, involving resources with higher integration costs (e.g., new transmission lines, energy storage) and lower energy generation for the same installed capacity. Several measures to support the integration of variable renewable generation start to become cost-effective in this range, including **electric boilers, hydrogen electrolysis,** and **power-to-liquids**. **New advanced nuclear** power deployment also becomes cost-effective and represents significant annual emission reduction potential by providing zero-carbon electricity for regions with constrained renewable resources.[4]

- **$90 to $150 per ton**

  Zero-carbon fuel measures, particularly those derived from biomass, become a significant driver of emission reductions in the $90-$150/ton cost range. Biomass-derived fuel measures (e.g., **biomass pyrolysis** and **fischer-tropsch diesel**) that capture their carbon emissions also interact with **power-to-liquids** measures and begin enabling the deployment of synthetic fuel technologies by providing them with required carbon feedstocks. Increases in the scale of low carbon hydrogen production also drive meaningful emission reductions as both **biomass H_2 with carbon capture** and **gas H_2 with carbon capture** become cost-effective. **Electric boilers** come online as an industrial heat alternative and enable substantial emission reductions, both by displacing natural gas boiler emissions and by interacting with the electricity sector to support renewable integration.

- **$150 to $180 per ton**

  As marginal abatement costs rise to the $150-$180/ton range, zero-carbon fuel measures become the major emission reduction driver. Deployment of **biomass pyrolysis** and

[4] The MAC analysis behind the curve represents the U.S. as 14 regions, which enables this approach to offer insights on when regional resource potential constraints drive the deployment of particular measures in a region.

fischer-tropsch diesel continues, but with higher marginal abatement costs due to supply constraints driving higher-cost biomass feedstocks. **Power-to-liquids** and **electric boilers,** both of which depend on linkages to other sectors that face the same higher marginal abatement costs, are large contributors to emissions reductions in this range as well.

- **$180 per ton and above**

  Deployment of **direct air capture with sequestration** plays a central role at costs exceeding $180/ton, where deployment could drive large-scale emission reductions. The abatement cost estimates for direct air capture with sequestration are primarily driven by the availability and cost of zero-carbon electricity, which depends on the interaction of electricity decarbonization measures with those supporting renewable resource integration.

Across the range of marginal abatement costs, this updated curve provides deeper insights than traditional MAC approaches into the suite of measures needed to achieve large emission reductions. These advantages become increasingly clear as abatement costs rise and the scale of measure deployment creates new dynamics that influence the next phase of deployment. Based on these insights, key takeaways for policymakers include:

- Significant emissions reductions are available at low or even negative costs if non-cost barriers can be addressed.[5] Under a supportive policy framework, zero-emissions vehicles, building efficiency and electrification, and electricity decarbonization measures (such as wind and solar deployment and nuclear relicensing) could save over two gigatons of CO_2 in 2050 – roughly 50% of the way to net-zero CO_2 emissions from industry and energy use – at marginal abatement costs ranging from negative to very modest costs (less than $60 per ton).
- Decarbonization beyond these initial two-plus gigatons will require further coordinated measure deployment. In the transportation sector, zero-emissions-vehicle deployment expands to more challenging vehicle classes and consumer segments. In the power sector, additional electricity decarbonization becomes more expensive due to integration needs and diminishing marginal output potential. Effective policy formulations will anticipate the need for both low-cost and higher-cost measures to meet ambitous decarbonization goals and focus on enabling the high levels of electric vehicle and renewables deployment that are required. Policy interventions, like streamlined transmission siting rules and efficient electricity rate design, will be essential for achieving these measures' full potential.
- Fuels decarbonization, including hydrogen and liquids fuels, could save a little over one gigaton of CO_2 by 2050 – roughly 20% of the way to net-zero CO_2 emissions from industry and energy use – but will require the deployment of technologies that are not yet commercial or not currently deployed at a significant scale. Support for these

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[5] Examples of non-cost barriers include lack of consumer awareness or incentive structures. These can be addressed with targeted policy or programs, such as electric efficiency incentive programs.

technologies today, through research and development, early-stage commercialization, and ultimately large-scale deployment, will be important to achieve net-zero emissions.
- Direct air capture (DAC) has a potentially significant role as a backstop technology. Cost-effective deployment of DAC could begin well before emissions from the U.S. energy and industry system are close to net-zero. The possibility of DAC playing this role should be anticipated, and policy should support near-term commercialization so the technology is available to be deployed at scale when it becomes economical for decarbonization (i.e., at higher levels of electricity decarbonization and marginal abatement costs).

A systems-level approach to MAC curves can be a valuable addition to the toolkit of policymakers who are formulating ambitious decarbonization policy. Our methodology improves on traditional MAC approaches to better estimate the cost and performance of measures over a range of marginal abatement costs as the energy system transforms. This type of analysis highlights the importance of the coordinated deployment of measures. It can help policymakers understand how measures must build upon one another to unlock deeper reductions on a path to net-zero emissions. Additional results from the analysis, discussed in the body of the paper, offer insights into the necessary scale and timing of measure deployment, illustrating how the energy system evolves at different marginal abatement costs in 2030, 2040 and 2050. This new MAC approach can serve as a foundation for developing decarbonization roadmaps, playing a central role in informing R&D, market transformation priorities, and measure deployment strategies to reduce emissions at the least cost.

Introduction

This paper proposes a novel methodology for constructing marginal abatement cost (MAC) curves and presents initial results, which offers insights on the cooperative and differentiated roles of carbon abatement measures as the economy deeply decarbonizes through 2050. This new approach seeks to build on the fluency policymakers have with MAC curves by addressing some of the limitations of traditional MAC methodologies when analyzing systems that approach or achieve net-zero CO_2 emissions by mid-century. Our initial implementation of this new approach examines measures for reducing CO_2 emissions from energy and industry in the US, but future work can adapt this analysis to incorporate more sectors and non-CO_2 emission reduction measures.[6]

For policymakers seeking to understand the relative costs and impact of the menu of carbon abatement strategies, the MAC curve has become one of the preferred tools. Traditional MAC analyses assess a group of emission reduction measures and provide a sequence of abatement actions ordered by increasing cost based on the analysis of each measure's marginal cost and emission reduction potential. The primary result from these analyses is a MAC curve, which distills the calculations from the analysis into a single figure that shows both the total abatement potential and marginal abatement cost of each measure.

MAC curves often appear deceptively simple, obscuring the nuances and limitations in the analysis behind the chart. While well-executed and appropriately caveated MAC curves can make for an effective communication tool, there are significant intrinsic limitations to traditional methodologies, including difficulty capturing cross-measure interactive effects and estimating context-specific measure costs. These underlying limitations become more problematic when analyzing emission reduction targets that could be compatible with the Paris Agreement, which will require a sustained effort over multiple decades along with many measures working together in coordination. Our new methodology can address these limitations and capture the dynamics between critical measures for achieving deep decarbonization.

The next section of the paper addresses the compelling features of traditional MAC curves. The following section lays out the intrinsic limits of current MAC approaches that make them ill-suited for supporting ambitious emission reductions. We then provide an overview of the new methodology, with a more detailed formulation in the appendix. And the final section of the paper presents the results, including key insights for policymakers.

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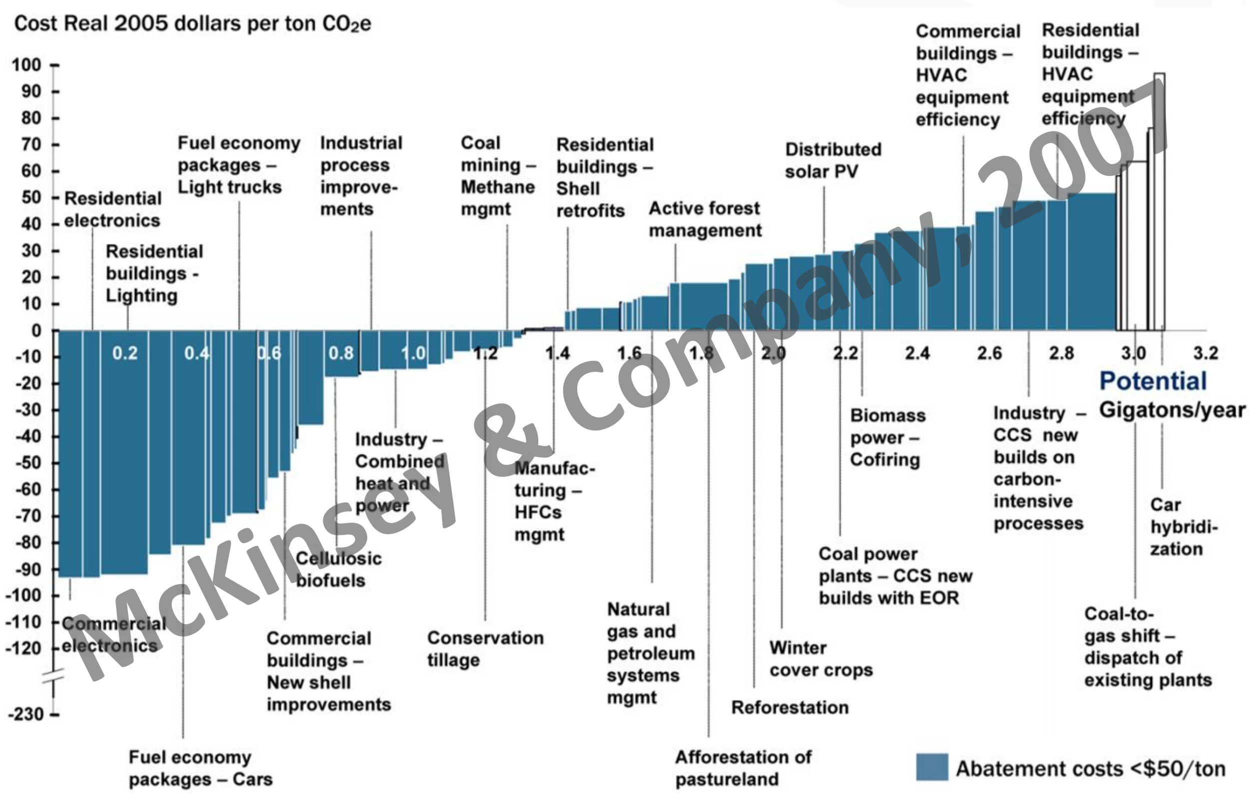
[6] This initial demonstration of our methodology focuses on energy and industry CO_2 emissions since they represent more than 80% of current US greenhouse gas emissions (https://www.epa.gov/sites/production/files/2020-04/documents/us-ghg-inventory-2020-main-text.pdf). Our MAC approach offers distinct advantages for assessing measures in the system that produces energy and industry CO_2 as it has strong interactive effects between measures, and the order of deployment can be critical. Measures for other sectors, like agriculture and other land uses, and for reducing other greenhouse gases could be incorporated into future analyses with additional modeling tools or results from other analyses, such as https://www.epa.gov/global-mitigation-non-co2-greenhouse-gases.

The Power of MAC curves

To date, MAC curves have served as a starting point for comparing different measures and technologies on an equivalent emission reduction basis. These curves have figured prominently in climate policy discussions. They have remained a compelling means of presenting measure reductions and cost (or savings) since the inception of this form of curve nearly forty years ago.[7] Since then, MAC curves in an emission reduction context have primarily been used to inform decisions about prioritizing between a wide array of options when achieving modest reductions over a near to medium term.

Figure 2 – 2030 marginal abatement cost curve from McKinsey & Company's 2007 study "Reducing US greenhouse gas emissions: How much at what cost?"



Traditional MAC curves all follow a similar form as Figure 2, which shows one of the best-known examples of a MAC curve from a 2007 McKinsey & Company analysis.[8] These curves order all the measures included in the analysis along the x-axis, where the width of each measure indicates the estimated emission reduction and the height along the y-axis represents the measures' estimated MAC. Measures with a negative marginal cost are, in theory, cost-effective at a marginal abatement cost of zero; they would reduce emissions and save money if they can be

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[7] Meier, A., J. Wright, et al. (1981). "Supply Curves of Conserved Energy for California's Residential Sector." Energy -- The International Journal 7: 347-358

[8] https://www.mckinsey.com/business-functions/sustainability/our-insights/reducing-us-greenhouse-gas-emissions

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deployed. The area swept by the curve through the targeted emission reductions estimates the policy cost to achieve those reductions.

The structure of the curve is both simple and accessible, even for audiences that are not fluent with the details of the MAC analysis that generated the results. MAC curves have also had success in helping readers better understand the relative costs and scale of reduction potential for different measures.

While traditional MAC curves directly present potential abatement and associated cost, they do not necessarily show the reader what order measures should be adopted. The curve's apparent simplicity can leave some readers to infer, incorrectly,[9] that the figure is a supply curve. Interpreting a MAC curve as a supply curve suggests that it shows the preferred order of adoption and that measures should be deployed sequentially by abatement cost, moving from the left side of the curve to the right. Many factors beyond marginal cost influence the order of measure deployment that will lead to decarbonization at the least cost, including interactive effects between measures and the time needed to develop mature markets to deliver technologies at scale.

[9] Vogt-Schilb, Adrien & Hallegatte, Stéphane. (2011). "When Starting with the Most Expensive Option Makes Sense: Use and Misuse of Marginal Abatement Cost Curves." The World Bank, Sustainable Development Network.

Traditional MAC Curve Limitations

There are structural issues with traditional MAC methodologies that make them ill-suited for analyzing the multi-decade effort needed for deep decarbonization. Previous work has identified some of the limitations of traditional MAC curves.[10] We summarize the issues for ambitious decarbonization into three main categories:

1. Traditional MAC methodologies fail to capture critical interactions between measures and across sectors, neglecting how the order of deployment influences the costs and emission reductions of subsequent measures (e.g., the cost and emission reductions from electric vehicles (EVs) depends on their level of adoption as well as the simultaneous deployment of clean electricity resources);
2. Traditional MAC curves poorly address how a measure's costs are highly context-specific (e.g., early solar PV additions might be a low or even negative cost measure, but at higher levels of deployment, the measure will require supporting resources, like storage or new transmission, which increases the cost of additional deployment). Typically these approaches struggle to represent how different levels of a measure's deployment influence its cost or provide limited insights on how the scale of deployment shapes the least-cost mix of measures;
3. Traditional MAC approaches typically exclude measures that can be critical components for deep decarbonization but only become cost-effective once there is significant deployment of other measures (e.g., electric boilers are often excluded as a measure because they tend to increase emissions in today's energy system, but they have the potential to decrease emissions if the electricity grid becomes cleaner).

These issues make traditional MAC curves poorly suited to address important questions about how measures interact as emissions decline and how to scale and sequence investments for deep emission reductions at the lowest cost.

The failure to capture interactive effects is illustrated most acutely with methodologies that assess measures in isolation. This approach can work for systems with limited interactive effects between measures. These are systems where the order of measure deployment has little or no impact on the marginal cost or achieving reductions (minimal 'path-dependency'). While this can be useful for simple systems, in practice, cross-sectoral interactions are the rule and not the exception for energy systems. The path-dependency of measures becomes more pronounced as emissions from the energy system decline, further complicating the application of traditional MAC approaches to deep decarbonization.

Updates to this MAC approach have used a pre-determined order for applying measures (sometimes using the isolated deployment methodology above), where each subsequent measure assumes the deployment of all others before it. This approach captures some degree of

[10] Kesicki, F. and Ekins, P. (2011). "Marginal Abatement Cost Curves: a Call for Caution." Climate Policy. Vol. 12, Issue 2. 219-236. https://doi.org/10.1080/14693062.2011.582347

interactivity. However, with marginal cost and abatement potential being path-dependent, the pre-determined order heavily influences the results, and determining the sequence of measures can be as much art as science. For example, if electric vehicles come after the deployment of renewables, the grid is cleaner and more carbon gets abated. By contrast, if electric vehicles come before the deployment of renewables, abatement from electric vehicles will appear smaller. Questions of allocating emission reductions are present in all MAC analyses, but because these approaches cannot deploy more than one measure at once, they face significant allocation challenges, and their results are difficult to interpret.

Not being able to model the deployment of concurrent measures at a single abatement cost is tied to the second structural issue for traditional MAC approaches, which is an inability to address highly context-specific measure costs. While many measures may have initial deployments that are cost-effective at low MAC, as their deployment increases their MAC rises. The reason for these increasing costs is the diminishing marginal returns of abatement measures. All emission abatement measures in an energy system show declining marginal impact and increasing marginal cost as their deployment grows. This is because all energy commodities exist on a supply curve where scarcity in an underlying resource (land for renewables, available biomass, oil wells) drives an increasing marginal cost with increasing volume.[11]

In a net-zero energy system with high renewable deployment, multiple terawatts of wind and solar might be deployed. However, this deployment will be accompanied by other measures that interact with renewable generation (e.g., electrification, deployment of batteries, construction of transmission). To properly assess cost and emission reductions, these measures need to be considered as a system that can fully account for cross-measure interactions and diminishing marginal returns. Instead, traditional MAC curves assess one measure (e.g., solar PV) and deploy its full potential before moving to the next measure. By neglecting cross-measure interactions and simplifying diminishing marginal returns, these analyses create an illusion of a definite sequence of deployment that implies policy priorities for ordering measures. In reality, measure deployment is more complicated; as increasing amounts of solar are deployed, its marginal value as a measure decreases and its marginal costs increase. As more electrification occurs demand for clean electricity increases raising the marginal value of new additions, this in turn creates room for more solar additions, making new solar deployment economical.

A partial solution to the diminishing marginal returns problem for traditional MAC curves is to break a single measure into multiple sub-measures, each representing a smaller portion of the total deployment. However, this often makes interpretation of the curve more complicated and does not necessarily provide new information about how and which measures should be deployed together. Our new methodology expands on this idea of sub-measures by allowing all measures to increase (or decrease) deployment at a single marginal abatement cost and re-

[11] This ignores 'technological learning' whereby greater deployment leads to cost reductions. This does not dispute the fact that all energy commodities exist on a supply curve but merely creates a countervailing trend within some resources after introducing a time dimension.

envisioning the resulting MAC curve to provide digestible information about concurrent measure deployment.

The final major limitation of traditional approaches is the exclusion of measures that can provide meaningful emission reductions once there is deployment of other measures at-scale. Traditional MAC methodologies assess measures against a mostly static counterfactual, which means measures are compared against a fossil-dominated counterfactual. This disadvantages measures that can only cost-effectively reduce emissions when the energy system has already started to decarbonize.

For example, electric boilers are often not included as an emissions abatement measure using a traditional MAC curve because deploying the measure today or in a system that looks a lot like today tends to increase emissions. However, electric boilers have significant potential to decrease emissions once the electricity grid becomes cleaner. Even modified MAC approaches that assume a sequence of measure deployment to capture some of the path-dependent effects can have issues with these kinds of measures, as the modelers may assume an order of measure deployment that never gives these measures an opportunity to become cost-effective. This structural issue with traditional approaches ends up excluding measures, limiting what they can tell us about which measures become cost-effective and how changes in the energy system drive these economics.

The limitations discussed above muddy the effectiveness of traditional MAC curves to inform policymakers. Addressing them can improve the accuracy of cost and emissions reduction estimates while also providing clearer insights about the most cost-effective order and bundling of measure deployment within a complex system.

The methodology presented in this white paper tries to embrace the aspects of MAC curves that make them so compelling (e.g., simplicity, accessibility) while also addressing these limitations. By utilizing the latest energy optimization models, our approach creates a MAC analysis that is more sophisticated and better suited for informing policy decisions around achieving deep decarbonization.

A MAC Methodology for Deep Decarbonization

The core of our MAC methodology is a comparison of least-cost systems over multiple years at different marginal abatement costs. The MAC curve from this approach offers deeper insights over a much longer time horizon than traditional approaches, assessing 2030, 2040 and 2050 over a range of marginal abatement costs. By comparing how changes in the marginal abatement cost affect the deployment of all measures, rather than stitching together the changes from examining a single measure at a time, this approach can address the limitations of traditional MAC methods and capture the dynamics within a system as it evolves to reach low, or even negative, levels of emissions.

Developing a MAC curve based on incremental changes in the least-cost energy system as cost increases contrasts significantly with previous MAC analyses. Many past studies have focused on narrow scopes and near-term abatement decisions. Generally, these have focused on addressing one or more of the following categories: retrospective or near-term prospective evaluation of the cost of specific policies,[12] characterizing the incremental addition of a select set of measures within a narrowly defined set of scenarios,[13] or exploring the retrofit of particular resources within the existing energy system.[14]

Compared to these other approaches, our methodology provides broader insights into the MAC of different measures over a 30-year time horizon by more explicitly incorporating path-dependent, cross-sector interactions, the diminishing returns of marginal measures, and considering measures that become cost-effective when other measures are deployed at scale. By addressing the limitations of previous approaches, this methodology provides better estimates of cost and emission reductions while also making the timing and optimal order of measure deployment an explicit result. With these methodological improvements, this approach can better internalize the complicated dynamics of decarbonizing the energy system at a level compatible with ambitious climate targets.[15]

Implementing this approach requires a different overall structure than previous MAC analysis. Whereas previous MAC work considered the change in cost and emissions associated with

[12] For a recent example, including a meta-analysis of studies in this category, see: Gillingham, Kenneth, and James H. Stock. 2018. "The Cost of Reducing Greenhouse Gas Emissions." Journal of Economic Perspectives, 32 (4): 53-72.

[13] For a recent example, see: Friedmann , S. Julio, and Zhiyuan Fan, Zachary Byrum, Emeka Ochu, Amar Bhardwaj, Hadia Sheerazi. 2020 "Levelized Cost of Carbon Abatement: An Improved Cost-Assessment Methodology For A Net-Zero Emissions World."

[14] For a recent example, see the CCUS economics portion of: National Petroleum Council. 2019. "Meeting the Dual Challenge: A Roadmap to At-Scale Deployment of Carbon Capture, Use, and Storage in the United States." https://dualchallenge.npc.org/downloads.php.

[15] While our new methodology addresses key limitations for using a MAC curve to understand deep decarbonization strategies, as with other MAC implementations it does not represent the non-financial costs that impede the adoption of measures, including measures that would reduce costs (represent a savings) while also reducing emissions.

implementing a single measure, this methodology considers all the system changes driven by changes in the marginal abatement cost. Under this approach, each incremental change in the marginal abatement cost drives measure deployment from a broader set of available measures. This requires a two-step process:

(1) Modeling the least-cost systems over the range of marginal abatement costs to find the changes in emssions and in measure deployment; and
(2) Allocating emission reductions to each measure, where reductions are allocated based on which measure is most proximal to the cause of the reductions.

The appendix expands on these two steps with a detailed discussion of the methodology, including the modeling requirements for the methodology's first step. While this approach requires more steps than a traditional MAC analysis, its implementation adds a small amount of complexity compared to traditional approaches but yields more insightful results. Key insights from this new methodology include:

- **The impact of cross-measure interactions as energy-consuming sectors increasingly rely on electricity.** Tighter coupling of energy-using sectors to the electricity sector, through electrification of transportation, buildings, and industry, along with hydrogen from electrolysis, will create new dynamics in the energy system. Large-scale energy conversion loads, like electrolysis for hydrogen production and industrial electric boilers for steam production, can have significant cross-measure interactions by supporting electricity balancing for high renewable systems and lowering marginal abatement costs for additional renewable deployment. Our approach captures these systems-level, sector-coupling interactive effects, and the results reflect better estimates of MAC for all measures in addition to capturing the differing costs of deploying a measure under different contexts.
- **The dynamics of cost-effective fuel-switching.** The cost-effectiveness of fuel-switching measures (e.g., light-duty electric vehicles, air-source heat pumps, medium-duty fuel-cell vehicles) depends on various factors as the energy system transforms, including how measure costs evolve and the cost of the low-carbon fuel that substitutes for the conventional fuel. Other measures—including low-carbon electricity, hydrogen, and decarbonized fuel measures—play a significant role in determining the cost-effectiveness of fuel-switching. Understanding when fuel-switching measures become an economical option for decarbonization can only be done by assessing a range of measures at a system-wide level. Our approach is built around the needed systems-level analysis to consider the many factors shaping the economics of fuel-switching.
- **Flexibility's role in a reliable electricity system.** Ensuring reliable hourly operation of the electricity system as emissions decline will require a changing set of resources with different utilization. An increasing share of variable renewable energy production technologies will create new dynamics in the electricity system. These dynamics will increase the value of flexibility and quick responses to system needs and, at the same time, lower the value of inflexible technologies. These changes impact the MAC

estimates of many different measures. For renewable generation measures increasing needs for integration resources like battery storage and transmission resulting in higher marginal abatement costs. For measures that depend on the availablity of zero-carbon electricity (e.g., electrficaiton of industrial heat and electrolysis), their ability to offer flexiblity to a high renewable system can improve their economics. A robust assessment of MAC and emission reductions requires need to address these flexibility dynamics. Our approach captures this, and ensures that MAC estimates reflect the costs of maintaining reliability in a high renewable electricity system.

- **Balancing tradeoffs between regional resource constraints and the cost of moving energy between regions.** Every geographical region faces resource constraints for renewable generation, geological carbon sequestration, and biomass feedstocks. A key planning question for deep decarbonization is how to manage the tradeoffs of meeting a region's energy demand with potentially higher cost local resources or investing in the ability to transfer energy into the region (e.g., new electricity transmission, new pipelines, or biomass transportation costs). Our approach considers these regional constraints and finds the tradeoffs that enable decarbonization at the least cost, [16] factoring the cost of energy transfers into the MAC of measures (e.g., the cost of incremental deployment of renewable measures reflects when new transmission upgrades are required).
- **The optimal order and timing of measure investments.** Over the next thirty years, declining resource costs and the range of potential marginal abatement costs can significantly impact the timing and order of measure deployment for the system, which is a critical component of effective climate policy. Our approach accounts for declining resource cost dynamics by modeling mutlipe years for each MAC, sheding light on difficult questions around the order and timing of measure deployment. These aspects of our new MAC approach are captured in additional results that suppliment the re-envisioned MAC curve, see the Additional Results and Insights section.

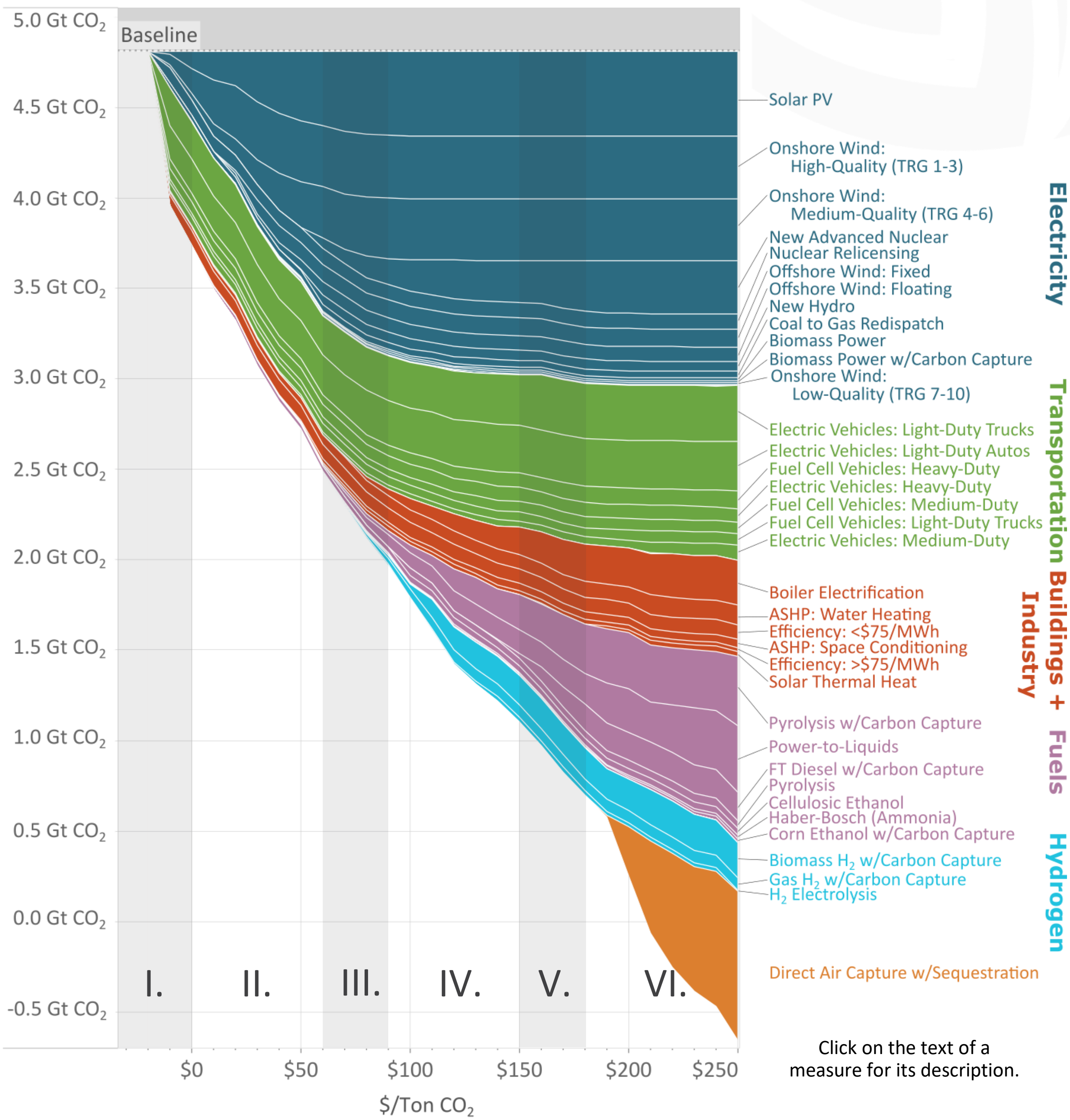
The analysis for this white paper includes a baseline scenario in addition to the range of least-cost systems at each marginal abatement cost. This scenario reflects what measure deployment looks like in the absence of policy intervention. The transition from the baseline scenario to the initial step in the range of marginal abatement costs shows how some measures are cost-effective even at negative marginal abatement costs if enabling policy is in place.

[16] Regional results are not shown in this initial demonstration of our new MAC approach. One example of where this insight can been found in the results presented here is the deployment of new advanced nuclear, which becomes cost-effective as a measure when regions with limited renewable resource potential face higher MAC and make tradeoffs between importing more clean electricity or building new nuclear.

MAC Curve 2.0

Figure 3 shows a MAC curve of measures to reduce US energy and industry CO_2 emissions developed with the methodology presented in this whitepaper. Rather than showing MAC against emission reductions like a traditional MAC curve, this curve plots reductions against MAC to make it easier to follow emission reductions for measures across multiple MAC. Color corresponds to a category of measures, and individual wedges provide measure level detail.

Figure 3 – A 2050 MAC curve for US energy and industry CO_2 where emission reductions are relative to a baseline scenario. The MAC ranges on the chart (e.g., I., II.) are addressed in the following section.



Click on the text of a measure for its description.

Figure 3 shows how emissions decline as more measures become cost-effective at higher marginal abatement costs.[17] At the high end of the cost range in the figure,[18] the measures included in this analysis could, if deployed in coordination, collectively lower emissions to net-negative CO_2 levels. The left-most point on the x-axis represents emissions from the baseline scenario.

The chart illustrates how our systems-level approach makes three critical improvements over traditional MAC approaches: multiple measures can be deployed at any marginal abatement cost, which means a measure's emission reduction potential depends on the deployment of other measures; deployment of each measure takes place over a range of marginal abatement costs depending on what is going on in the rest of the energy system rather than at a single cost level, which shows the importance of coordinated deployment for achieving the least-cost mix of measures; and the curve provides robust insights about how these measures could collectively reduce 2050 CO_2 emissions to net-zero, or even to net-negative levels by also including measures that only become cost-effective once there is significant deployment of other measures.

Insights by Marginal Abatement Cost Range

The curve in Figure 3 shows measure costs and emission reduction potential, just as traditional MAC curves do, but also illustrates how an increasing marginal abatement cost will drive system-wide effects and the relative strengths of our updated MAC methodology. To demonstrate how these are represented in the curve, the x-axis of Figure 3 has been divided into six different cost ranges. The following section discusses key insights for each range along the curve and explains the dynamics of additional emissions reduction in these cost ranges.

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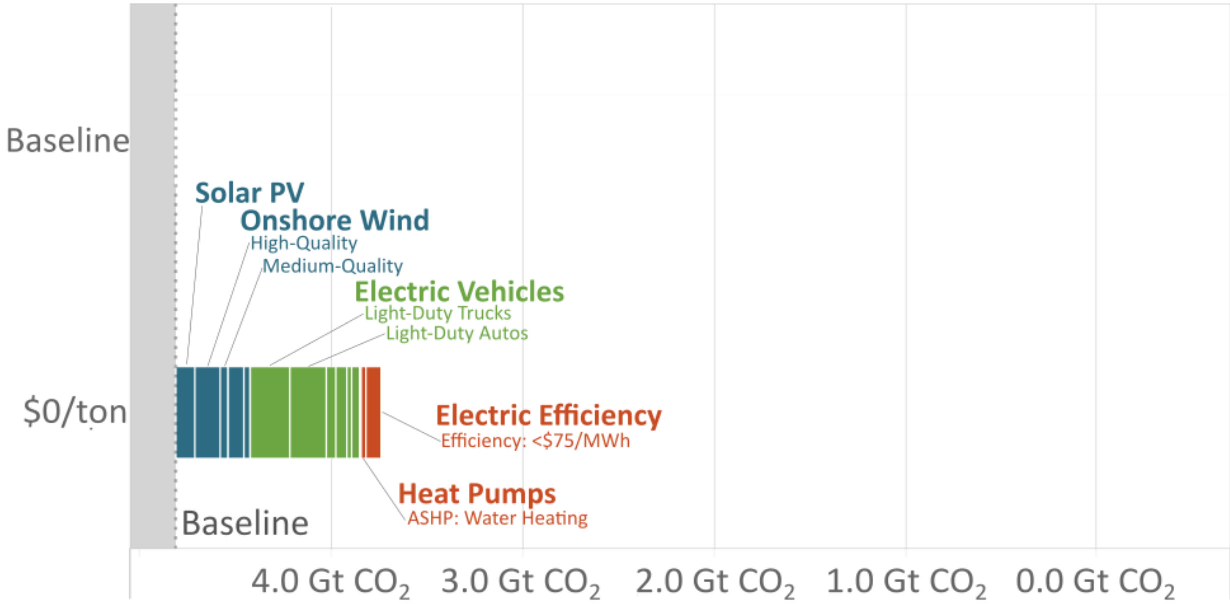
[17] The structure of the chart is analogous to climate stabilization wedges charts popularized by Stephen Pacala and Robert Socolow (https://science.sciencemag.org/content/305/5686/968), but this MAC curve shows reductions against marginal abatement cost rather than reductions against time.

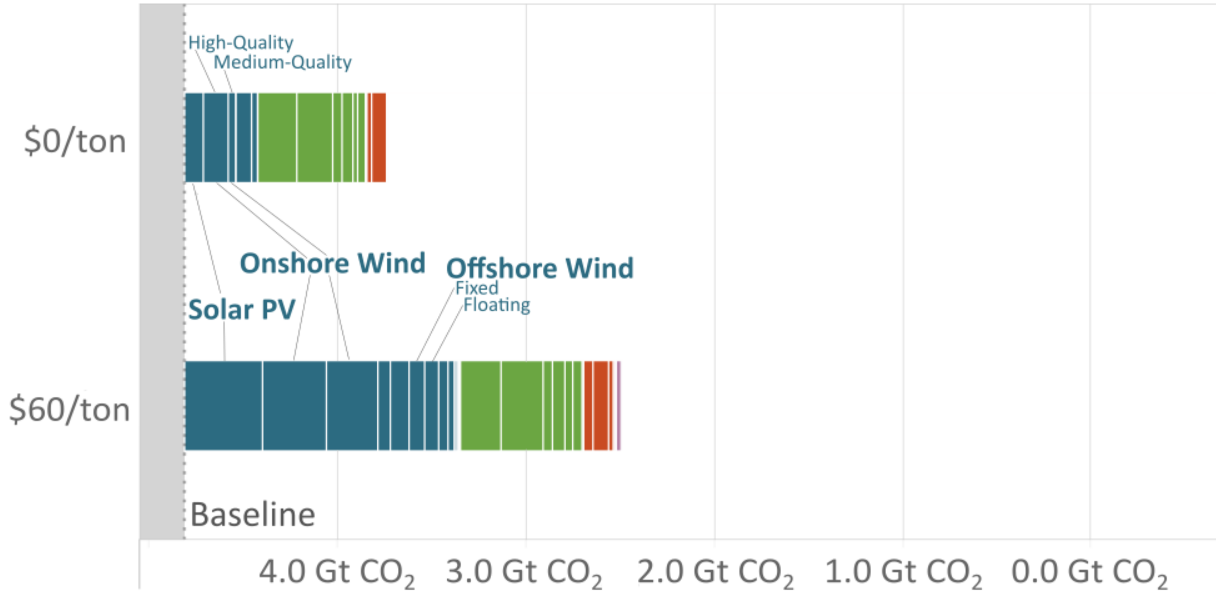
[18] This range of marginal abatement costs fits with recent studies of achieving net-zero energy and industry CO_2 emissions for the US by 2050 at modest cost, where annual energy system costs as a percentage of GDP are comparable or lower than recent energy system costs, including a paper on US Carbon-Neutral Pathways, and the Princeton University Net-Zero America study. As a specific example from the Princeton study, several scenarios achieve net-zero greenhouse gas emissions by 2050 at a modest incremental cost in the range of 1-3% of GDP. All these scenarios have 2050 marginal abatement costs in the range of $250 to above $350 per ton, with the differences driven by assumptions about the availability of key technologies.

Figure 4 – The change in measure emission reductions over range I, which spans the Baseline to a marginal abatement cost of $0 per ton (including negative costs), representing a decrease of 1 gigaton.



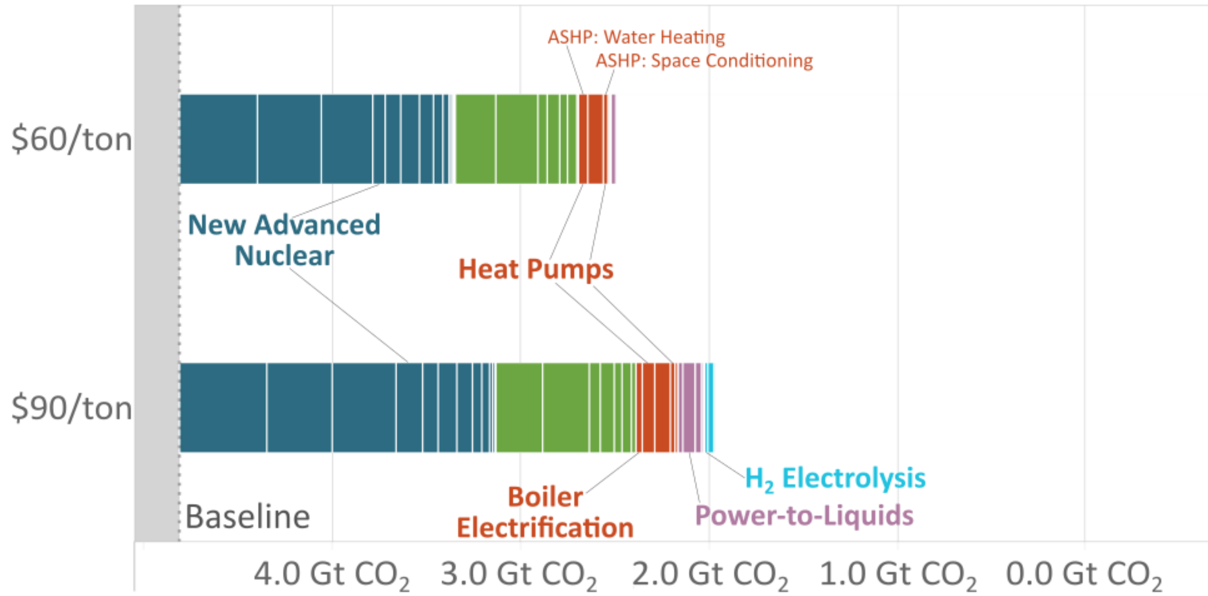
I. Measures within this range are cost-effective at marginal abatement costs at or less than **$0 per ton** and represent emissions reductions that can be achieved at a cost savings. We do not assume these are achieved in our baseline because they may still require additional policy support. Though cost-effective across many vehicle classes, **electric vehicles** still need support in the form of enabling policies (EV charger investment, efficient electricity rate design, etc.). **Electric efficiency** may also not be deployed without incentive or awareness programs, even when such investments are cost-effective. Finally, as **heat pump** technology improves, these measures may still necessitate market transformation programs in areas where they are not prevalent today or not understood to be cost-effective. Specifically, some regions where older technologies were not cost-effective, like the Northeast, may require policy support even if future measure deployment is cost-effective. In electricity, negative cost reductions are available through the deployment of high-quality **solar PV** and **onshore wind** resources**. Nuclear relicensing** for the existing fleet up to 80 years is a negative cost measure that may not be achieved given existing market and incentive structures. Together, the measures in this range represent more than a gigaton of annual emission reductions that could be achieved at cost savings if the non-cost barriers that prevent their adoption can be addressed. While other MAC approaches also find negative cost measures, a fundamental improvement in our approach is tracking the continued deployment of these measures at higher MAC. Our systems-level approach offers insights on how changing energy system dynamics make it cost-effective to deploy more of these measures at higher abatement costs.

Figure 5 – The change in measure emission reductions over range II, which spans marginal abatement costs of $0 to $60 per ton, representing a decrease of roughly 1.3 gigatons.



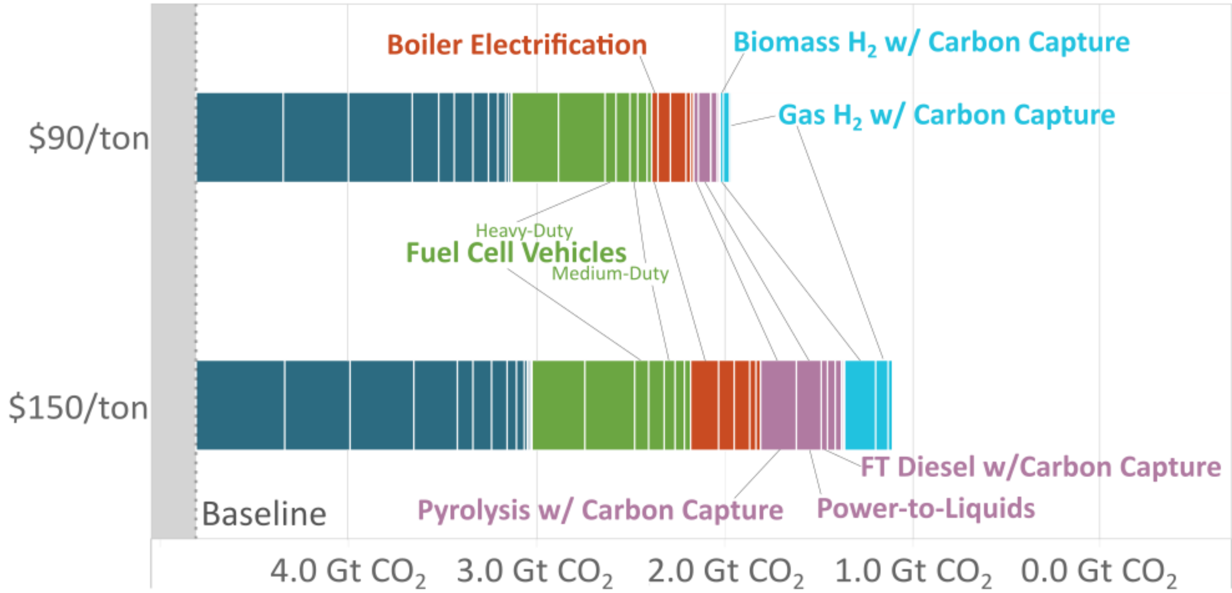
II. In this range, **$0-$60/ton**, electricity decarbonization represents the majority of modest cost emissions reductions. Roughly one gigaton of annual reductions in CO_2 is available by 2050 at modest marginal abatement costs. Even current technology costs suggest an approaching tipping point where aggressive electricity decarbonization policy becomes a low-cost means of reducing emissions. This decarbonization is achieved with the additional deployment of **solar PV** and **onshore wind** as well as **offshore wind** (which increases from effectively no deployment). Whereas traditional MAC approaches can present complications in understanding if the order measures were assessed is driving a similar result, our methodology directly resolves this issue and provides more robust findings that account for cross-measure interactions.

Figure 6 – The change in measure emission reductions over range III, which spans marginal abatement costs of $60 to $90 per ton, representing a decrease of half a gigaton.



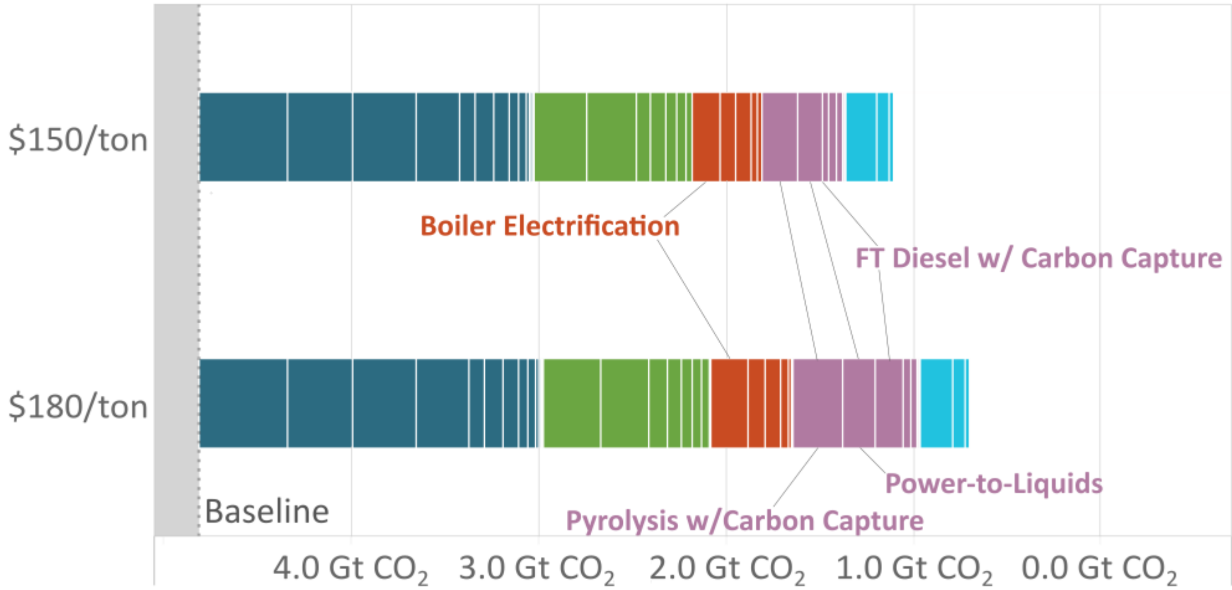
III. Additional electricity decarbonization is available in the **$60-$90/ton** range. Higher marginal cost measures result from lower energy production for the same installed capacity as the supply of the highest-quality and lowest-cost resources is exhausted, along with growing integration needs as renewable penetration increases. These integration solutions take the form of battery storage, new transmission, **electric boilers, hydrogen electrolysis,** and **power-to-liquids**. The interactions of these measures with the increasing deployment of electricity decarbonization measures drive their cost-effectiveness. The same dynamics that slow the deployment of renewables, principally the oversupply of renewable energy in some hours, improve the economics of these integration measures. The ability to capture how cross-measure interactions impact the costs and emission reductions from all measures represents an improvement over traditional MAC approaches. Market structures that encourage investment in these types of integration solutions that do not currently exist at scale and are not supported in electricity markets today will be imperative to achieving renewables at this scale. Deployment of **new advanced nuclear** power becomes cost-effective at this level, providing electricity in areas with constrained renewable resources. Additional **heat pump** deployment in regions with less conducive climates to heat pump performance and **electric efficiency** also become available in this range.

Figure 7 – The change in measure emission reductions over range IV, which spans marginal abatement costs of $90 to $150 per ton, representing a decrease of roughly 0.9 gigatons.



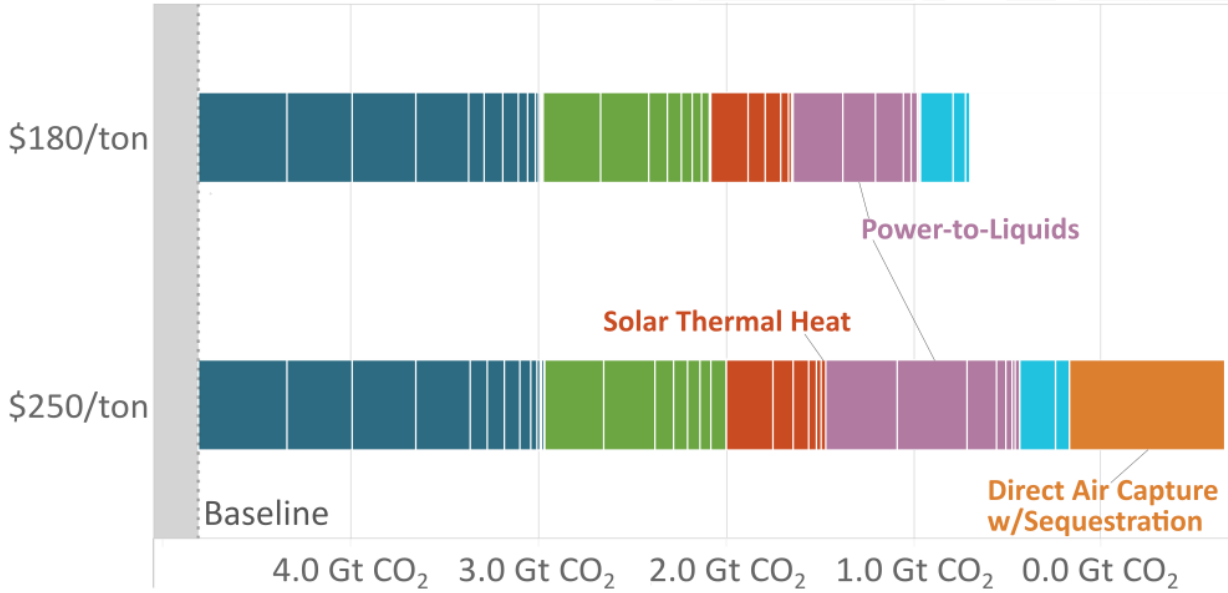
IV. Zero-carbon fuels make more significant emissions contributions from **$90-$150/ton** with the increased deployment of biofuels, specifically **biomass pyrolysis** and **fischer-tropsch** diesel (increasing from no deployment). **Biomass H_2 with carbon capture** contributes to the decarbonization of hydrogen supplies that would be produced from natural gas reformation at lower marginal abatement costs. **Reformation with carbon capture** also contributes to hydrogen decarbonization to supply industry as well as the growing use of hydrogen in transportation applications (**fuel-cell medium-duty and heavy-duty trucks**). Decarbonization of industrial heat with **electric boilers** contributes to additional emissions reductions due to its ability to link the supply of steam, which otherwise would come from natural gas boilers, to the electricity sector. This linkage, referred to as “sector-coupling,” lowers industrial emissions while also helping to integrate more renewables on the electricity grid. Additional **power-to-liquids** is also deployed in this range to displace liquid fossil fuels. At marginal abatement costs of this level and above, our methodology provides marked improvements over traditional approaches since interactive effects between measures become a significant driver of MAC and emission reductions of each incremental measure.

Figure 8 – The change in measure emission reductions over range V, which spans marginal abatement costs of $150 to $180 per ton, representing a decrease of 0.4 gigatons.



V. Zero-carbon fuels in the form of additional **biomass pyrolysis** and **fischer-tropsch** facilities become the major emission reduction driver at **$150-$180/ton.** This set of biofuel measures is more expensive due to the rising costs of zero-carbon feedstocks driven by supply constraints. Additional **electric boilers** and **power-to-liquids,** both of which depend on linkages to other sectors that all face the same higher marginal abatement costs, are also significant contributors to emissions reductions in this cost range. As with the previous range of costs, the improvements in our methodology enable the analysis to generate these insights. Traditional MAC approaches cannot determine when the shift in focus from electricity to fuel decarbonization occurs because this depends on how costs change with a lower emission electricity grid. These measures only become cost-effective once there is already large-scale deployment of other measures. Traditional MAC approaches rely on assessing measures against counterfactuals that have higher emissions and do not reflect the same large-scale deployment of other measures on the system.

Figure 9 – The change in measure emission reductions over range VI, which spans marginal abatement costs of $180 per ton or above, representing a decrease of roughly 1.3 gigatons.



VI. **Direct air capture** plays a central role at costs exceeding **$180/ton**, where direct air capture with carbon sequestration is deployed. Direct air capture for utilization (**power-to-liquids**) is deployed at lower costs as well as in this range, but for additional emission reductions through sequestration, marginal costs need to approach $200/ton to deploy these measures. The abatement cost estimates for direct air capture with sequestration are primarily driven by the availability and cost of zero-carbon electricity, which depends on the interaction of electricity decarbonization measures with measures that support the integration of renewable generation. Without a systems-level approach, it is difficult to assess the MAC of direct air capture with sequestration under very-low or even net-negative CO_2 emissions. Within this cost range, industrial **solar thermal heat** also becomes an option to displace natural gas usage in certain regions with high solar insolation.

Key Takeaways from the New Curve for Policymakers

We represent a curve with emission reductions measures in excess of what is needed to achieve net-zero energy and industrial CO_2 in 2050. Net-zero energy and industrial CO_2 is consistent with a net-zero economy for all emissions (including non-energy, non-CO_2 emissions).[19] It is an important caveat to note that the curve represented here, despite achieving net-zero emissions, is not exhaustive of the potential pathways for doing so. Specifically, significant reductions may be available from measures that are not represented in our analysis, such as carbon capture in industries like cement as well as iron and steel; additional process heating electrification may be available in industry; and there are additional efficiency, electrification, and fuel-switching reductions that may be available in off-road transportation (aviation, freight rail, shipping, etc.).

[19] https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2020AV000284

These measures may be lower-cost than some of the fuel substitution or direct air capture opportunities represented in the curve's higher-cost regions. They could be incorporated into the curve with additional analysis and modeling tools.

Even with the appropriate caveats, the messages for policymakers from the curve are clear:

1. Significant emissions reductions are available at low or even negative costs if non-cost barriers can be addressed. With policy action, zero-emissions vehicles, building efficiency, and electrification, and electricity decarbonization measures, such as wind and solar deployment and nuclear relicensing, could save over two gigatons of CO_2 in 2050 from a baseline scenario at marginal abatement costs ranging from negative to very modest costs (less than $60 per ton).
2. Decarbonization beyond these initial two-plus gigatons will require further coordinated measure deployment. Zero-emissions-vehicles are deployed to more vehicle classes and to energy consumers who are more reluctant to adopt vehicles with higher up-front costs even if they are cost-effective over their lifetime. Additional electricity decarbonization becomes more expensive. This is due to rising marginal abatement costs of renewables as penetration increases, caused by the need for more renewable integration solutions, such as new transmission lines or energy storage, and lower energy production for the same installed capacity as the supply of the highest quality resources declines. To meet ambitious decarbonization goals, both low-cost and higher-cost measures will be needed to achieve the necessary scale of deployment. Effective policy formulations will anticipate this need and focus on enabling very high levels of electric vehicle and renewables deployment. Policy interventions, like streamlined transmission siting rules and efficient electricity rate design, will be essential for achieving these measures' full potential.
3. Fuels decarbonization, including hydrogen and liquids fuels, will require the deployment of technologies that are not yet commercial or not currently deployed at a significant scale. Support for these technologies today, through research and development, early-stage commercialization, and ultimately large-scale deployment, is necessary to achieve net-zero emissions.
4. Direct air capture (DAC) has a potentially significant role as a backstop technology. Cost-effective deployment of DAC could begin well before emissions from the US energy and industry system are close to net-zero. The possibility of DAC playing this role should be anticipated, and policy should support near-term commercialization so the technology is available to be deployed at scale when it becomes economical in a low-carbon future.

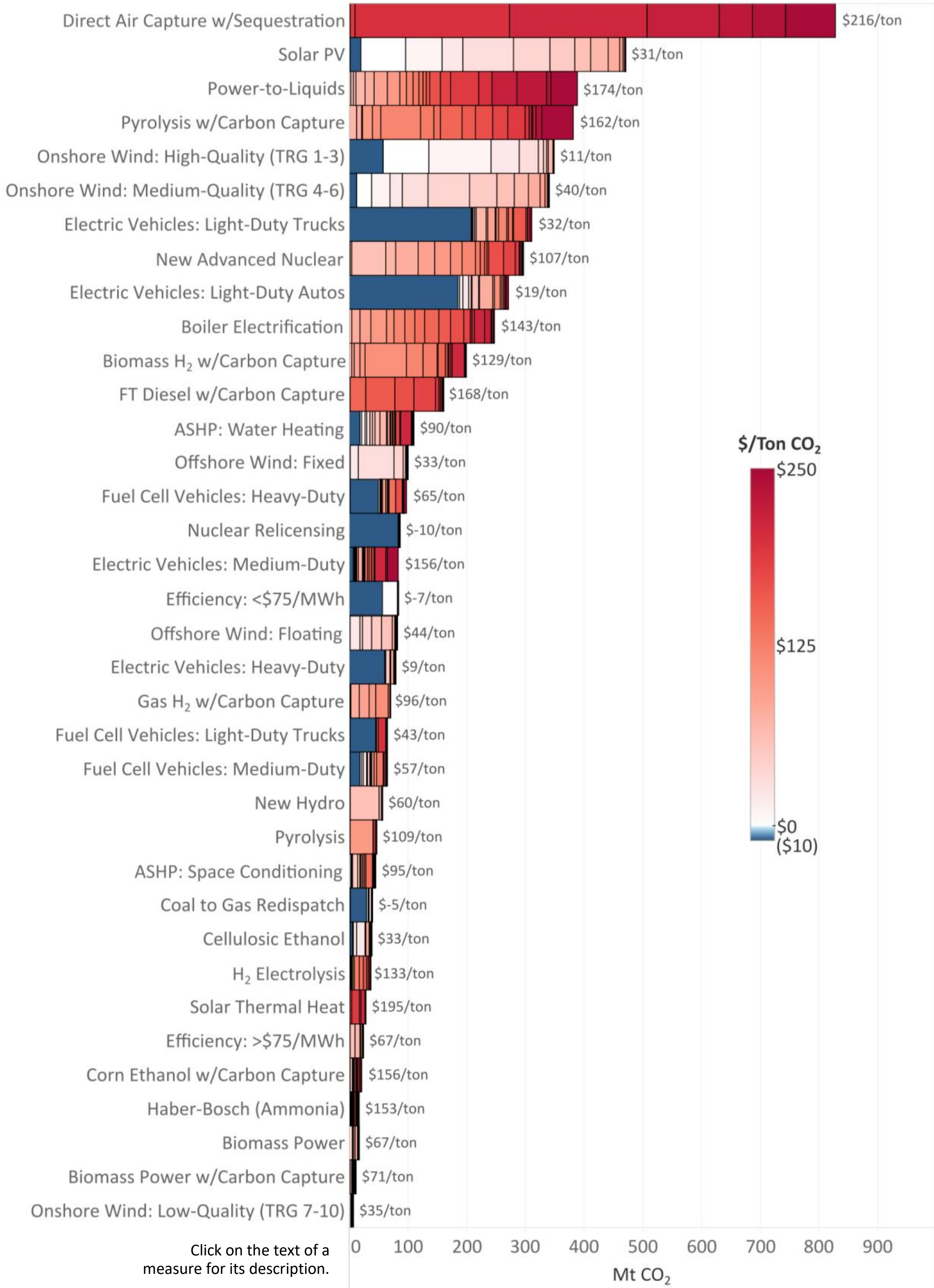
Additional Results and Insights

Our novel approach can also provide much more detail about the amount of emission reductions from each measure across a range of marginal abatement costs than traditional analyses. These results are presented by measure below, in Figure 10, with the bars representing the emission reductions from each measure and the colors corresponding to the range of marginal abatement costs. Dark blue represents our lowest cost measures, and dark red represents our highest cost measures. The measures are ordered by the total emissions in 2050. This measure level presentation of the results reflects the critical insights discussed in the previous section. In Figure 10, electrification, efficiency, and electricity decarbonization represent nearly all of the dark blue in the chart as the lowest cost group of measures, while fuels decarbonization, direct air capture with sequestration, and industrial heat decarbonization represent the greatest emission reductions from higher-cost measures.

Even within a single measure, there is significant heterogeneity in cost. The ability to capture how measures deploy over a range of abatement costs is a critical structural advantage of this approach as opposed to previous MAC approaches, which assessed reductions from largely static baselines. Our methodology deploys measures dynamically as part of a changing system. The results from this technique illustrate that for almost all measures, they are deployed over a range of costs, and different marginal abatement costs drive different levels of emission reductions, not a point estimate.

This range for a single measure can be extremely large and represents how the dynamics of the system influences multiple measures. Power-to-liquids, for example, shows reductions at a cost as low as $40/ton. At this cost, power-to-liquids measures utilize renewable energy that would otherwise be oversupply and curtailed to operate hydrogen electrolysis (and eventually synthesize liquids fuels). However, measure costs rapidly rise at higher volumes since this renewable oversupply is a limited resource. Eventually, at higher costs, additional power-to-liquids necessitates new dedicated renewable facilities to produced hydrogen from electrolysis.

Figure 10 – An alternative presentation of the same MAC curve results in Figure 3, showing 2050 emission reductions by measure across the range of marginal abatement costs. The text to the right of each bar is the average MAC for each measure.



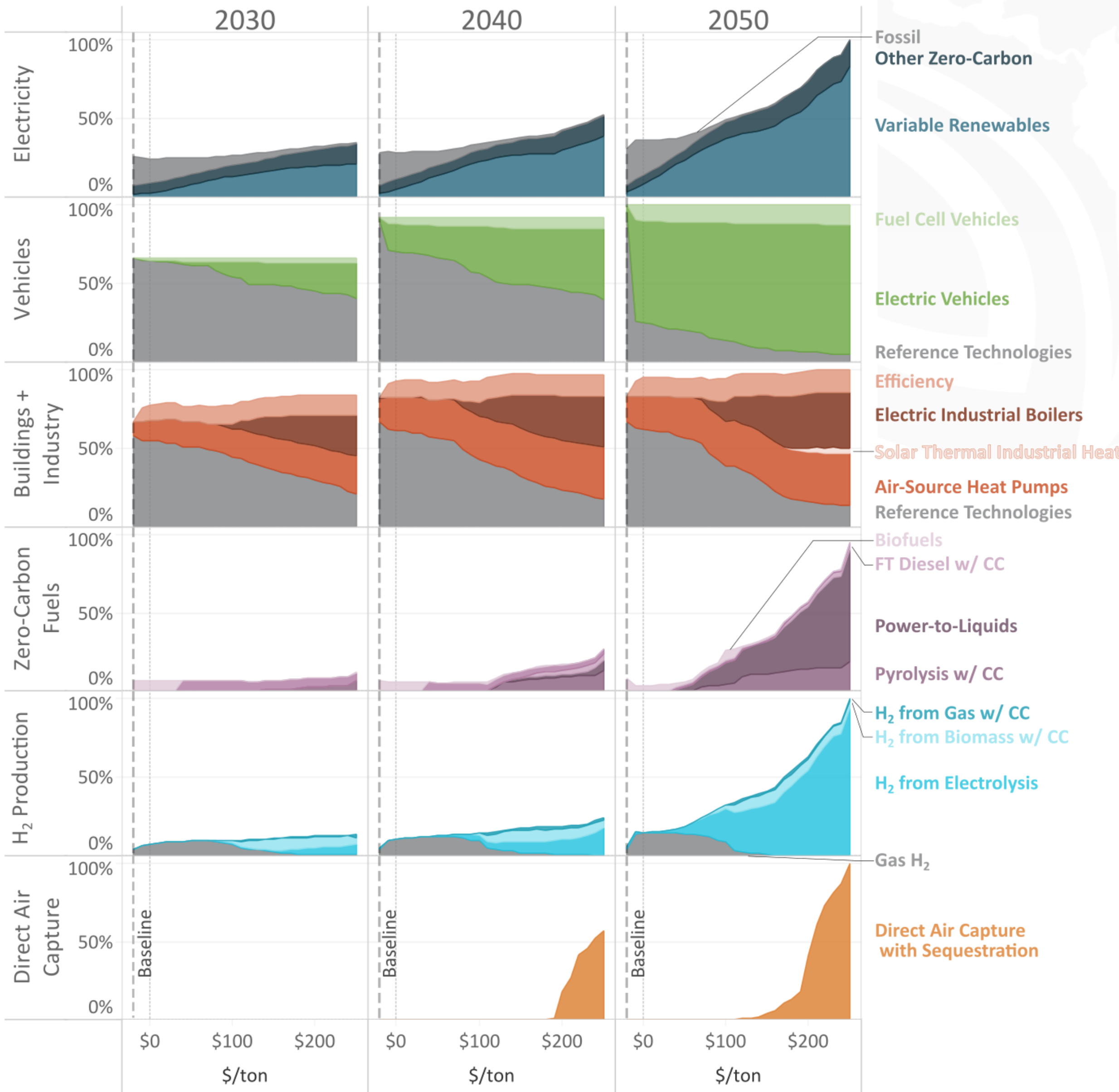
Click on the text of a measure for its description.

Another advantage of our new approach is that it offers much more insight into the overlapping roles of measures and timing of deployment as the physical transformation of the system unfolds. With multiple measures being deployed at nearly all marginal abatement costs, the order and timing of measure deployment are critical for developing effective policy. Our MAC approach provides insights on the timing of measure deployment, a marked improvement over traditional MAC curve approaches that typically leave it to the reader to determine when and what order measures should be deployed. Understanding the evolution of measure deployment through 2050 can support policy and regulatory mitigation strategies that can differentiate between a near-term focus of scaling existing commercial solutions and a longer-term focus that includes technologies that are not yet deployed at a commercial scale.

Figure 11 shows an additional visualization of the results with the timing of major infrastructure changes. This figure compares measure deployment at 2030, 2040, and 2050, with measure deployment organized into categories and normalized to maximum deployment for the category across all years and marginal abatement costs. It is important to note that the chart illustrates the scale of measure deployment for least-cost decarbonization at each year and marginal abatement cost, but not the time required to deploy measures.[20] The figure shows both the change in technology composition for particular categories (e.g., the decline in conventional vehicles, "reference technology," as electric and fuel cell vehicle adoption increases over each decade at the same marginal abatement cost) and the increase of particular categories over time and marginal abatement cost (e.g., the market for decarbonized fuels grows significantly between 2040 and 2050).

[20] Our methodology captures several factors that shape the time required to deploy a measure, including construction time and stock turnover dynamics to ensure there is no early retirement.

Figure 11 – Measure deployment in 2030, 2040, and 2050 as a share of the maximum deployment across all marginal costs and years for each category. "CC" is an abbreviation for carbon capture.



The insights around the timing of measure deployment from Figure 11 reinforce the policymaker takeaways discussed above. Heat pump and efficiency measures see significant deployment across all marginal abatement costs in 2030 and beyond, while renewables and zero-carbon generation measures play a central role in lowering electricity emissions over most marginal abatement costs as early as 2030 and expand in later decades. As the vehicle fleet turns over and technology prices decline, there is a major increase in electric vehicles' deployment, and higher marginal abatement costs can drive this deployment in earlier periods. On the other hand, decarbonized fuel measures and clean hydrogen, which is the driver for significant hydrogen production increases in 2050, do not begin meaningful deployment until 2040. Direct air capture with sequestration measures are also not deployed until 2040 at very high marginal abatement costs or until 2050 at high marginal abatement costs. This evolution of measure deployment illustrates the timing of additions of critical enablers of emission reductions.

New MAC curves, built on a systems-level approach to estimating the cost and emission reduction potential of mitigation measures, can provide critical insights for achieving ambitious emission reduction targets. Our novel approach shows what actions will be needed to follow a pathway to achieve emission reductions necessary to align with Paris Agreement targets and how to bundle measures together and time their deployment to decarbonize at least cost. This approach and the resulting visualizations can help policymakers develop strategies for near-term action and a roadmap to ensure R&D and long-term investments are ready for when they are needed in future decades.

Technical Appendix

Measure Descriptions

		Measure	Description	Data Source
Buildings + Industry	Space Conditioning & Water Heating	ASHP: Space Conditioning	Technologies that utilize an air-source heat pump (ASHP) to provide space conditioning (both heating and cooling) with electricity. ASHP heating technologies can achieve much higher efficiency than fuel combustion or electric resistance technologies. Packaged heating and cooling units achieve comparable to or better cooling performance than standalone air conditioning.	Jadun, Paige, Colin McMillan, Daniel Steinberg, Matteo Muratori, Laura Vimmerstedt, and Trieu Mai (2017). *Electrification Futures Study: End-Use Electric Technology Cost and Performance Projections through 2050.* Available at: https://www.nrel.gov/docs/fy18osti/70485.pdf
Buildings + Industry	Space Conditioning & Water Heating	ASHP: Water Heating	Technologies that utilize an air-source heat pump (ASHP) to heat water with electricity. ASHP heating technologies can achieve much higher efficiency than fuel combustion or electric resistance technologies.	
Buildings + Industry		Boiler Electrification	This technology can supply heat directly to industrial processes from electricity rather than fossil fuels burned directly in the boiler.	EU ASSET (2018). *Technology Pathways in Decarbonisation Scenarios.* Available at: https://asset-ec.eu/wp-content/uploads/2019/07/2018_06_27_technology_pathways_-_finalreportmain2.pdf
Buildings + Industry	Electric Efficiency	Efficiency: >$75/MWh	A suite of energy efficiency measures for buildings and industry where the levelized cost of saved electricity is less than $75 per MWh.	Assumed 2.5% of load could be reduced for $100 and 5% of load could be reduced for $125 levelized cost of efficiency. Also assumed $50/MWh distribution cost savings for each range.
Buildings + Industry	Electric Efficiency	Efficiency: <$75/MWh	A suite of energy efficiency measures for buildings and industry where the levelized cost of saved electricity is greater than $75 per MWh.	Assumed 2.5% of load could be reduced for $25, $50, and $75 levelized cost of efficiency. Also assumed $50/MWh distribution cost savings for each range.
Buildings + Industry		Solar Thermal Heat	This technology can supply heat directly to industrial processes by collecting the sun's thermal energy directly. It can avoid the use of fuel in industrial processes that are overwhelmingly provided by fossil fuels today.	IRENA (2015). *Solar Heat for Industrial Processes.* Available at: https://www.irena.org/publications/2015/Jan/Solar-Heat-for-Industrial-Processes
Transportation	Electric Vehicles	Electric Vehicles: Heavy-Duty	Battery electric heavy-duty vehicles.	Vehicle battery pack costs adjusted based on: Cole, W. and A.W. Frazier (2019). *Cost Projections for Utility-Scale Battery Storage*. Available at: https://www.nrel.gov/docs/fy19osti/73222.pdf
Transportation	Electric Vehicles	Electric Vehicles: Light-Duty Autos	Battery electric light-duty cars.	
Transportation	Electric Vehicles	Electric Vehicles: Light-Duty Trucks	Battery electric light-duty trucks.	
Transportation	Electric Vehicles	Electric Vehicles: Medium-Duty	Battery electric medium-duty vehicles.	

Transportation	*Fuel Cell Vehicles*	Fuel Cell Vehicles: Heavy-Duty	Fuel cell vehicles are powered by fuel cells that consume hydrogen to generate electricity to run the vehicle's drivetrain. Heavy-duty trucks are amongst the set of mobile applications where current fuel cell technologies and projections suggest the technology will be most competitive, particularly for specific use cases.	Costs are derived from International Council on Clean Transportation (2017). *Transitioning to Zero-Emission Heavy-duty Freight Vehicles.* Available at: https://theicct.org/sites/default/files/publications/Zero-emission-freight-trucks_ICCT-white-paper_26092017_vF.pdf and Whiston, Michael, Inês L. Azevedo, Shawn Litster, Kate S. Whitefoot, Constantine Samaras, and Jay F. Whitacre (2019). *Expert assessments of the cost and expected future performance of proton exchange membrane fuel cells for vehicles.*
		Fuel Cell Vehicles: Light-Duty Trucks	Fuel cell vehicles are powered by fuel cells that consume hydrogen to generate electricity to run the vehicle's drivetrain. Light-duty trucks are amongst the set of mobile applications where current fuel cell technologies and projections suggest the technology will be most competitive, particularly for specific use cases.	
		Fuel Cell Vehicles: Medium-Duty	Fuel cell vehicles are powered by fuel cells that consume hydrogen to generate electricity to run the vehicle's drivetrain. Medium-duty vehicles are amongst the set of mobile applications where current fuel cell technologies and projections suggest the technology will be most competitive, particularly for specific use cases.	
Electricity	*Biomass-Fired*	Biomass Power	Biomass-fired generation	NREL 2019 Annual Technology Baseline (ATB) Available at: https://atb.nrel.gov/electricity/2019/
		Biomass Power w/Carbon Capture	Biomass-fired generation with carbon capture capabilities	NREL ATB 2018 with adjustments based on coal with CCS from NREL ATB 2018
		Coal to Gas Redispatch	Gas-fired generation displacing coal-fired generation	Driven by the economics of coal and gas generation
		New Hydro	New stream reach development and upgrades	Data from NREL ReEDS model
	Nuclear (New & Relicensed)	New Advanced Nuclear	A range of advanced nuclear technologies that incorporate advantages such as modularization.	Based on Energy Options Network (2018). *What Will Advanced Nuclear Power Plants Cost? A Standardized Cost Analysis of Advanced Nuclear Technologies in Commercial Development.* Available at: http://www.innovationreform.org/wp-content/uploads/2018/01/Advanced-Nuclear-Reactors-Cost-Study.pdf
		Nuclear Relicensing	Extension of existing nuclear licenses.	$500/kW for a 20-year extension
	Offshore Wind	Offshore Wind: Fixed	Fixed offshore wind technologies	NREL 2019 Annual Technology Baseline (ATB) mid values. Available at: https://atb.nrel.gov/electricity/2019/
		Offshore Wind: Floating	Floating offshore wind technologies	

Electricity	*Onshore Wind*	Onshore Wind: High-Quality (TRG 1-3)	High-quality onshore wind, representing techno-resource groups 1-3 in NREL ATB 2019	NREL 2019 Annual Technology Baseline (ATB) mid values. Available at: https://atb.nrel.gov/electricity/2019/
		Onshore Wind: Low-Quality (TRG 7-10)	Low-quality onshore wind, representing techno-resource groups 7-10 in NREL ATB 2019	
		Onshore Wind: Medium-Quality (TRG 4-6)	Medium quality onshore wind, representing techno-resource groups 4-6 in NREL ATB 2019	
		Solar PV	Solar photovoltaic generation.	
Hydrogen		Biomass H_2 w/Carbon Capture	Technologies that derive hydrogen from biomass and have carbon capture. This hydrogen production is zero-emission and can result in net-negative emissions if the captured carbon is sequestered.	Princeton Net Zero America Project Available at: http://netzeroamerica.princeton.edu
		Gas H_2 w/Carbon Capture	Technologies that derive hydrogen from natural gas at facilities with carbon capture.	International Energy Agency (2019). *The Future of Hydrogen*. Available at: https://iea.blob.core.windows.net/assets/a02a0c80-77b2-462e-a9d5-1099e0e572ce/IEA-The-Future-of-Hydrogen-Assumptions-Annex.pdf
		H_2 Electrolysis	Hydrogen production technologies that convert clean electricity into hydrogen and oxygen by splitting water. This measure only uses zero-carbon electricity as an input.	
Fuel	*Zero-Carbon Fuel*	Cellulosic Ethanol	Advanced ethanol production technologies.	IEA Bioenergy (2020). *Advanced Biofuels – Potential for Cost Reduction.* Available at: https://www.ieabioenergy.com/blog/publications/new-publication-advanced-biofuels-potential-for-cost-reduction/
		Corn Ethanol w/Carbon Capture	Facilities that produce ethanol from corn feedstocks with carbon capture.	NETL (2017). *Carbon Capture Retrofit Analyses*. Available at: https://www.netl.doe.gov/projects/VueConnection/download.aspx?id=70379c6b-e2e2-4410-91db-f01a9c371a21&filename=CarbonCaptureRetrofitAnalysisPresentation_080917.pdf
		FT Diesel w/Carbon Capture	Technologies that produce synthetic diesel using biomass in a Fischer-Tropsch (FT) process.	Agora Verkehrswende (2018). *The Future Cost of Electricity-Based Synthetic Fuels.* Available at: https://www.agora-energiewende.de/en/publications/the-future-cost-of-electricity-based-synthetic-fuels-1/
		Haber-Bosch (Ammonia)	Technologies to produce ammonia from hydrogen and captured nitrogen, used as a zero-carbon liquid fuel.	Bartels, Jeffrey Ralph (2008). *A feasibility study of implementing an Ammonia Economy*. Available at: https://lib.dr.iastate.edu/cgi/viewcontent.cgi?article=2119&context=etd
		Power-to-Liquids	Technologies that produce synthetic liquid fuels from hydrogen and captured carbon.	Agora Verkehrswende (2018).
		Pyrolysis	Technologies that produce biomass-derived replacements for very long-chain hydrocarbons, like lubricants or petroleum coke.	Princeton Net Zero America Project Available at: http://netzeroamerica.princeton.edu
		Pyrolysis w/Carbon Capture	Technologies that produce biomass-derived replacements for very long-chain hydrocarbons, like lubricants or petroleum coke. These technologies include carbon capture.	

DAC		Direct Air Capture w/Sequestration	Technologies that directly capture CO_2 from the atmosphere and sequesters it.	Rhodium Group (2019). *Capturing Leadership: Policies for the US to Advance Direct Air Capture Technology*. Available at: https://rhg.com/research/capturing-leadership-policies-for-the-us-to-advance-direct-air-capture-technology/

Overview of Key Modeling Inputs

Input	Source/Notes	2050 Value
Natural Gas Prices	Annual Energy Outlook 2020 - High Oil & Gas Supply	Henry Hub: $2.54/MMBTU
Oil Prices	Annual Energy Outlook 2020 - High Oil & Gas Supply	Brent Spot Price: $91/Barrel
Biomass Availability	Princeton Net Zero America	1.0 BDT
Annual Sequestration Injection Potential	Princeton Net Zero America	1.9 Gt CO2
Onshore Wind Potential	NREL REEDS (2019); 25% of available technical potential	2.0 TW
Offshore Wind Potential	NREL Reeds (2019); 25% of available technical potential	1.0 TW
Utility-Scale Solar Potential	NREL REEDS (2019); 25% of available technical potential[21]	12.8 TW
Rooftop Solar Potential	NREL Rooftop Solar Photovoltaic Technical Potential in the United States: A Detailed Assessment	1.1 TW

[21] Further constrained to 1% of available land area in every region.

Supplemental Results for 2030

Figure 12 - A 2030 MAC curve for US energy and industry CO_2 where emission reductions are relative to a baseline scenario. Electricity measures are the major driver of emission reductions through 2030. A number of factors could lead to lower marginal abatement costs by 2030, including: a broader set of measures than considered in this analysis, innovation that lowers technology cost or improves performance, or faster market adoption.

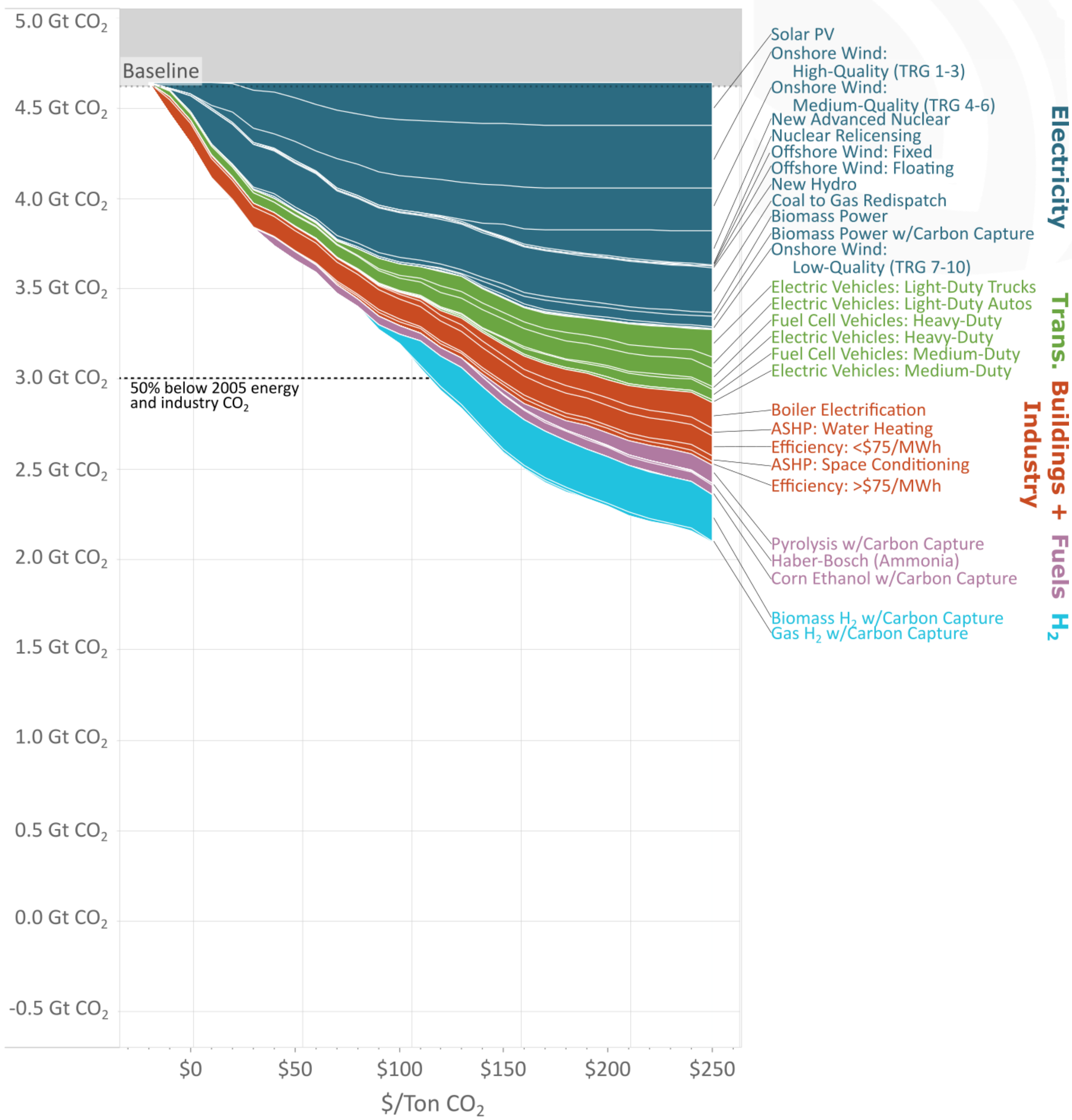
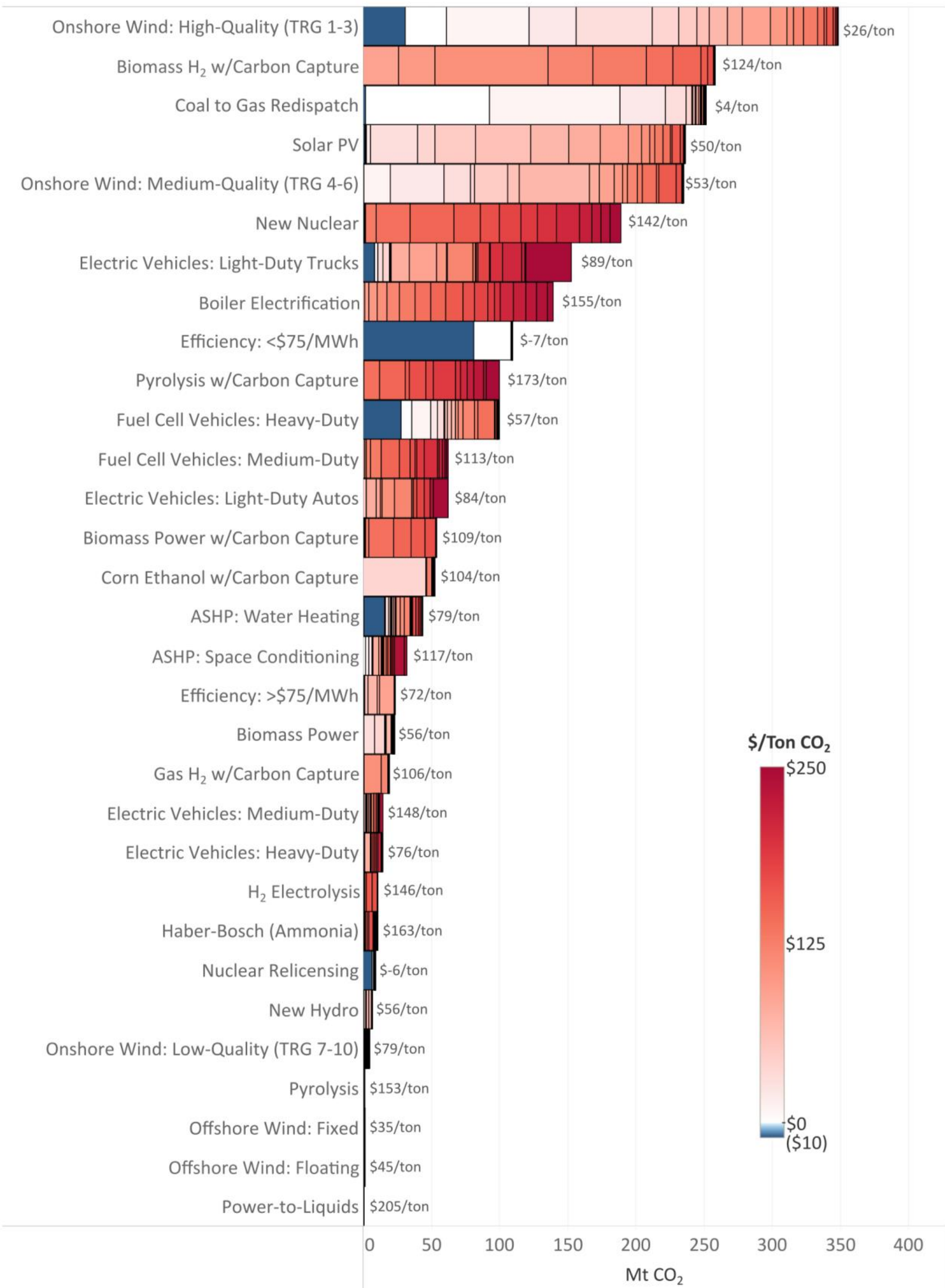


Figure 13 – An alternative presentation of the same MAC curve results in Figure 12 showing 2030 emission reductions by measure across the range of marginal abatement costs. The text to the right of each bar is the average MAC for each measure.



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Methodology Details: Modeling the Range of Least-Cost Systems

The methodology begins by performing a systems-level analysis over a range of marginal abatement costs[22] through the end of the study's time horizon (typically through 2050). This creates a least-cost system of energy supply and demand technologies for each incremental marginal abatement cost in the range included in the analysis. With the complete set of least-cost systems, it is possible to track the changes to individual measures that drive emissions reductions from other resources or technologies in the system of energy and industry CO_2 emissions at each step in the range of marginal abatement costs.

Each least-cost system at a unique marginal abatement cost (or 'step' in the range of marginal abatement costs) represents an individual scenario. The analysis compares all the scenarios, where scenarios that make up the range of marginal abatement costs share the same inputs (e.g., technology costs, fuel prices, resource constraints, projections for service demand) except for their different marginal abatement cost. The scenarios model energy supply, both electricity and fuels, and deployment of energy demand technologies over multiple years and multiple geographic regions. The incremental changes between a given step ('step n') and the previous step ('step n-1') represent the set of measures that have become cost-effective at marginal abatement cost for step n. The changes from step n-1 to step n show which measures have increased their production or deployment, and which resources or technologies have been displaced by these measures.[23] Modeling system-level changes over many steps creates a MAC curve with layers of insights beyond what previous MAC analysis can provide.

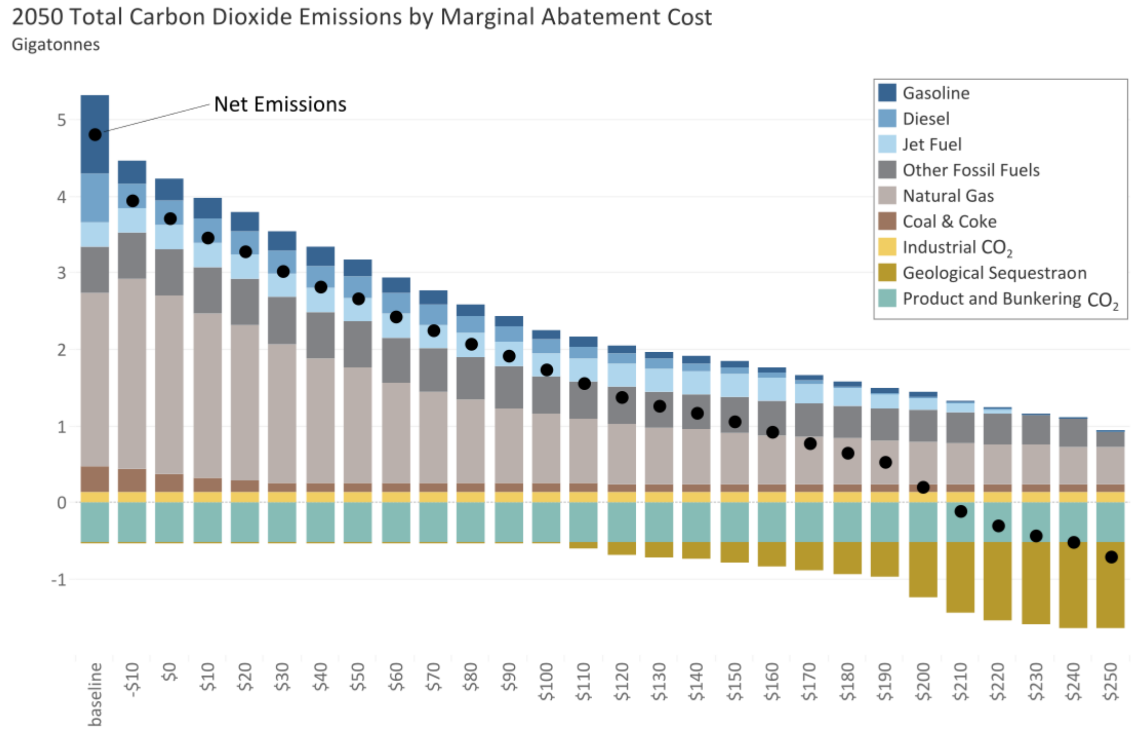
Figure 14 illustrates how the multiple modeled scenarios fit together to produce the full range of marginal abatement costs considered in an analysis. Each bar in the figure represents gross CO_2 emissions by fuel or sequestration for a scenario, and the dot represents net emissions for that scenario. The analysis for this white paper includes a baseline scenario (the left-most bar). This scenario has different input assumptions than the other scenarios and is included to show measure deployment in the absence of policy intervention. The transition from the baseline scenario to the initial step in the range of marginal abatement costs shows how some measures

[22] The methodology can work for either a range of marginal abatement costs or for a range of emission reductions. For simplicity, this paper only discusses incremental changes in marginal abatement costs, but the methodology would be identical for a range of emission reductions. Given the type of modeling that is needed for this optimization methodology, a range of marginal abatement costs is functionally equivalent to a range of emission reductions. The process of finding the least-cost system based on an emission limit provides the associated marginal abatement cost as a result, while the process of finding the least-cost system based on a marginal abatement cost provides the total system emissions as a result.

[23] Incremental changes in marginal abatement costs need to be small enough to resolve incremental changes in resource deployment and utilization. Increments in MAC that are too large muddle this approach's ability to resolve when individual abatement measures become cost-effective. For example, stepping from a marginal abatement cost of $0 to $50 per ton will cause many changes in the system and make it difficult to determine which measures would have been cost-effective at $10 per ton rather than $40 per ton.

are cost-effective even at negative marginal abatement costs if enabling policy is in place. A baseline scenario is not strictly necessary but can be a helpful addition in most implementations of this methodology.

Figure 14 – Declining total emissions from US energy and industry for the marginal abatement cost scenarios and the baseline scenario in 2050.



The holistic approach of comparing changes in least-cost energy systems across decades enables this type of MAC analysis to capture the complex and dynamic nature of many abatement measures. For example, consider medium-duty fuel cell vehicles as a candidate abatement measure. A critical determinate of when these vehicles will become cost-effective for decarbonization is when there will be a sufficient supply of low-carbon hydrogen production at a particular cost threshold. Until these vehicles can access low-carbon fuel at the required cost, other measures will reduce emissions in the energy system at lower costs. Achieving the needed scale and cost of low-carbon hydrogen production will depend on many factors, including the scale of renewable deployment, the availability of resource-constrained biomass feedstocks, and the value of captured carbon for beneficial uses or sequestration. In turn, each of the factors governing the cost and availability of low-carbon hydrogen is subject to other factors that shape their economics. Characterizing the emission savings and associated costs of medium-duty fuel cell vehicles requires a system-wide analysis, which co-optimizes for the decision to purchase and operate one of these vehicles rather than an alternative and for the provision of their fuel and all the associated upstream decisions.

Requirements for Modeling Platforms

Modeling platforms that can support this methodology will need to evaluate a range of least-cost scenarios across a range of marginal abatement costs while also addressing critical analytical requirements. Because this approach depends on understanding changes across the whole system, the underlying modeling tools must be able to robustly model the many dynamics that will shape the planning and operations of future low-carbon energy systems. To produce the necessary set of scenarios for this MAC analysis, the modeling platforms solving for the least-cost systems must be able to:

- Represent a full suite of the critical demand and supply decisions for least-cost, low-carbon energy systems. These include a range of renewable and low-carbon electricity resources, measures for decarbonizing fuels, measures to capture and utilize or sequester CO_2, and demand-side measures that address efficiency and fuel-switching for key energy end-uses in buildings, transportation, and industry.
- Evaluate scenarios with a study horizon through at least 2050, with time steps that can provide insights into key milestone years between today and the end of the study horizon.
- Incorporate reliability constraints for the electricity system, including the challenges of operating a system with a high share of variable energy resources with production profiles that vary across geographical regions.
- Capture the dynamics in the energy system that encourage additional sectors to utilize more electricity ('sector coupling'), which are shaped by variable energy resources, electricity reliability constraints, and flexible loads of varying scales.
- Provide a representation of multiple geographic sub-regions in the study area, all of which have differences in energy demand and differences in resource potential and quality for renewables, carbon sequestration, and biomass feedstocks.

Our implementation of this MAC analysis utilizes a paired set of models to model the range of least-cost systems: EnergyPATHWAYS and Regional Investment and Operations (RIO) platforms. See the Overview of Energy System Modeling Tools section of the appendix for additional detail on these models.

Methodology Details: Allocating Measure Emission Reductions

Comparing incremental changes in least-cost systems enables this approach to estimate MAC through 2050 for deeply decarbonized systems, but it also requires an additional analytical step to translate system-level changes into measure-level results. The second portion of the methodology translates the differences in deployment and emissions between step n-1 and step n into a measure level allocation of emission reductions.

Questions of how to allocate emission reductions when multiple changes are occurring can be complicated. Our allocation methodology centers around a simple principle of allocating reductions to measures that are the most proximate to their cause. Measures are divided into categories to enable the allocation process, and the remainder of this section explores how

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emission reductions are allocated for each category. Table 1 lays out the categories addressed in the sub-sections below and gives an overview of each allocation approach.

Table 1 - Overview of allocation categories

Category	Emission Reduction Allocation Overview
Carbon capture	• Carbon capture measures are allocated reductions directly anytime the carbon is sequestered. • When captured carbon is utilized rather than sequestered, typically to create synthetic hydrocarbon drop-in fuels, reductions are allocated to the measures that utilize the carbon rather than the measure that does the carbon capture.
Electricity supply	• Cleaner fossil generation is allocated reductions based on improvements in emission intensity over the dirty generation it displaces. ○ Fossil emission reductions are always based on a 'reference fuel' (e.g., natural gas for combined-cycle combustion turbine plants). • Renewables and zero-carbon resources are allocated with a similar approach based on an emission intensity of zero. • A counterfactual is used to address growing electricity demand.
Cleaner fuels and energy conversion	• Measures that decarbonize fuels (e.g., biofuels or E-fuels) are allocated reductions based on the displacement of the fossil alternative. • Hydrogen is a special case, on account of growing demand, and uses a counterfactual approach similar to electricity.
Demand measures	• Measures are allocated reductions based on their reductions to emission intensity from efficiency improvements and potentially switching fuels. ○ For example, EVs are allocated reductions for efficiency gains and the difference in emissions per unit of energy between electricity and gasoline.

Carbon Capture

Measures with carbon capture are a subset of measures in the energy supply categories. Carbon capture measures are allocated reductions for the portion of their captured carbon that is geologically sequestered. For any carbon that is captured and utilized rather than sequestered, potentially through conversion to synthetic fuels or utilized in an industrial process, reductions are allocated toward the measure that utilizes the carbon rather than the measure that captures the carbon. Depending on the system, this means that measures with carbon capture can receive no emission reduction allocation for capturing carbon if none of that carbon is sequestered. For most measures, the allocation of carbon captured is just one component of a measure's final emission reduction allocation. The following sections discuss the complete allocation for each category, including when there are carbon capture measures as a subset of the category.

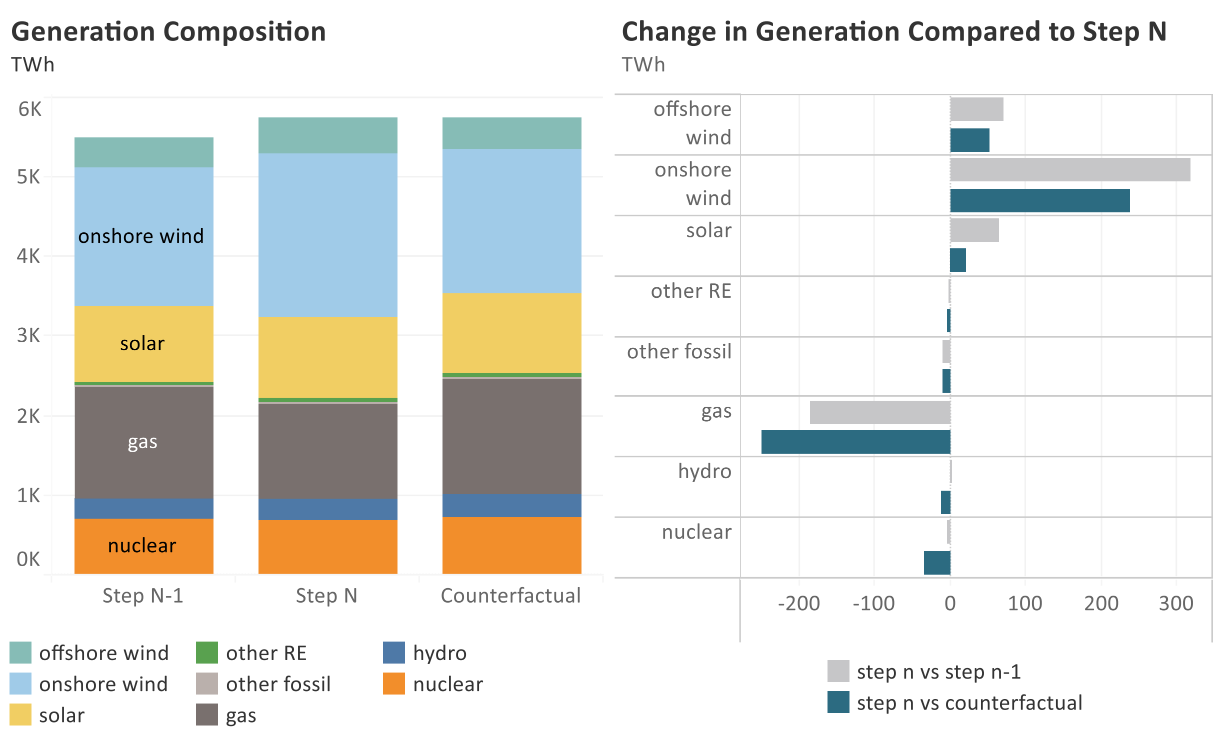
Electricity Supply

Conceptually, the allocation of declining emissions from the electricity supply to measures is straightforward. As in other MAC analyses, each additional GWh produced by a lower emission intensity resource that displaces a GWh from a higher-emitting resource is allocated reductions for the difference in emissions between the dirty and cleaner GWh of generation. However, to apply this frame to comparing incremental changes in full systems, there are two other considerations: (1) adjusting allocation for growing load that is the result of higher marginal abatement costs leading to increased fuel-switching and energy conversion loads; (2) determining which measures are displacing which resources within the system.

Comparing against a counterfactual to account for load growth

Across the range of marginal abatement costs, all the scenarios share the same electricity demand input. When there is an increase in total generation moving from step n-1 to n, this is driven by incremental load growth from either addition of electric demand technologies or increases in energy conversion loads that consume electricity (e.g., electric boilers, electrolysis). Increases in total load represent an issue for allocation. There is a need to untangle which measures generate more to reduce emissions and which generate more to meet growing electricity demand.[24] Rather than simply comparing the changes between step n and step n-1, our methodology constructs a counterfactual of step n. This counterfactual is based on step n-1 and acts as the point of comparison against step n.

Figure 15 – An illustration of total generation for step n-1, step n, and the counterfactual (L), and change in generation moving from step n-1 to step n, and from the counterfactual to step n (R)



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[24] Allocation for demand measures and energy conversion measures that consume electricity incorporates any potential increases in emissions due to growing electricity demand. See those respective sections for more detail.

Figure 15 illustrates an example of this counterfactual approach. The left panel contrasts generation between step n-1, step n, and the counterfactual of step n. The counterfactual is calculated by scaling up each resource's share of total generation in step n-1 to the total generation in step n. The counterfactual is used to approximate the step n-1 generation mix if its total generation had been the same as step n. The counterfactual approximation is used to determine the incremental increases and decreases in generation between step n-1 and step n. The right panel of Figure 15 shows the impact of the counterfactual on increases or decreases of generation by resource type. In this example, comparing step n to step n-1 would overestimate the increases in wind and solar generation and underestimate how much other resources displace gas generation. Once the counterfactual adjusts for the impact of load growth, more gas generation is displaced, and the increases from wind and solar measures are smaller. The net result is these measures receive a greater allocation of emission reductions for displacing gas generation than they would under a simple step n versus step n-1 comparison.

Mapping displaced generation to the increased generation from measures

After determining which resources have their generation displaced and which resources increase generation at each increment in marginal abatement cost, the changes in generation need to be mapped back to a resource level to determine emission reductions. Whereas previous MAC analyses are built around a predetermined course of which measures are increasing their generation and displacing other generation, this systems-level approach requires a methodology for connecting the resources that have their generation displaced to measures that are increasing generation. In our formulation, increases and decreases are mapped to one another on a resource level. Once this mapping is complete, displaced emissions can be calculated based on each resource's efficiency and the fossil fuel it consumes.[25] This is particularly important for situations where lower emission intensity fossil generators are displacing higher emission intensity plants, like switching from coal to gas.

A matrix is developed to map all generation increases on a resource level to all the displaced generation. Figure 16 shows an example of the generation allocation matrix, which is analogous to an I-O table, where each row represents a resource that is increasing generation, and each column represents a resource that is decreasing generation. Each element in the matrix represents the amount of incremental generation coming from the resource that is increasing (row) and which resource is being displaced (column).

[25] Fossil generators are assumed to always consume only fossil fuel, as allocation for decarbonized fuels goes to the measures that produce the decarbonized fuel.

Figure 16 – The upper left-hand portion of an example generation allocation matrix

Rows are resource increases,
Columns are displaced resources

			Resource	d.1	d.2	d.3	d.4	d.5	d.6	d.7	d.8	d.9	d.10	d.11	d.12	d.13	d.14	d.15
			Category	other fossil	other fossil	gas	gas	other fossil	other fossil	other fossil	coal	other fossil	coal	coal	other fossil	coal	coal	other fossil
			Displaced GWh	2.3	2.5	3.6	2.9	3.4	4.3	4.5	16.9	4.2	17.6	28.4	5.1	18.9	11.2	5.3
			kt per GWh	2.5	2.2	2.0	1.9	1.8	1.4	1.3	1.2	1.2	1.2	1.1	1.1	1.1	1.1	1.1
Resource	Category	Increase in GWh	kt per GWh															
i.1	gas	13.3	0.4	2.3	2.5	3.6	2.9	2.1	-	-	-	-	-	-	-	-	-	-
i.2	gas w/ccu	3,442.4	0.04	-	-	-	-	1.4	4.3	4.5	16.9	4.2	17.6	28.4	5.1	18.9	11.2	5.3
i.3	gas w/ccu	250.9	0.04	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
i.4	gas w/ccu	148.1	0.04	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
i.5	gas w/ccu	85.8	0.04	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
i.6	gas w/ccu	33.1	0.04	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
i.7	gas w/ccu	296.3	0.04	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
i.8	gas w/ccu	1,439.2	0.04	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
i.9	gas w/ccu	15.7	0.04	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
i.10	nuclear	5,510.9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
i.11	nuclear	341.9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
i.12	biomass with CCU	5,952.5	-0.7	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
i.13	biomass with CCU	20.8	-1.5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
i.14	biomass with CCU	0.8	-1.5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

The order of the rows and columns is critical for ensuring emission reductions are not over- or under-allocated. To order the displaced generation, all resources are separated into three tranches: (1) thermal generation, (2) all other generation with non-zero emissions, and (3) zero-emission resources.[26] Within each tranche, resources are ordered from most emitting[27] to least emitting, and tranches are joined in ascending order to form the columns in the matrix. Resources with increasing generation are separated into the same tranche categories and sorted by emission intensity, but only tranches (1) and (2) are joined to form the matrix rows. An algorithm goes row by row to fill the matrix, accounting for all increasing generation from a resource before moving to the next row. The rows and columns ordering process results in the increasing resources with the highest emission intensity displacing the decreasing resources with the highest emission intensity.

The emission reduction allocation for increasing resources in tranches (1) and (2) is calculated with Equation 1. This is calculated by determining the incremental displaced emissions for each measure and netting the measure's direct emissions. In Equation 1, total displaced emissions are calculated as the dot product of the allocation matrix discussed above (denoted as $\mathbf{M}$, indexed

[26] Decreased generation in the third tranche is typically very small, and generally from existing nuclear resources or older, lower resource quality renewable resources.

[27] For generation resources with carbon capture, their emission intensity should be adjusted in accordance with the carbon capture accounting methodology, and should only receive allocation for the share of captured carbon that is sequestered.

by i for the rows of increasing resources and d for the columns of decreasing resources) and a vector of the emission intensities for all resources which have their emissions displaced (denoted as $\mathbf{s}$ which is indexed by d). The dot product calculation determines the emissions displaced from each decreasing resource and sums to the total displaced emissions for each increasing resource (measure). The second term in Equation 1 represents the incremental change in emissions for each increasing resource, based on its emission intensity[28] and its increase in generation.[29] The incremental emissions increase is netted from the displaced emissions for each resource to determine the emission reduction allocation.

Equation 1 – Emission reduction allocation for measures, indexed by i, with non-zero emissions

$$allocation_i = \boldsymbol{M}_{id} \cdot \boldsymbol{s}_d - \left(\sum_{d=1}^{n} \boldsymbol{M}_{id}\right) \circ \boldsymbol{r}_i$$

The remaining tranche of increasing resources, zero-carbon non-thermal resources, is pooled together for the final allocation step. Any remaining displaced generation that is not accounted for within the allocation matrix is converted to emissions and totaled. Each increasing resource in the last tranche is allocated a share of the total remaining displaced emissions based on its share of the tranche, effectively spreading the balance of emission reductions across these measures on a pro-rata basis.

Combining the allocation for the first two tranches of increasing resources based on the equation above with the pro-rata allocation for the third tranche produces emission reduction allocations for all electricity measures. Based on how the tranches of increasing generation are treated, when there is significant load growth between incremental steps, this third tranche is generally assumed to meet growing demand.

Cleaner Fuels and Energy Conversion

Measures for cleaner fuels and energy conversion are allocated emission reductions based on the difference between a reference emission intensity and the measure's emission intensity. Regardless of the destination of the output from these measures, whether meeting demand for final energy or going to a power plant,[30] the measure that creates the fuel is always allocated emission reductions for displacing a more carbon-intensive fuel. Technologies that consume

[28] For all resources, emission intensity is based on their respective efficiencies and the carbon content of the fossil version of any fuel the resource combusts. Where there are instances of power generation burning decarbonized fuels that displace fossil fuels, allocation for those emission reductions go to the measures that produce the decarbonized fuels.

[29] This is calculated by summing the generation for each increasing resource across all decreasing resources in matrix $\boldsymbol{M}$, which results in a vector indexed by i. Element-wise multiplication is performed on this vector and $\boldsymbol{r}$, which represents the emission intensity of all increasing resources.

[30] The accounting for hydrogen production is slightly different, and addressed in the following section.

these fuels are allocated emission reductions for replacing other technologies that have higher emission intensities.

Emissions reduction allocation for these measures is calculated using Equation 2. The reference emission intensity, int_{ref}, is based on user-defined reference values, which define this value for each measure. Generally, the reference intensity is the emission intensity of the displaced fossil fuel (e.g., corn ethanol would have gasoline as a reference).[31] The emission intensity of the measure, int_{meas}, is calculated based on all of the direct inputs to the measure, including biomass use, electricity use, hydrogen use, and captured carbon that is sequestered. The difference in these two intensities is multiplied by the incremental increase in energy from the measure between step n-1 and step n, GJ_{inc}.

Equation 2 – Emission reduction allocation for clean fuel and energy conversion measures

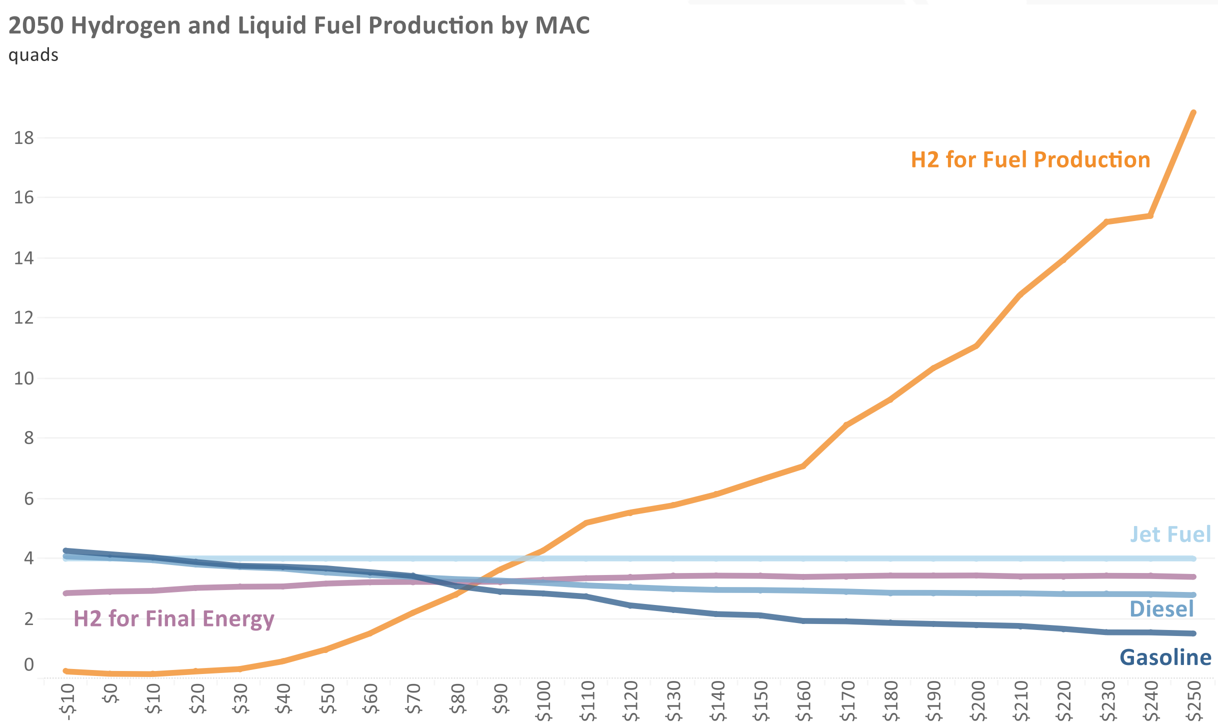
$$allocation = \left(int_{ref} - int_{meas}\right) \times GJ_{inc}$$

Hydrogen Production

Hydrogen production is a unique subset of fuel measures that requires a more detailed allocation than other clean fuel measures. While other fuels generally see limited growth or declines in final energy share as fuel switching becomes increasingly attractive at higher marginal abatement costs, hydrogen production materially increases at higher marginal abatement costs. Figure 17 shows this significant increase in production, with hydrogen for final energy demand separated from hydrogen for fuel production. Increases in overall demand for hydrogen require a counterfactual accounting, similar to electricity supply, to disentangle increased hydrogen measure output to meet growing demand or lower emissions.

[31] Measures which produce multiple fuels get a reference intensity which reflects a combination of displaced fossil fuels. Synthetic fuels that are allocated emission reductions for utilizing captured carbon have reference intensities of zero to prevent double counting of emission reductions.

Figure 17 – Illustration of the growth in hydrogen production as compared to liquid fuels in 2050.



To develop the counterfactual to compare against step n, the two types of hydrogen production are tracked separately:

- Production for final energy demand, which can come from natural gas steam reformation or conversion from the other types of hydrogen; and
- Production for conversion to other fuels, which can come from other lower emission intensity forms of hydrogen production.

Each type of production uses the same counterfactual approach, where step n is compared to an alternative where total production is the same as step n, but the shares of hydrogen production technologies are based on step n-1. Both displaced production and increased production from hydrogen measures are based on the difference between step n and the counterfactual.

Equation 3 – Emission reduction allocation for hydrogen measures

$$allocation = \left(\frac{emissions_{dis}}{GJ_{dis}} - int_{meas}\right) \times GJ_{inc}$$

Allocation for hydrogen measure emission reductions is calculated with Equation 3, which compares the average emission intensity of all displaced production to each measure's emission intensity. Rather than a resource-by-resource comparison between step n and the counterfactual, the small number of technologies and the homogeneity of emission intensity[32] for each technology within a step make it possible to use an average intensity. This average is calculated based on the total hydrogen production that is displaced, GJ_{dis}, and the associated emission reduction from that displacement, $emissions_{dis}$. All measures are compared against this average intensity. Each measure's emission intensity, int_{meas}, is based on all direct inputs to the measure, including biomass use, electricity use, and captured carbon that is sequestered. The difference in emission intensity is multiplied by the measure's incremental increase in output, GJ_{inc}, to allocate the emission reduction for each measure.

Demand Measures

Energy demand measures allocate emission reductions in the same manner as cleaner fuel measures, based on the difference between a reference emission intensity and the measure's emission intensity. The reference emission intensity is generally based on the emission intensity of the incumbent technology. Demand measures are allocated to any emission reductions associated with emission intensity improvements, including fuel switching, but not for changes in the composition of fuel they consume.

Equation 4 – Emission reduction allocation for demand measures

$$allocation = \left(int_{ref} - int_{meas}\right) \times SerivceDemand_{inc}$$

Emissions reduction allocation for these measures is calculated using Equation 4. The reference emission intensity, int_{ref}, is based on user-defined reference values, which define this value for each measure and represent emissions per unit of service demand. The emission intensity of the measure, int_{meas}, is calculated based on all of the energy consumption for the measure per unit of service demand, including electricity use, hydrogen use, and any other fuel use. The difference in these two intensities is multiplied by the incremental increase in service demand met by the measure between step n-1 and step n, $ServiceDemand_{inc}$.

Overview of Energy System Modeling Tools

We use two models developed by Evolved Energy Research to simulate the U.S. energy system, as described in Table 2. Both models have been used extensively to evaluate low-carbon energy systems at the national and sub-national levels. For this study's purposes, EnergyPATHWAYS (EP) is used to simulate energy system service demand for the MAC analysis.

In contrast, the Regional Investment and Operations (RIO) platform operates by finding the set of energy system decisions that are the least cost. This includes detailed capacity expansion functionality for the electricity, fuels, carbon management, select demand-side measures, and industrial heat sectors of the economy. Consumer decisions are optimized for vehicle choice in

[32] Emission intensity for some technologies can change depending on other system conditions, namely electrolysis which will depend on the grid's emission intensity and production that incorporates carbon capture which depends on the share of sequestered versus utilized carbon. Emissions from the counterfactual are based on step n-1 values.

light-duty autos, light-duty trucks, medium-duty vehicles, heavy-duty vehicles (short and long-haul), and space heating. These consumer decisions incorporate customer payback curves and therefore reflect plausible customer constraints on the adoption of demand-side technologies.

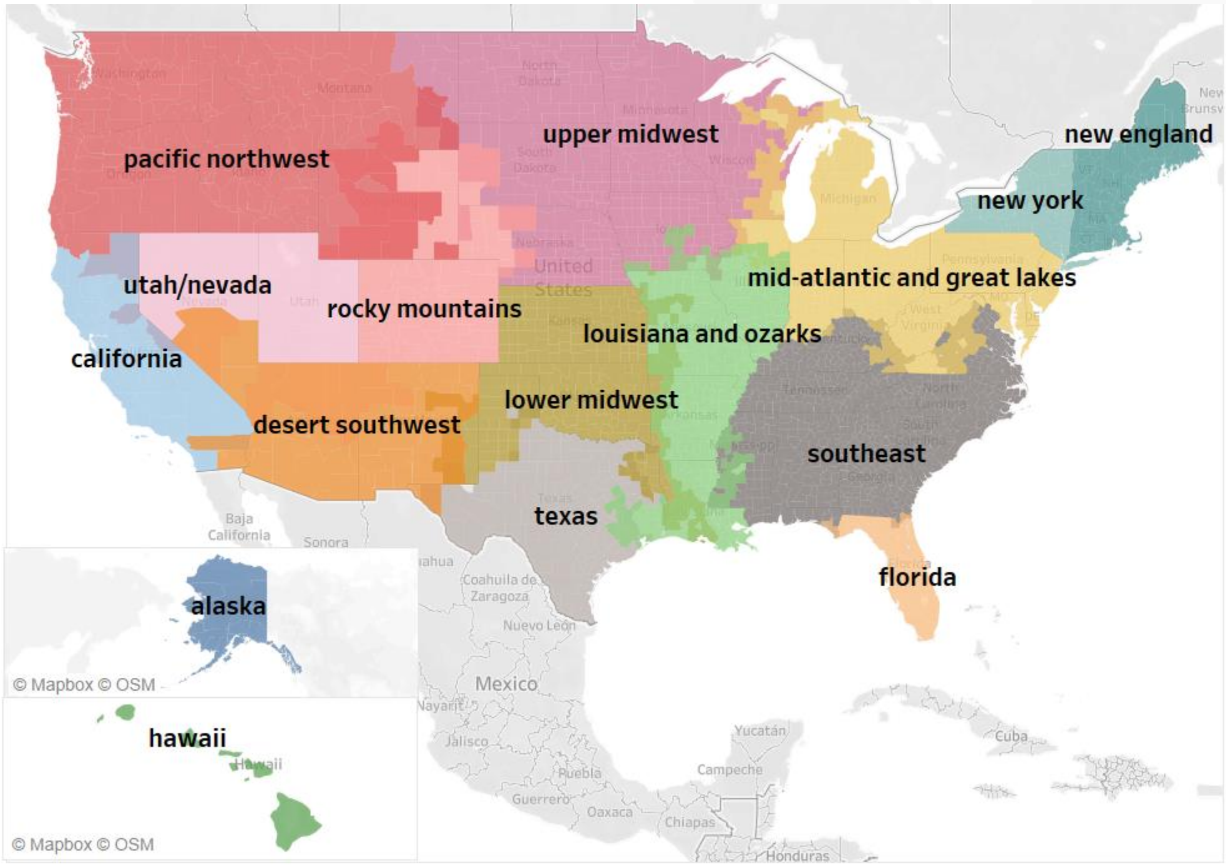
Table 2 - Models Used to Evaluate Technology Areas

	Description	Use in this Study
EP	• Bottom-up energy sector planning tool • Represents all producing, converting, storing, delivering, and consuming energy infrastructure • <u>Energy system decisions are scenario-based and not a result of an optimization</u>	• Establishes service demand boundary conditions for optimization within RIO
RIO	• Capacity expansion tool used to produce cost-optimal resource portfolios across the electric and fuels sectors • Simulates hourly electricity operations and annual investment decisions • <u>Energy system decisions are a result of a least-cost optimization</u>	• Optimize the deployment of demand- and supply-side technologies, representing the first step of the methodology

This paired modeling approach allows for parameterization of energy sector boundary conditions and allows for economy-wide CO_2 emissions accounting while focusing on measures pertinent for this MAC analysis. RIO optimizes resource build and operations for the system where measures can lower emissions and other supply-side technologies that support measure deployment for a reliable, low-carbon energy system (e.g., battery storage for electricity).

For this study's purposes, the U.S. energy system is characterized using a customized geography based on an aggregation of the U.S. Environmental Protection Agency's eGRID geographies, as shown in Figure 18. The aggregation was done for computational purposes to reduce the total number of zones to a manageable number but characterizes important regional differences that affect energy system transformation, including (a) resource endowments such as renewable resource potential and quality, bioenergy feedstock supply, and geologic sequestration availability; (b) climate, which drives space heating electrification impacts; and (c) electric transmission constraints.

Figure 18 - Model Regions



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