A State Policymaker's Guide to Power Sector Modeling

March 2017

BIPARTISAN POLICY CENTER

Duke
NICHOLAS INSTITUTE
FOR ENVIRONMENTAL POLICY SOLUTIONS

Authors

Blair Beasley
Senior Policy Analyst, Bipartisan Policy Center

David Hoppock
Senior Policy Associate, Climate and Energy Program,
Duke University's Nicholas Institute for Environmental Policy Solutions

Jennifer Macedonia
Fellow, Bipartisan Policy Center

Martin Ross
Senior Research Economist, Environmental Economics Program,
Duke University's Nicholas Institute for Environmental Policy Solutions

Tracy Terry
Director of Energy, Bipartisan Policy Center

ABOUT THE BIPARTISAN POLICY CENTER

The Bipartisan Policy Center is a non-profit organization that combines the best ideas from both parties to promote health, security, and opportunity for all Americans. BPC drives principled and politically viable policy solutions through the power of rigorous analysis, painstaking negotiation, and aggressive advocacy.

ABOUT THE NICHOLAS INSTITUTE FOR ENVIRONMENTAL POLICY SOLUTIONS

Established at Duke University in 2005, the Nicholas Institute for Environmental Policy Solutions at Duke University helps decision makers create timely, effective, and economically practical solutions to the world's critical environmental challenges. Through its six programs, the Nicholas Institute mobilizes objective, rigorous research to confront the climate crisis, clarify the economics of limiting carbon pollution, harness emerging environmental markets, put the value of nature's benefits on the balance sheet, develop adaptive water management approaches, and identify other strategies to attain community resilience.

DISCLAIMER

Table of Contents

Introduction

The U.S. energy sector has undergone a sweeping transformation over the past decade. Technological advances have driven down the price of natural gas and renewable energy technologies, and the future of the nation's aging nuclear fleet is still in flux. Looking forward, more changes lie ahead, with the continuing evolution of technology driving changes in electricity markets, major decisions impacting the nuclear fleet, inevitable changes in fuel markets as well as potential policy shifts. Despite the near certainty of rapid change in the sector, there is uncertainty about the exact direction of this change and the major drivers. This is coupled with the fact that most utility investments continue to have long financial and operating lifetimes of 20 to 30 years or more. Policymakers at all levels of government and investors have to live with this uncertainty and need to take the long view to understand the consequences of different futures and policy choices. But because of the complexity of the sector and multiple sources of uncertainty, this is difficult. Economic modeling of the electricity sector in response to policy and other changes is a valuable tool to understand the long-term impact of different potential futures and policy changes, but modeling can be hard to understand.

The prior administration made climate change mitigation a major focus of its energy and environmental policy and in October 2015, the Environmental Protection Agency (EPA) published the final Clean Power Plan as a way to limit carbon dioxide (CO_2) emissions from existing power plants for the first time. Regardless of the fate of the Clean Power Plan as noted above, electricity sector investors tend to take a long-term view when planning for challenges like carbon regulations because investments last for decades and the long-term pressure to mitigate climate change remains.

Numerous groups have released analyses that explore possible impacts of the Clean Power Plan, many of which are underpinned by sophisticated economic modeling. Regardless of the future of the Clean Power Plan, this paper is useful for decision makers because it shows how modeling can be used to simulate possible policy, market, and technology changes in the electricity sector and produce useful information. It also serves as a guide for state policymakers who have both the benefit and challenge of unpacking modeling results and figuring out how best to learn from the diverse findings. This paper specifically focuses on:

- Understanding what economic models do well and how best to utilize them;
- Summarizing many of the modeling platforms being deployed to model carbon regulations such as the Clean Power Plan;
- Exploring key modeling structures and input assumptions that impact power sector modeling results; and
- Understanding how to interpret results that come out of these models.

Clean Power Plan

The Clean Power Plan limits CO_2 emissions from existing power plants under Section 111(d) of the Clean Air Act. The rule calls for states to submit implementation plans to the EPA. States can choose to regulate covered sources' emission rates or total emissions (either for existing units only or for existing and new units). States can allow affected units to trade emission rate credits under rate-based compliance or allowances under mass-based compliance. The rule has been challenged in federal court. The U.S. Supreme Court has stayed the rule while it makes its way through the legal process.

What Can Economic Models Tell Us?

Economic models are important tools when thinking through the possible impacts of the Clean Power Plan on the electric power sector. The power system is immensely complex. There are more than 7,300 power plants in the United States, producing power from diverse resources such as coal, natural gas, wind, solar, hydro, and nuclear. These plants are connected to about 160,000 miles of high-voltage transmission lines.[1] The sector is required to comply with a range of environmental regulations and laws.

The Clean Power Plan adds an additional layer of complexity. The regulation calls on states to adopt state-specific implementation plans that can draw on various policy pathways. Their choices will impact both in-state generating sources that must adhere to the state's policy, as well as out-of-state generating sources that compete to serve regional electric load. To simply think through how the Clean Power Plan would interact with all of these factors is a daunting task.

As a result, economic models have served as a key tool for simulating the electric sector and planning for the future. Models are stylized versions of the real world. There are many different types of economic models that policymakers, companies, and planners rely on when making policy and investment decisions. Each model has its own strengths and limitations. However, some generalities can be made.

What Do Modeling Analyses Do Well?

Models are able to project how the electricity system might respond to new policies. A modeling analysis begins by developing a "business-as-usual" case, generally referred to as a Reference case, which does not include potential new policies. However, the Reference case does incorporate assumptions about the electricity system going forward, such as assumptions about future demand growth, technology costs, fuel prices, etc. Once the Reference case is established, then the new policy is added—such as the Clean Power Plan. Analysts can determine the potential impact of the policy by comparing the Reference case results with the results of the policy case. Clean Power Plan analyses are complicated by the fact that there are multiple ways of complying with the regulation. As a result, analyses often test several different policy cases, including variations of rate-based compliance and mass-based compliance.

In addition, because trying to project the future is inherently uncertain, most modeling analyses will also include a number of "sensitivity" cases, in which an individual input assumption is changed to understand how that particular assumption affects the results. For example, what would be the impact of the policy if renewable costs are lower than assumed in the Reference case? Modeling a number of sensitivity cases across a range of assumptions provides a more robust assessment of possible policy impacts. Models can:

Highlight findings that are robust

Modeling output based on multiple policy and sensitivity cases that incrementally change assumptions about the policy or input assumptions can highlight big-picture results that are robust under different assumption sets. For example, many analyses have found that allowing for the broad trading of allowances or Emission Rate Credits (ERCs) in Clean Power Plan compliance lowers costs under a variety of assumptions compared to policy cases that restrict this flexibility.

Reveal the sensitivity of results to different assumptions

All modeling exercises are based on assumptions about what the future will look like. While some findings remain consistent across differing assumptions, other findings are likely to be sensitive to underlying assumptions. For example, many analyses have found that the projected size of the future coal fleet is sensitive to assumptions about the future price of natural gas.

1. EIA, http://www.eia.gov/todayinenergy/detail.cfm?id=27152&src=email

Showcase least-cost compliance options

Many models, often referred to as optimization models, provide a "least-cost" solution. That is, the model mathematically determines the lowest-cost way to meet a given policy constraint, such as a limit of CO_2 emissions, given the assumptions regarding fuel prices, technology costs, etc. While the real world may deviate from any least-cost path, it is helpful for policymakers to explore least-cost solutions.

What Are the Limitations of Modeling Analyses?

While models can provide useful projections about many possible future outcomes, they are not crystal balls and cannot predict the actual future. Important limitations of all modeling exercises include:

Anticipating disruptive events and technological innovation

As noted above, modeling results are strongly influenced by key input assumptions. However, it is often difficult for analyses to anticipate major changes in the real world. This includes both rapid changes within the sector as well as technology innovation over time. For example, past modeling efforts tended to initially overestimate the prices of sulfur dioxide (SO^2) allowances under the Acid Rain Program by not anticipating changes such as the availability of western, low-sulfur coal that affected the industry's ability to lower SO^2 emissions. There are certain to be significant changes over the coming years that current modeling efforts are missing as well. For example, advancements in energy storage could alter projections about renewable energy penetration and overall capacity needs.

Accurately capturing state policy decisions that have yet to be made

Under the Clean Power Plan, each state is charged with submitting a state implementation plan. States that opt not to submit a plan, or that have plans disapproved by the EPA, are subject to a federal implementation plan. As a result, compliance plans could vary substantially from state to state. For example, states may select rate- or mass-based compliance, choose to include or exclude new units from a mass-based plan, or expand or limit trading of allowances or ERCs. While modeling various policycombinations can provide key insights, models are unlikely to capture the true compliance landscape until states submit plans to the EPA. Submission deadlines are currently stayed while the Clean Power Plan makes its way through the courts.

Capturing real-world decision making, including information gaps and non-economic factors

As noted above, many models estimate the least-cost compliance options for a given set of assumptions about future market conditions. In addition, many optimization models have "perfect foresight" i.e., they assume that all actors know, for example, the true, future gas price and can choose to build new units or retire existing ones accordingly. However, in the real world, people do not operate with perfect foresight or perfect information. Decision makers across the industry make long-term investments based on their own set of assumptions that often vary from other actors in the same market.

In addition, real-world actors may make investment decisions for reasons other than economics. For example, a company may choose to continue operating an existing power plant that is "in the red" due to reliability requirements that may not be accurately characterized in the models or due to an expectation that market conditions may rapidly change. Or, customers may choose not to invest in end-use energy efficiency (EE) measures that are cost-effective due to longer than desirable payback timelines or misaligned incentives, even when offered participation in utility-sponsored EE programs. As a result, the real-world response will likely deviate from the perfect foresight, least-cost pathways identified by models in unpredictable ways.

Representing both localized detail and broader impacts

Models vary in both geographic and sectoral scope as well as the amount of detail devoted to characterizing specific aspects of the power sector. Every model has some level of real-world details that are represented with rough approximations because the models have limited dimensions and make difficult tradeoffs on which complexities to include and which to simplify. As a result, it can be hard for any single model to excel at capturing both localized detail and broad trends. For example, some models capture a high-level of detail for a relatively small universe. These models may include lots of information about a specific company's generation fleet or the electricity sector in a specific state. However, these models may not capture the impact of decisions that occur outside of their area of interest. Other models provide insights for a much larger universe, such as an entire region or the entire country. These models often capture big-picture trends and the impacts of an interconnected electric grid at the expense of some localized detail.

What Are Some of the Modeling Platforms Being Used to Model the Clean Power Plan?

There are many models being deployed to test the impact of the Clean Power Plan on the electricity system. These models have different strengths and limitations. They vary in scope. Some models cover the United States (and Canada), while others are specific to a particular state or region. Some models focus exclusively on the electric power sector, while others include detail about the larger economy.

Broadly speaking, most modeling of the Clean Power Plan seeks to find the "optimal" solution to Clean Power Plan compliance for a user-identified set of input assumptions. In economic modeling, an optimal solution typically is least-cost (lowest cost) or maximizes total net benefits accounting for both the costs and benefits of a set of actions. The majority of the publicly released Clean Power Plan modeling thus far is based on determining least-cost compliance under a variety of policy designs (i.e. rate- or mass-based emission limits). In other words, what are the electricity sector investment, retirement, and operations decisions that minimize the total cost of operating the electricity system nationally or regionally while simultaneously meeting customers' demand for electricity, maintaining reliable electricity service, and complying with other requirements such as state and federal environmental regulations? These "optimal" solutions to Clean Power Plan compliance, as determined by the various models, depend critically on the input assumptions entered into the model.

Broadly, three types of economic models are being used to project optimal compliance with the Clean Power Plan: production cost models, capacity expansion models, and multi-sector models. Some of the models summarizein this report are a combination of these categories of models, and some analyses rely on outputs from more than one type of model.

Summary of Model Types [a]

Production Cost Models

Production cost models provide detailed projections of how utilities and grid operators operate power plants to meet electricity demand and maintain reliability. These models minimize the total cost of operating plants chronologically over time—such as every hour or 15-minute period in a day, week or year—accounting for:

1. The physical properties of a plant, i.e. efficiency, emissions rates, etc., often at the unit level,
2. The technical constraints of the plants included in the model,
3. Transmission limits on importing or exporting power into different regions, and
4. Detailed representation of how consumers' demand for electricity changes over time.

Examples of technical constraints at power plants include the ability of individual plants to increase or decrease output over time (ramping), the fuel available to a plant over time, as well as detailed representation of when plants are unavailable due to planned and unplanned maintenance. These models have a high level of detail for plants included in the model but do not determine what new power plants are needed or when existing plants should retire. Users can manually make changes in new plants and retirements to test impacts of externally determined investments. Production cost models can be thought of as the best representation of how the grid will operate given a known set of power plants in the near-term (up to 3-5 years).

Capacity Expansion Models

Utility-scale capacity expansion and dispatch models project optimal power plant additions and retirements as well as power plant operations to meet electricity demand over long planning horizons (generally at least 10 years).[b] These models determine what type of plant is needed in each region of the model as well as region-specific retirements given future demand as well as other constraints such as environmental regulations, renewable portfolio standards, and reliability standards. Because they are making both capacity decisions (retirements and new unit additions) and operational decisions over long time periods and large areas, they lack some of the detail that production cost models have regarding power plant operations. For example, utility scale capacity expansion and dispatch models tend to simulate electricity demand over blocks of hours in a year or season (winter, summer, spring/fall) rather than modeling each hour chronologically. Similar to production cost models, capacity expansion models can vary in the area over which they are optimizing decisions (national or regional).

National models are larger and more complicated and can sometimes require greater aggregation of local data, for example creating categories of existing plants rather than modeling each plant individually. Capacity expansion models can be thought of as the best tools for determining what new plants will be built and what existing plants will be retired given the input assumptions into the model. It is important to note that the cost of a policy applied to the electricity sector, especially a policy that is likely to result in new plant investments and existing plant retirements, will depend both on long-term capital costs as well as operating costs. Capacity expansion models optimize both long-term operations and investment decisions, making them good tools for determining long-term costs.

Multi-Sector Models

Multi-sector models provide projections for multiple sectors of the U.S. energy system, accounting for interactions between different parts of the economy as well as factors such as overall economic growth and international trade. For example, a multi-sector model could be used to provide projections of how increased natural gas generation in the electricity sector would impact other parts of the economy that also use natural gas, such as residential and commercial heating, manufacturing, and industry. These models could also project how the oil and gas sector would respond to the increase in demand. Multi-sector models typically include the transportation, commercial and residential, manufacturing, and heavy industry sectors in addition to the electric power sector. They also capture different facets of energy production including oil and gas production, refining, and coal mining. A key feature of multi-sector models is their ability to project the impact of changes in electricity price on different types of consumers (residential, commercial, manufacturing, etc.) including increasing or decreasing electricity consumption. Because these models cover multiple sectors in the U.S. economy and provide projections 20 years or more into the future, they tend to aggregate power plants and other facilities into model plants and facilities. Due to their size and complexity, multi-sector models can take a long time to optimize. Multi-sector models can be thought of as the best tools for determining how policies and changes in the electricity sector will impact other parts of the economy.

[a] This summary of model types benefited from the work by Synapse Energy Economics and Argonne National Laboratory, Fisher et al. (2016). A Guide to Clean Power Plan Modeling Tools: Analytical Approaches for State Plan CO2 Performance Projections. http://www.synapse-energy.com/sites/default/files/Guide-to-Clean-Power-Plan-Modeling-Tools.pdf.

[b] Power companies often use capacity expansion models when making projections for integrated resource planning.

Summary of Select Models Being Used to Model the Clean Power Plan

Model Name	Type of Model	Examples of Organizations Using the Model	Sectoral Scope	Geographic Scope
DIEM	Combined multi-sector and electricity capacity expansion model; only using capacity expansion model for Clean Power Plan (CPP) analysis	Nicholas Institute for Environmental Policy Solutions at Duke University	Multi-sector model covering major sectors of U.S. economy including international trade with a detailed electricity capacity expansion and dispatch model	National model with regional and international results. Electricity model regions based on states
EGEAS	Capacity expansion model	Midcontinent Independent System Operator (MISO)	Power Sector Only	MISO
FACETS	Multi-sector model	Developed by Amit Kanudia & Evelyn Wright; Environmental Defense Fund, U.S. EPA	Multi-sector model with detailed end-use sectors; only using power sector model for CPP analysis	National, with generation modeled in 32 sub regions
Haiku	Capacity expansion model	Resources for the Future (RFF)	Power sector model (with price responsive fuel supply sectors)	National, with 26 defined regions
Integrated Planning Model (IPM)	Capacity expansion model	Bipartisan Policy Center, M.J. Bradley & Associates, U.S. EPA	Power Sector Only*	Continental U.S. and Canada, divided into over 100 zones
NEMS	Multi-sector model	Georgia Institute of Technology, Rhodium Group, U.S. Energy Information Administration (EIA)	12 sectoral modules of the U.S. energy system	National, 22 electricity regions
PLEXOS	Security constrained commitment and economic dispatch model	MISO (production cost modeling only), PJM (used for modeling final rule)	Power sector	Majority of the Eastern Interconnect
PROMOD	Security constrained commitment and economic dispatch model	PJM (used for modeling proposed rule)	Power sector	Eastern Interconnect
US-REGEN	Combined multi-sector model and electricity capacity expansion model: only using capacity expansion model for CPP analysis	Electric Power Research Institute (EPRI)	Power sector only for CPP analysis	National, with each of the lower 48 states represented individually

* IPM can be run with the Integrated Gas Model, which solves for gas production and cost to satisfy power and non-power sector demand. Alternatively, IPM can be run with price responsive fuel supply curves that reflect aggregate gas availability at a given price to serve the power sector.

What Key Input Assumptions Help Drive Clean Power Plan Modeling Results?

Modeling outcomes are sensitive to input assumptions. Some input assumptions are particularly influential in Clean Power Plan modeling exercises. These include assumptions about: EE costs and availability; natural gas prices; nuclear capacity; renewable energy costs; technological innovation; and demand projections.

End-Use Energy Efficiency

EE helps to reduce power sector emissions by reducing electricity demand. While EE measures were not part of the EPA's methodology for setting the emission rate standards for the final Clean Power Plan, EE can contribute to state compliance under rate- or mass-based policies. Under rate-based plans, qualified EE measures are able to earn ERCs. Under mass-based plans, EE makes mass caps easier to achieve by lowering demand. In treating EE as a Clean Power Plan compliance measure, it is useful to distinguish between EE that consumers undertake on their own in response to market conditions,(i.e. electricity prices or availability of technologies), and EE that is stimulated by utility- or state-level policies.

EE is likely to play a prominent role in compliance, but EE poses some unique challenges. These include: measuring and verifying EE savings, determining whether the savings are due to short-term price response or longer-term investments in more efficient technologies, understanding the barriers associated with consumer adoption of EE, and the cost and availability of EE measures. These complexities are difficult to reflect in modeling. Organizations modeling the Clean Power Plan have made different choices about how to characterize EE cost and availability.

EE in the Reference case

Almost all Reference cases inherently include some EE adoption by consumers. This is typically captured in the Reference case demand forecast. However, analyses differ over whether they explicitly represent incremental EE opportunities. Some analyses leave incremental EE out of Reference cases to simulate real-world barriers to EE uptake. Including incremental EE in policy cases assumes that the Clean Power Plan would provide the regulatory push to overcome real-world barriers and incentivize investment in cost-effective EE.

Why it matters: Leaving incremental EE out of the Reference case typically leads to relatively higher electricity demand, power system costs, and emissions in the Reference case. It also makes direct comparison to policy cases that include EE difficult.

Exogenous vs. endogenous treatment of EE

The treatment of EE varies considerably across models. Many electricity sector models include representations of incremental EE costs and availability. Some assume incremental EE investments are made endogenously, meaning the model can decide whether to select EE as a compliance option when coming to a least-cost solution. Other electricity sector models hardwire EE uptake into the model as an exogenous choice, often representing EE uptake as an assumed reduction in electricity demand that comes at a given cost. Multi-sector models treat EE differently. These models project electricity demand endogenously, and incremental EE may or may not be fully optimized alongside power sector decisions.

Each of these approaches has advantages and disadvantages. Multi-sector models can provide more consistency between the Reference case demand projections and incremental EE opportunities. However, these models may not be able to fully represent utility

investment trade-offs between demand and supply options. Electricity-only models with endogenous approaches require characterizing or over-simplifying the complex and differential financing options inherent in a wide variety of end-use EE programs and non-cost factors that influence consumer purchase decisions (this can also be true in some multi-sector models). Exogenously specifying incremental EE uptake may require sensitivity cases to determine how much is cost-effective based on off-line derived costs.

Why it matters: Together with the treatment of incremental EE in the Reference case, the way it is represented in models as a compliance option will influence EE's role in compliance. Whether endogenously or exogenously modeled, sensitivity cases are often used to analyze the impact of the uncertainties associated with stimulating incremental EE investments.

Cost and supply assumptions

Input assumptions vary on how much EE is projected to cost, how much supply of EE will be available, what scope of potential EE project types is captured, and what financing types are considered. Analyses base their EE cost and supply assumptions on a wide range of EE studies. In addition, organizations treat projected EE costs differently. Some groups that endogenously model EE uptake consider only rate-payer funded EE and assume utilities make EE investments based solely on the portion of the EE project cost that is born by the utility. Other groups assume EE investments are based on the combined cost born by the utility and the customer.[2] There is also a range of sensitivities that different organizations have tested to try to capture what a future with differing EE uptake levels could look like.

Why it matters: Modeling results are sensitive to the amount of EE uptake. Cost-effective EE in modeling runs can lower projected costs of compliance, provide a source of ERCs in rate-based compliance cases, and decrease the need to build new generating units by reducing demand.

Treatment of "legacy EE"

The Clean Power Plan allows states that adopt rate-based policies to issue EE ERCs for EE investments made as early as 2013 that are still generating emission reductions in 2022 or beyond. However, many models do not account for "legacy EE" investments made as early as 2013. For example, many modeling exercises rely on the U.S. Energy Information Agency's (EIA) Annual Energy Outlook (AEO) demand forecasts to reflect past investments in EE. However, the exact amount and location of those EE investments is not specified in the AEO forecast, making ERC crediting within the model difficult.

Why it matters: Modeling efforts that award EE ERCs to "legacy EE" increase the number of available ERCs compared to modeling efforts that do not award ERCs to "legacy EE." These additional ERCs make compliance easier to achieve in rate-based states.

Representation of current state programs

Models represent existing state EE programs differently and capture state EE programs to varying degrees. Many states have existing energy efficiency resource standards (EERS). Some models capture state-specific programs, while others represent savings from state-level EE programs at a regional scale. In addition, input assumptions are locked in at different times for different analyses. As a result, not all analyses will include the most up-to-date state laws.

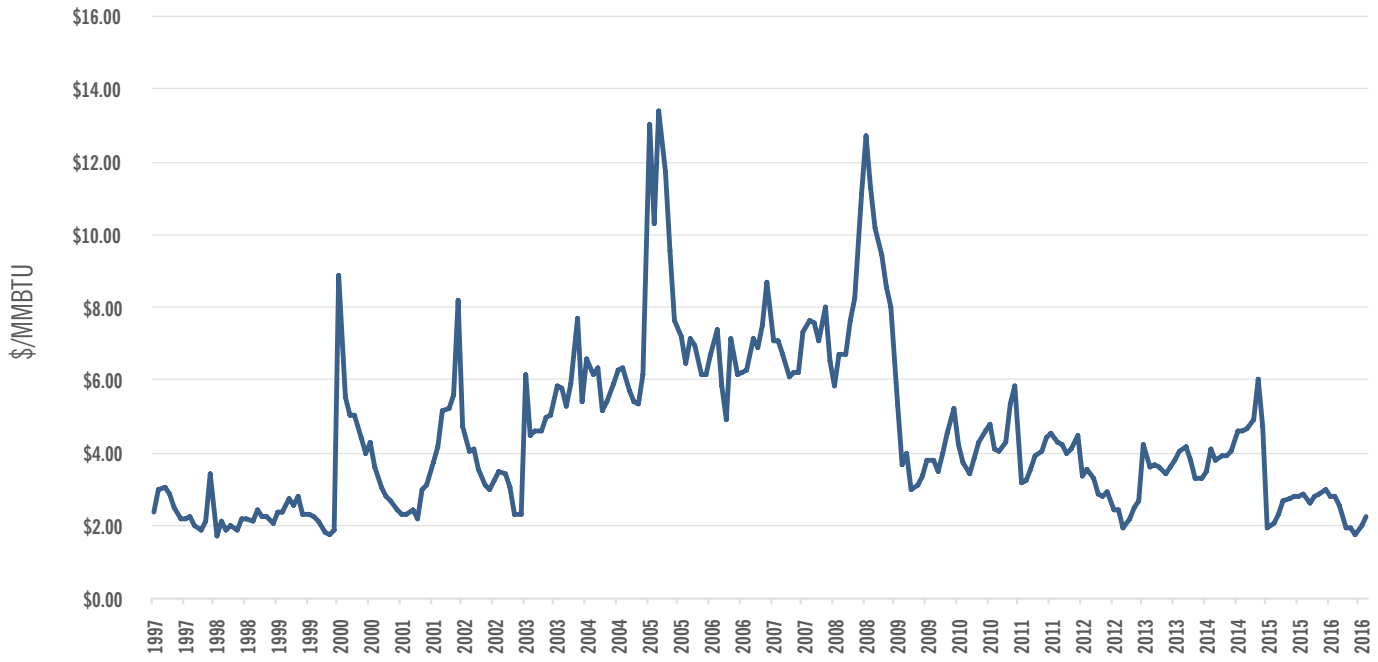
Why it matters: If an update to input assumptions or a change to the specification of state-level EERS programs would increase the modeled uptake of EE, it would make compliance easier to achieve under rate-based policies that use ERCs to meet emissions goals and under mass-based policies if electricity demand forecasts are too high because of EERS programs.

[2] Many organizations assume that the cost of a utility-funded EE project is divided more or less evenly between the utility and the customer.

Natural Gas Prices

Projecting the future price of natural gas has historically been a challenge. Gas prices have fluctuated in often unpredictable ways over time.

Figure 1. Henry Hub Natural Gas Spot Price ($/MMBtu)



SOURCE: EIA

Due to this uncertainty, modeling analyses of the electric sector have long relied on gas price sensitivity cases to explore the impact of future gas prices that are higher or lower than current expectations. In recent years, gas prices have remained lower than many projections. This is largely due to the rapid growth of domestic gas production from hydraulic fracking. For example, AEO 2015's Reference case projected Henry Hub prices in 2030 would be $5.61/MMBtu . AEO 2016's No CPP Reference case lowered the projected 2030 price by more than one dollar to $4.53/MMBtu.[3] Despite the decrease in projected gas prices, current gas prices remain below what many modeling analyses are assuming. As a result, gas price sensitivity cases continue to play an important role.

The impact of differing gas price assumptions

Analyses are based on different input assumptions about the projected cost of natural gas going forward, or, in the case of multi-sector models, natural gas resource and extraction costs that impact projected prices.

Analyses with relatively lower gas prices tend to show an increase in share of gas in the generation mix, more coal retirements, and an impact on how gas and renewables compete. For example, the Bipartisan Policy Center's June 2016 analysis included a Reference case with relatively low gas prices, which were similar to AEO 2016 projections. In addition, a sensitivity case explored Reference

[3] All dollars lists in 2012$.

case outcomes if gas prices were relatively higher, based on AEO 2015 projections. The Reference case with relatively low gas prices has about 25% more gas generation and slightly more coal retirements in 2030 than a Reference case with relatively higher gas prices.

Why it matters: Analyses based on relatively high gas prices tend to show less movement toward Clean Power Plan goals in the Reference case compared to analyses based on relatively lower gas prices. As a result, analyses based on higher gas pricestend to show that relatively more effort is needed to achieve Clean Power Plan compliance, such as highercompliance costs and higher allowance/ERC prices. Many analyses with relatively low gas prices project low or zero allowance/ERC prices during the early years of Clean Power Plan compliance. Gas prices may also influence the relative attractiveness of rate versus mass policy options.

Nuclear Retirements

The U.S. nuclear fleet is aging. Most existing nuclear plants will reach 60 years of operation sometime in the 2030s or 2040s. At that point, plants will need to be relicensed by the Nuclear Regulatory Commission in order to continue operating. No nuclear plant has gone through the relicensing process to allow operation through 80 years. It is, therefore, unclear how many units will seek to continue operating after 60 years and how many units will receive approval to do so by nuclear regulators.

In addition to uncertainty around relicensing, some existing nuclear plants have shut down or announced closures due to market forces. These closures have primarily occurred in deregulated states where nuclear plants are facing competition from low natural gas prices and an increase in renewable generation. These closures have yet to have a significant impact on national-scale modeling projections. However, the closure of a nuclear plant can have a substantial impact on an individual state's generation mix and emissions profile.

The impact of differing nuclear retirement assumptions

Analyses often make projections beyond the year 2030. As a result, analyses include assumptions about future age-based retirements in the nuclear fleet. For simplicity sake, most analyses either assume all nuclear units retire by the time they turn 60 or that all nuclear units could receive relicensing approval, in some cases with an assumed increase in cost.

Why it matters: Nuclear power plants provide a significant amount of carbon-free, baseload power. Assumptions about age-based retirements of nuclear units can impact near-term and long-term projections of the generation and capacity mix. Analyses that force all nuclear units to retire by 60 years must replace that capacity. Depending on capital cost and other assumptions, nuclear units are often projected to be replaced by a combination of new gas and new renewable units. The increased need for gas generation raises carbon dioxide emissions and makes Clean Power Plan compliance relatively more difficult to achieve. This can result in relatively higher ERC or allowance prices as well as relatively higher compliance costs.

Renewable Energy Costs

The cost of building new wind and solar projects has continued to decline in recent years, due to industry- and government-sponsored research and development as well as improvements associated with increased deployment. Many analysts have recently updated input assumptions to try to capture these trends. For example, the projected capital costs for new utility-scale solar decreased by about 26% between AEO 2015 and AEO 2016, while the costs for new utility-scale wind fell by about 18%.

In addition, in December 2015 Congress extended the Federal Production Tax Credit (PTC) for wind and the Investment Tax Credit (ITC) for solar and wind. These tax extensions further decreased the near-term costs for building new renewables.

Inclusion of the PTC/ITC extension

The omnibus appropriations bill passed by Congress in December 2015 brought back the PTC for wind, which had expired at the end of 2014. The PTC provides a 2.3 cents per kilowatt hour (kWh) incentive for qualified facilities that begin construction in 2015 and 2016. The incentive then begins to ramp down to expiration by January 2020. The ITC also received an extension under the omnibus bill. The 30 percent ITC for solar and geothermal was set to fall to 10 percent at the end of 2016. Now, the 30 percent ITC will continue through 2019, before tapering down to 10 percent by 2022. Analyses that capture these policy changes have relatively lower near-term costs for building new renewable energy sources.

Why it matters: Lower renewable build costs lead to more projected renewable builds. As a result, analyses that include the extension of the PTC and ITC tend to show more early investment in wind and solar in both Reference and policy cases than analyses that do not capture the tax extensions. The increased renewable investment tends to offset conventional generation, decreasing the need to build new natural gas combined cycle (NGCC) and lowering coal and existing gas generation. As a result, CO_2 emissions are lower in Reference cases that include the tax extensions. This makes the projected path to Clean Power Plan compliance easier to achieve. In addition, in policy cases, lower renewables costs allow wind and solar to more effectively compete with new gas-fired generation to serve load.

Common sources for wind and solar cost assumptions

The projected costs for new wind and solar can vary substantially from source to source. Sources differ both on projected near-term costs as well as the trajectory of how costs decline over time. For example, recent analyses relied on a range of outside studies to project capital costs for utility wind and solar. M.J. Bradley & Associates based their 2030 solar costs on a recent National Renewable Energy Laboratory (NREL) study, leading to a capital cost assumption of $1,053 per kilowatt. Rhodium Group based their 2030 solar costs on AEO 2015 data, leading to a capital cost of $2,755 per kilowatt. (See Appendix Table 4 for more information of renewable energy cost assumptions)

Why it matters: Analyses that assume lower renewable build costs in the near term and/or a faster decline in build costs over time, see more renewable investments projected in the model. In cases that project substantial coal or nuclear retirements, renewable energy and natural gas both ramp up to replace the generation. When renewable costs are lower, these sources are better able to compete with gas.

Integration of variable resources

As the costs for renewable energy sources decline, more renewable capacity, in particular wind and solar, is expected to be built. Wind and solar generation both provide variable renewable energy (VRE), as the wind does not always blow and the sun does not always shine. As a result, sufficient dispatchable resources, such as natural gas turbines or energy storage, must be available that can either start-up or ramp up to ensure that electricity demand can reliably be met in all hours.

Models represent VRE grid integration in a variety of ways. Some models broadly assess a cost to VRE technologies for "grid integration" and/or impose regional limits on the share of VRE generation. Other models include specific factors such as reductions in capacity credits for VRE technologies as VRE generation increases, requirements for additional operating reserves, and VRE generation curtailments. When VRE technologies compete with more conventional technologies for market share, models should consider not just the costs of the technologies but also their mode of operations, their contribution to supplying peak capacity, and the value of energy, which may vary by time of day or season. Solar generation is often more valuable than wind because it is more

coincident with peak load. Wind generation, on the other hand, is generally highest at night and in the winter months. However, both technologies can play an important role in reducing CO_2 emissions.

Temporal resolution is especially important for solar generation where output varies considerably on a daily and seasonal cycle. When solar becomes a substantial share of generation, curtailments may be necessary to accommodate periods of low demand that coincide with high solar availability (such as spring weekend days) as well as the availability of dispatchable units that can ramp up generation quickly as the sun sets. The California Independent System Operator (CAISO) published a "duck chart" in 2013 describing the potential for "overgeneration" as solar deployment increases.[4] Because most of the models analyzing the Clean Power Plan do not represent an hourly dispatch, but rather aggregate time periods into larger blocks, they must rely on various other constraints as a proxy to prevent overgeneration from VRE.

Why it matters: Analyses that project high levels of renewable builds and do not fully characterize the factors associated with VRE integration may overestimate the value of expanded renewables deployment on the grid. This increased, carbon-free generation would alter the forecast for Clean Power Plan compliance. On the other hand, analyses that overly constrain the generation potential of wind and solar may artificially hinder Clean Power Plan compliance by decreasing the projected potential for renewables to contribute.

Treatment of distributed generation

Distributed generation refers to smaller-scale generating sources that produce power in close proximity to the end-user, such as rooftop solar photovoltaic systems.[5] Models capture investments in distributed generation to various degrees. Some models explicitly model these generation sources, predicting future levels of distributed generation investments. Other models are limited to projections about utility-scale generation. However, these models can still implicitly approximate investments in distributed generation through demand forecasts. As distributed generation increases, the demand for utility-scale generation decreases.

Why it matters: Analyses that explicitly report out distributed generation tend to show more renewable generation and capacity than analyses that only report out utility-scale capacity. These analyses also have the potential for more variability in the level of demand for utility-scale generation, as distributed generation uptake varies from case to case.

Technology Innovation

The electricity-sector is in a state of evolution. There are many new technologies entering the marketplace that have the potential to substantially change Reference case projections. However, there is a high degree of uncertainty about how these technologies will evolve over the next several decades. Despite this challenge, many analyses do attempt to capture some of the more nascent technologies to varying degrees, including advanced nuclear, energy storage, next-generation renewable energy, carbon capture and storage, and demand-side management. Some analyses attempt to capture innovation through input assumptions that predict declining cost trajectories or increased performance over time. In addition, some analyses attempt to highlight possible futures through sensitivity analyses. For example, the Nicholas Institute's modeling of the Clean Power Plan includes a low renewable cost case based on the low capital cost estimates from the NREL's Alternative Technology Baseline study.[6] These lower costs lead to 18% more renewable generation in 2030 under a mass-based policy case that covers existing units with national trading, compared to Nicholas Institute's standard renewable cost assumptions.[7]

4. https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf

5. This definition does not include demand-side resources such as end-use energy efficiency, which is treated separately for the purposes of this paper.

6. NREL. 2015. Annual Technology Baseline. http://www.nrel.gov/analysis/data_tech_baseline.html

7. Renewable generation does not include generation from biomass.

Why it matters: Modeling that covers a realistic range of possible technology futures will provide a better sense of likely out comes. If new technologies substantially lower the cost or increase the opportunity for carbon-free generation, it would likely change the cost and the path to Clean Power Plan compliance.

Demand Projections

The future demand for electricity, and its projected growth rate overtime, are important input assumptions to economic models.[8] Because all models require that the supply of electricity meet the demand for electricity, higher demand forecasts require more generation, more EE, and/or more demand response in the system. This could require additional generating sources to be built. Depending on how demand is forecast to increase, it could also change the pace of investment in these new builds.

Why it matters: Analyses with relatively higher forecasted demand will require more generation, energy efficiency, and/or demand response to serve load. Depending on the Clean Power Plan compliance pathway adopted by a state, this has the potential to make compliance relatively more difficult to achieve. Some analyses have used sensitivity analysis to test the impact of high demand forecasts on key outcomes. For example, the Nicholas Institute found that the cost of compliance under a mass-based policy case that covers new and existing sources is considerably higher when higher load growth is assumed.

[8] Some models project electricity demand endogenously while other models include demand curves as an exogenous input assumption.

How do Models Capture Clean Power Plan Compliance?

The Clean Power Plan requires states to meet emission-rate or mass-based compliance targets starting in 2022. Requirements ramp up over time until the final goals are achieved in 2030. The rule provides states with various policy pathways to achieve Clean Power Plan requirements. This includes state plans based on:

I. Uniform, state-specific emission rates;

II. Subcategory emission rates for fossil fuel-fired electric steam generating units (i.e. coal-fired power plants) and natural gas combined cycle (NGCC) units;

III. Mass-based targets for existing units only; or

IV. Mass-based targets for new and existing units.

In addition to these "emissions standards" approaches, the Clean Power Plan allows states to comply using a state measures approach. Here, states can use state-level policies and programs, which are not federally enforceable, to meet a mass-based goal. These plans do require a federally enforceable backstop to be put in place. For example, California has formally proposed using a state measures approach based on its state cap-and-trade program to comply with the Clean Power Plan.[9]

Due to the Supreme Court stay, states have yet to submit compliance plans to the EPA. As a result, analyses have had to make assumptions about compliance pathways that cover a range of possible compliance outcomes.

Rate-Based Compliance

States can adopt a compliance pathway that requires affected, existing units to meet emission-rate goals starting in 2022. The Clean Power Plan provides a state-specific uniform rate that each state could adopt. By doing so, the state would require all affected units in the state to comply with the same emission-rate goal. In addition, the Clean Power Plan provides national, technology-specific emission-rate targets, a standard often referred to as the dual-rate standard or subcategory rate standard. Here, affected units would have different emission-rate standards depending on whether they are fossil steam or NGCC units. In 2030, the emission rate goal for fossil steam units is 1,305 lbs/MWh. The goal for NGCC units is 771 lbs/MWh.

Affected units that are unable to cost-effectively achieve the given emission-rate standard on their own have the option to purchase ERCs to adjust their emission rates and come into compliance. ERCs can be generated by several sources.

I. New, zero-emitting resources: Sources such as new renewable energy generation, generation from new and under construction nuclear, and new energy efficiency savings can generate ERCs.[10]

II. Efficient fossil units: Any fossil unit that operates below the emission-rate standard can generate ERCs.

III. Gas shift ERCs: Under subcategory rate-based compliance, NGCC generation can earn gas shift ERCs (GS-ERCs). The proposed federal rate-based model rule includes an equation to determine the number of GS-ERCs generated by NGCC units.[11] GS-ERCs can only be used by affected coal units.

9. http://www.arb.ca.gov/cc/powerplants/meetings/09222016/proposedplan.pdf

10. To qualify as an ERC generator, renewable energy sources must be installed on or after 2013 and generate power in 2022 or beyond. Similarly, EE measures implemented on or after 2013 can generate ERCs for MWh savings that occur in 2022 or beyond.

11. The equation includes the MWhs of generation by an NGCC unit and its emissions rate. The more a NGCC unit generates and the lower its emissions rate, the more GS-ERCs it earns.

Trading

States can decide whether ERCs can be traded within the state, within a broader region, or nationally. Interstate ERC trading is most easily achieved by states that adopt the technology-specific emission-rate standards. This compliance pathway is "trading ready" because all fossil steam units and all NGCC units face the same standard, regardless of location. No formal interstate agreement is needed to align interstate programs.

More coordination between states would be required to make interstate trading workable if a state adopts state-specific uniform rate goals. Each state has a unique uniform rate goal based on its historic generation mix. In order to make state-specific standards interstate trading compatible, states would likely have to enter into formal interstate agreements to align their diverse standards. This could involve averaging emission rate goals across state lines.

Why it matters: Many analyses have found that as trading regions grow, so do the associated savings and efficiencies. Therefore, analyses that allow for broad trading tend to have lower associated costs, on average, than they would if they limited trading to smaller regions or states. This includes lower average ERC costs and average compliance costs.

ERC Markets

Analyses capture the complexities of the ERC market to varying degrees. For example, some analyses specify the difference between ERCs and GS-ERCs within the model. Analyses also differ on what generation sources are eligible to earn ERCs. For example, as noted above, some models capture "legacy EE" ERCs while other models do not. Finally, no analyses surveyed to date have included any transaction costs associated with verifying and certifying ERCs as required by the Clean Power Plan or the risks buyers assume when purchasing ERCs. Instead, all models assume that all ERCs are verified and have no transaction costs.

Why it matters: The cost and availability of ERCs directly impacts the projected cost and ease of compliance under a rate-based policy. Analyses that award credits to more types of ERCs at lower costs will result in overall lower ERC prices and compliance costs. If analyses included transaction costs associated with the buying and selling of ERCS, the price of ERCs would likely increase.

Mass-Based Compliance

States can adopt compliance plans that require affected units to meet mass-based goals starting in 2022. The EPA provides state-specific mass-based goals that cover existing fossil units only or that cover both new and existing fossil units. Under either mass-based policy pathway, states can choose how to allocate allowances equal to the state's mass budget. An allowance represents the right to emit one ton of CO_2. At the end of each compliance period, affected units must hold one allowance for each ton of CO_2 released during the timeframe. The Clean Power Plan allows states to decide whether unused allowances can be banked for use in future compliance periods, how allowances are distributed, and what the rules are for allowance trading.

Trading

States that adopt mass-based compliance plans can decide whether allowances can be traded within the state, within a broader region, or nationally. States do not have to allocate allowances using the same methodology to have compatible trading programs. Moreover, states that cover new and existing units can decide whether to allow trading with states that cover existing units only, and vice versa. Analyses capture varying allowance trading regions.

Why it matters: Allowance trading encourages least-cost reductions to occur first. Affected units can decide whether it is more cost effective to reduce emissions or to continue emitting and purchase allowances in the marketplace. The benefits to trading allowances

under mass-based compliance are similar to the benefits of trading ERCs under rate-based compliance. Many analyses have found that as trading regions grow, so do the associated savings and efficiencies. Therefore, analyses that allow for broad trading regions tend to have lower associated costs, on average, than they would if they limited trading to smaller regions or states. This includes lower average allowance costs and average compliance costs.

Allowance Allocation

States that adopt mass-based policies have numerous options for how to distribute allowances to affected units.[12] These options include:

- **I.** Auctioning allowances;
- **II.** Distributing allowances to affected units based on past metrics that do not change from one compliance period to another, such as emissions or generation from 2012;
- **III.** Distributing allowances to affected units based on updating metrics, such as emission or generation from the last compliance period; and
- **IV.** Distributing allowances to sources not covered by the policy, such as renewable energy sources or load serving entities. These sources can then sell allowances to affected units.

Because allowances have monetary value, allowance distribution can impact who bears the cost of compliance. For example, states could opt to allocate allowances to renewable energy sources to subsidize wind or solar generation. Alternatively, states could allocate allowances to load-serving entities. This allocation method can help mitigate retail bill impacts, since load-serving entities can use revenue earned from the sale of allowances to offset increases in customer bills. Interest in different allocation methods will likely vary by state, depending on state policy goals and market structure. Rate-regulated states, for example, may opt to address retail bill impacts through ratemaking procedures rather than through allocation methods.

Although extremely important, whether allowance allocation affects modeling results, including wholesale electricity prices, depends on whether the allocation impacts dispatch and price response by consumers. The only form of allocation to generators that directly affects dispatch is an updating output-based allocation because it creates an incentive to generate. Under an updating output-based allocation scheme, allowances are distributed based on updating metrics, such as emissions or generation from the last compliance period, rather than historic metrics that do not change over time. An allocation scheme that favors different capital investments (e.g. using allowances to subsidize new generation) will impact capacity expansion decisions and therefore future dispatch. Similarly, allowance allocation can impact modeling if it changes the reaction of electricity consumers to changes in electricity price. If modeling includes consumer price response and the allocation approach changes prices for ratepayers, then it may change modeling results.

Why it matters: Analyses vary on how allowance allocation is treated in the model. This can impact projected retail rate impacts. For example, in AEO 2016, allocating allowances to generators leads to higher electricity rates than allocation to load serving entities under mass-based compliance. Variances in allocation methods can also impact compliance metrics. Several analyses, including ongoing work by Resources for the Future (RFF), have found that updating output based allocation can impact the generation mix and CO_2 emissions, particularly when all allowances are distributed this way.

[12] States that adopt mass-based policies covering existing units only are required to address the possibility of "leakage." Leakage mitigation may include allocation methods.

Banking of Allowances

The Clean Power Plan allows affected units to bank unused allowances for use in future compliance periods. Banking can increase the value of early emission reductions and can ease compliance obligations in later years, when the Clean Power Plan targets tighten. As a result, banking tends to smooth the allowance price out over time, with higher allowance prices in the early years and lower allowance prices in the later years relative to results without banking.

Why it matters: Many analyses assume that no banking is allowed. Doing so allows analysts to more easily compare modeling results from different cases for any given year. However, removing the option to bank allowances in a model can lower near-term allowance prices and undervalue near-term reduction opportunities, increasing overall compliance costs. For example, the Bipartisan Policy Center's analysis found $0/short ton allowance prices in 2022 in a mass-based policy case that covered new and existing sources but did not allow for banking. However, in an identical mass-based policy case that allowed for banking, the 2022 allowance price rose to around $5/short ton. By 2040, the allowance price in the case without banking was around $25/short ton, while the identical run with banking had an allowance price around $12/short ton.

Treatment of New Units

The Clean Power Plan allows states to decide whether to cover new units under a mass-based compliance plan, or whether to cover existing units only and otherwise mitigate potential leakage to uncovered sources. The EPA provides state-specific mass goals for both pathways.

For states that opt to cover existing units only, the Clean Power Plan requires compliance plans to address the possibility of "leakage." As defined by the Clean Power Plan, "Emissions leakage, or increased CO_2 emissions due to increased utilization of unaffected sources, is contradictory to objectives of this rule and should, therefore, be minimized."[13] For example, possible leakage indicators could include a relative increase in new natural gas builds or a relative decrease in capacity factors for existing gas units. Policies laid out by EPA to mitigate leakage are complex and therefore difficult to model. Various analyses have taken different approaches to their representation, although many analyses have included them in some form.

Why it matters: Models can be used to test the impact of including or excluding new units under mass-based policies. In addition, models can help explore the location and extent of leakage as defined by the Clean Power Plan in cases that do not cover new units. Some analyses also use models to explore the impact of allocation methods to address leakage, such as the updating output-based allocation.

Patchwork of Compliance

Many modeling analyses consider trends when all states opt for the same compliance pathway, such as all states opting for the technology-specific emission-rate standards or all states opting for mass-based policies that cover existing units only. However, it is unlikely that all 47 states facing Clean Power Plan compliance obligations will select the same compliance pathway. As a result, some analyses have explored what happens when states opt for a patchwork of different compliance pathways.

Why it matters: While it is unlikely that any analysis perfectly captures state policy choices that have not yet been made, patchwork analyses can highlight how key results fare when not all states make the same policy choices. On a national or regional level, patchwork analyses can showcase how sensitive broad findings are to changes in the policy mix. For example, these cases

[13] Clean Power Plan, 40 C.F.R. Part 60 2015.

can explore whether moving a few states from mass-based compliance to rate-based compliance changes key metrics such as compliance costs, emissions, or generation. On a state-level, patchwork analysis can highlight the sensitivity of a given state's compliance path, including compliance cost and generation mix, to another state's policy choice. For example, does a state's least-cost compliance pathway change if some of its neighbors alter their compliance choices.

Future Carbon Reduction Policies

Some analyses consider how investment decisions would change if the Clean Power Plan was not the final U.S. carbon policy, either due to an update of the Clean Power Plan by the EPA or federal carbon legislation. For example, AEO 2016's CPP Extended case, assumes that the Clean Power Plan becomes more stringent after 2030, instead of maintaining stringency as the rule is currently written. The Bipartisan Policy Center explores a case that assumes Clean Power Plan is the law of the land until 2030 when a more stringent federal policy kicks in for all new and existing sources.

Why it matters: Modeling a more constrained carbon future can highlight how near-term and long-term outcomes would differ if a more stringent carbon policy is expected to be enacted in the future. These policy cases can explore whether, and to what extent, various near-term state policy options under the Clean Power Plan send a signal for investment decisions that would put them on a least-cost path to meeting a more carbon-constrained future. These cases can highlight the extent that the expectation today of more stringent carbon policies in the future beyond the Clean Power Plan would increase investments in low- and zero-carbon generating sources. These cases can also explore whether near-term investments would be altered if investors consider that carbon constraints may be more stringent in the future. For example, would more wind and solar be built in coming years to take advantage of the renewable tax extenders? Would existing nuclear delay early retirements? Would more or less gas generation be built?

How do Models Shed Light on the Economic Impacts of the Clean Power Plan?

There are a variety of economic indicators that could help state policymakers answer the question, how much does the Clean Power Plan cost? These metrics include:

I. **Total system costs:** This represents the costs faced by the electric generators as they generate electricity, including variable and fixed costs. Variable costs change depending on how much electricity is produced. This includes fuel costs and variable operating and maintenance costs. Fixed costs do not change based on changes in dispatch. This includes fixed operating and maintenance costs, capital build costs for new generation capacity, retrofits, and, in some cases, new transmission.[14]

II. **Compliance costs:** This represents the difference in total system costs between a Reference case, where there is no Clean Power Plan obligation, and a policy case, where states must comply with the Clean Power Plan.

III. **Wholesale electricity price:** This is the price generators receive for producing electricity in wholesale electricity markets.

IV. **Retail costs:** This is the price of electricity paid by retail customers to utilities or other suppliers of electricity. Retail prices differ from the wholesale price based on state-specific retail rate policies. For example, retail pricing structures may differ by customer class, including residential, industrial, and commercial classes. Prices also reflect the cost of moving electricity over local distribution system.

Most retail rate analyses report state or regional estimates. These estimates typically do not separate out rate differences among intrastate utilities or customer classes and are based on estimates of states' existing rate bases. To account for the range of assumptions that feed into these estimates, many analyses focus on the extent that the retail rates in a policy case deviate from retail rates in a Reference case, rather than projecting absolute retail rates associated with different futures.

V. **Allowance prices:** This is the cost of purchasing one allowance under a mass-based compliance plan. Allowance prices are denoted in $/ton.

VI. **ERC prices:** This is the cost of purchasing one ERC under a rate-based compliance plan. ERC prices are denoted in $/MWh.

Models are programmed to provide some, if not all, of the cost metrics listed above. In addition, some analyses make adjustments to some of these outputs to report costs at greater levels of regional or state detail. These adjustments include:

I. **Adjusting total system costs to reflect generation flows between states**—As noted above, total system costs represent the costs faced by electric generators as they produce electricity. If a generator increases its output, its variable costs will rise. State-level total system costs, therefore, would go up if a state ramps up production, even if the ramp up serves regional load. Conversely, total system costs would decrease if a state's in-state generation wanes and is replaced by electricity from out-of-state sources. Most analyses adjust the total system cost metric to reflect these interstate generation shifts. These adjustments lower reported costs to reflect revenue from sales when interstate exports increase. Conversely, adjustments can increase reported costs when in-state sales decrease to reflect increases in out-of-state power purchases.

II. **Adjusting total system costs to reflect ERC/allowance flows between states**—In addition to adjusting total system costs to reflect changes in generation flows between states, some analyses make adjustments to total system costs to better reflect

[14] Total system cost does not include sunk costs unless it is exogenously added to the output data.

interstate flows of ERCs between states engaged in rate-based trading and allowances between states engaged in mass-based trading. Here, total system costs would be lowered if a state was a net seller of ERCs or allowances, reflecting the revenue flowing to in-state generators. Conversely, total system costs would be increased if a state was a net buyer of ERCs or allowances, reflecting the additional cost faced by in-state generators.

III. **Treatment of allowance auction revenue**—As noted above, state policymakers in states that adopt mass-based compliance plans will have to decide how to distribute allowances. One option is to auction allowances. Here, parties bid on allowances in an open market and prices are set by the level of demand. States that choose to auction allowances will have to decide what to do with the revenue that auctions generate. For example, a state could opt to use auction revenue to offset retail rate increases or promote other policy goals, such as subsidizing EE or renewable energy. As in the real world, the decision about how auction revenue is used will impact modeling projections about how costs are distributed and what generating sources are deployed. For modeling analyses, this is particularly relevant in cases that include allowance auctioning and report retail rates.

Why it matters: State policymakers will likely consider the cost of compliance as a key metric when selecting a compliance pathway. However, there are several cost metrics that different models provide. State policymakers will want to understand what cost metrics models are able to provide, what metrics are most important to their decision making process, and how these metrics may need to be adjusted to better reflect real-world conditions.

Key Modeling Outputs

Economic models can provide some key information to help state policymakers think through the possible impacts of policy decisions. In the context of Clean Power Plan modeling, some key modeling outputs include*:

- **Generation:** How much electricity does an electric generating unit produces during a given period of time?
- **Capacity:** What is the maximum amount of electricity an electric generating unit can produce?
- **New Builds:** What new electric generating units will be built, including the type, size and location of the new generating source?
- **Retirements:** What existing electric generating units will retire, including the type, size, and location of the retiring unit?
- **CO_2 emissions:** How many tons of CO_2 are emitted by the power sector?
- **Costs:** Models can report a variety of different cost metrics, including total system costs, wholesale prices, retail prices, allowance prices, and ERC prices. See "How Do Models Shed Light on the Economic Impacts of the Clean Power Plan," on page 23 for more detailed information about the reported costs.

*Note: Production cost models do not project what electric generating units will be retired or what new capacity will be built.

Conclusion

Modeling analyses can help state policymakers think through the possible impacts of implementing the Clean Power Plan. However, models are not crystal balls and cannot predict the actual future. Instead, models attempt to analyze how the industry is likely to respond to policies under specific sets of assumptions about future conditions. In order best utilize modeling projections, it helpful to understand what models do well, what differences exist between modeling platforms, how key analytical choices and assumptions impact results, and what key results come out of modeling exercises. This modeling user guide serves as a resource for state policymakers as they unpack different modeling analyses and make sense of the results.

Appendix A: Summary Tables of Key Modeling Assumptions

Below is a synopsis of some key modeling assumptions from a range of recent public Clean Power Plan (CPP) analyses. All of the analyses featured focused on national and regional outcomes. The tables are not intended to be exhaustive representations of the featured organizations' modeling assumptions. Many of the organizations included in the Appendix tables have published reports in the past with different assumptions and have ongoing modeling efforts. Note: All dollars are listed in 2012$ unless otherwise noted.

Table 1: Key Energy Efficiency (EE) Input Assumptions

Organization	Date of Report Publication	Reference Case Treatment	Exogenous or Endogenous	Cost Assumption (in runs with EE)	Supply Assumption (in runs with EE)	Treatment of State Energy Efficiency Resource Standards (EERS)	Issuance of Legacy EE Emission Rate Credits (ERCs)
Bipartisan Policy Center	June 2016	Includes Reference cases with and without incremental EE	Endogenous	Three-step cost curve for the utility portion of EE costs: $23-$32/MWh	Half of the supply assumed in EPA's Regulatory Impact Analysis (RIA) modeling of the final CPP	Yes- Modeled at the regional level	No
Electric Power Research Institute (EPRI)	February 2016	Reference case includes EE investment option	Endogenous	Costs based on EPA's proposed CPP: $77/MWh	Supply based on EPA's proposed CPP	No	Yes
FACETS	April 2016	Includes Reference cases with and without incremental EE	Exogenous	Several cost assumptions tested	Supply based on EPA's RIA modeling of the final CPP	No	No

Table 1: Key Energy Efficiency (EE) Input Assumptions (Continued)

Georgia Institute of Technology	June 2016	Includes Reference cases with and without additional EE	Endogenous, based on more stringent equipment and appliance standards, improved building shells, more stringent building codes, 30% Investment Tax Credit (ITC) for combined heat and power projects, and improved efficiencies at five industrial sectors	Costs for new purchases and retrofits drawn from published studies	EE side case reduces electricity demand 13% vs Reference case levels	Yes- Modeled at the regional level	Yes
M.J. Bradley & Associates	June 2016	Includes Reference cases with and without additional EE	Endogenous	From 2015 Lawrence Berkeley National Laboratory (LBNL) cost study[15]	3 supply levels tested: "Current" EE: based on 2013 annual savings rate, "Moderate" EE: 1% incremental savings rate achieved, "Significant" EE: 2% incremental savings rate achieved	Yes- Modeled at the regional level	No

15. https://emp.lbl.gov/sites/all/files/total-cost-of-saved-energy.pdf

Table 1: Key Energy Efficiency (EE) Input Assumptions (Continued)

Nicholas Institute for Enviromental Policy Solutions at Duke University	July 2016	Includes Reference cases with and without additional EE	Endogenous	EPA RIA: $1,100/MWh decreasing to $674/MWh (first year costs)	Supply based on EPA's RIA modeling of the final CPP: increasing over time to 1% incremental demand. Sensitivity analyses 0.5% and 1.5% incremental savings	No	No
MISO	July 2016	Reference case does not include incremental EE	Exogenous	EPA RIA	EE rates increase at the rate of 0.2% a year, starting in 2017, until 1.5% annual target is reached	Yes- Modeled as a hybrid of state and regional representation	No
PJM	September 2016	Reference Case includes EE embedded in the PJM 2016 load forecast released January 2016	Exogenous	NA- EE is taken as a given from the PJM 2016 load forecast	Supply is exogenously fixed in each year as part of the PJM 2016 load forecast. The supply grows over time	Yes- State EERS policies are accounted for in the PJM 2016 load forecast to determine the amount of EE each year	Yes
Resources for the Future (RFF)	June 2016	Includes EE investment option	Exogenous (programmatic) and Endogenous (price responsive demand)	$40/MWh undiscounted lifetime cost	In 2030, programmatic EE supply is roughly ½ of the supply assumed by EPA in its final rule RIA modeling. This varies by year	No – But in other runs EERS policies vary by state and are paid for with a systems benefits charge	Yes

Table 1: Key Energy Efficiency (EE) Input Assumptions (Continued)

Rhodium Group	May 2016	Endogenous; largely modeled in demand sectors	Endogenous	Equipment choices have embedded efficiency and cost assumptions	Equipment choices have embedded efficiency and cost assumptions	No	No
U.S. Energy Information Administration (EIA)	April 2015 (AEO 2015)	Endogenously model end-use sector equipment purchase decisions accounting for efficiency and costs of different options	Endogenous	Equipment choices have embedded efficiency and cost assumptions	Equipment choices have embedded efficiency and cost assumptions	No	No
U.S. EIA	July 2016 (AEO 2016)	Endogenously model end-use sector equipment purchase decisions accounting for efficiency and costs of different options	Endogenous	Equipment choices have embedded efficiency and cost assumptions. Costs are lower based on utility rebate programs for CPP cases	Equipment choices have embedded efficiency and cost assumptions	No	No
U.S. Environmental Protection Agency (EPA)	August 2015	Reference case does not include incremental EE	Exogenous	$1,100/MWh decreasing to $674/MWh (first year costs)	1% incremental demand	Yes	No

Table 2: Natural Gas Price Assumptions

Organization	Date of Report Publication	Core Gas Price Assumption	Other Gas Price Sensitivities Reported
Bipartisan Policy Center	June 2016	Average of Annual Energy Outlook (AEO) 2015 Reference case and High Oil and Gas Resource case	AEO 2015 Reference case
EPRI	February 2016	AEO 2015 High Oil and Gas Resource case	AEO 2015 Reference case
FACETS	April 2016	AEO 2015 Reference case	AEO 2015 High Oil and Gas Resource case & AEO 2014 Low Oil and Gas Resource case
Georgia Tech	June 2016	Endogenously determined using AEO 2015 Reference case supply.	None
MJ Bradley	June 2016	Average of AEO 2015 Reference case and High Oil and Gas Resource case	None
Nicholas Institute	July 2016	Average of AEO 2015 Reference case and High Oil and Gas Resource case	AEO 2015 Reference case, AEO 2015 High Oil and Gas Resource case
MISO	July 2016	Ventyx Forecast $4.52 starting in 2015	$2.59 starting in 2015 & $6.46 starting in 2015
PJM	September 2016	ABB Ventyx Fall 2015 forecast going from $3/MMBtu in 2017 to $10/MMBtu by 2037 (prices listed in nominal years)	IHS CERA February 2016 forecast starting at about $3/MMBtu in 2017 to nearly $6/MMBtu in 2037 (prices listed in nominal years)
RFF	June 2016	Endogenously determined using AEO 2013 Reference case supply	None
Rhodium Group	May 2016	Endogenously determined using AEO 2015 Reference case supply	None
U.S. EIA	April 2015 (AEO 2015)	Endogenously determined, baseline without CPP Henry Hub $3.65-$7.69 from 2015-2040	High Oil and Gas Resource case
U.S. EIA	July 2016 (AEO 2016)	Endogenously determined, baseline with CPP Henry Hub $3.87-$4.84 from 2019 through 2040	High Oil and Gas Resource case, Low Oil and Gas Resource case as well as other cases
U.S. EPA	August 2015	Endogenously determined using AEO 2015 Reference case supply	

Table 3: Nuclear Retirement Assumptions

Organization	Date of Report Publication	Assumed Age of Nuclear Retirements	Nuclear Retirement Sensitivities	Economic Nuclear Retirements in Reference case
Bipartisan Policy Center	June 2016	All nuclear plants are forced to retire by 60 years of age	No age-based retirement requirements	8.8 GW by 2020
EPRI	February 2016	3/4 of nuclear plants retire at 80 years, ¼ retire at 60 years	None	None
FACETS	April 2016	All nuclear plants are forced to retire by 60 years of age	None	None (nuclear plants are not retired endogenously)
Georgia Tech	June 2016	No age-based retirement requirements	None	None (nuclear plants are not retired endogenously), 3 GW of nuclear capacity assumed retired by 2021
MJ Bradley	June 2016	All nuclear plants are forced to retire by 60 years of age	None	10 GW by 2030, includes 3 GW of firm retirements after 2016
Nicholas Institute	July 2016	80 years	None	None
MISO	July 2016	No age-based retirement requirements	Removed assumption about a 1,560 MW nuclear build in Michigan	None
PJM	September 2016	No age-based retirement requirements	Assumed retirement decisions for all existing resources, including nuclear, are based on a five-year time horizon between 2018 and 2022. This assumption was tested at Reference case and low gas price levels.	None
RFF	June 2016	No age-based retirement requirements	None	None
Rhodium Group	May 2016	No age-based retirement requirements	None	None

Table 3: Nuclear Retirement Assumptions (Continued)

U.S. EIA	April 2015 (AEO 2015)	No age-based retirement requirements	None	None (nuclear plants are not retired endogenously), 2 GW of nuclear capacity assumed retired by 2020 due to financial risk
U.S. EIA	July 2016 (AEO 2016)	No age-based retirement requirements	None	None (nuclear plants are not retired endogenously), 3 GW of nuclear capacity assumed retired by 2020 due to financial risk
U.S. EPA	August 2015	All nuclear plants are forced to retire by 60 years of age	None	1-2 GWs

Table 4: Renewable Energy Cost Metrics

Organization	Date of Report Publication	Inclusion of the Production Tax Credit/ Investment Tax Credit Extensions	Source for wind and solar costs	Capital Costs for Utility-Scale Wind (2030)	Capital Costs for Utility-Scale Solar (2030)	Inclusion of distributed generation
Bipartisan Policy Center	June 2016	Yes	ICF market research	$1,470/kW	$1,508/kW	No
EPRI	February 2016	Yes	EPRI TAG Program	$1,864/kW, includes a $450/kW adder for distribution and transmission connection	$1,302/kW, includes a $450/kW adder for distribution and transmission connection	Model rooftop solar in California only
FACETS	April 2016	Yes	National Renewable Energy Laboratory (NREL) Annual Technology Baseline 2015 mid case	$1,600/kW	$1,318/kW	No
Georgia Tech	June 2016	Yes	Multiple sources			Yes

Table 4: Renewable Energy Cost Metrics (Continued)

MJ Bradley	June 2016	Yes	EPA RIA (except 2030 solar PV costs, which come from NREL)	$1,697/kW	$1,053/kW	No
Nicholas Institute	July 2016	Yes	EPA RIA	$1,703/kW	$1,321/kW	No
MISO	July 2016	No	Multiple (AEO 2015, NREL Annual Technology Baseline 2016, & MISO stakeholder input)	Tested a range of costs (model does not optimize based on cost)	Tested a range of costs (model does not optimize based on cost)	No
PJM	September 2016	Yes	NREL's 2018 costs, held constant over time in real terms	NREL's 2018 year costs inflated to 2030$ using a 2.25% inflation rate	NREL's 2018 year costs inflated to 2030$ using a 2.25% inflation rate	Yes (as part of the PJM 2016 load forecast)
RFF	June 2016	No	NREL	$1,491/kW- $2,718/kW (varying across regions)	$1,750/kW- $3,476/kW (varying across regions)	No
Rhodium Group	May 2016	Yes	AEO 2015 Reference Case	$1,882/kW	$2,755/kW	Yes
U.S. EIA	April 2015 (AEO 2015)	No	Internal	$1,883/kW	$2,761/kW	Yes
U.S. EIA	July 2016 (AEO 2016)	Yes	Internal	$1,673/kW	$1,686/kW	Yes
U.S. EPA	August 2015	No	ICF	$1,703/kW	$1,321/kW	No

Table 5: Demand Projections

Organization	Date of Report Publication	Source of Demand Projection	Demand Growth Rate
Bipartisan Policy Center	June 2016	AEO 2015	0.7% national
EPRI	February 2016	AEO 2015	0.7% national
FACETS	April 2016	AEO 2015	0.7% national
Georgia Tech	June 2016	AEO 2015	0.7% national w/o additional EE
MJ Bradley	June 2016	AEO 2015	0.7% national
Nicholas Institute	July 2016	AEO 2015	0.7% national
MISO	July 2016	Based on load serving entity submissions	0.8% MISO average
PJM	September 2016	PJM 2016 load forecast	0.9% across PJM
RFF	June 2016	Endogenous- based on regionally specific price-responsive demand functions, which are calibrated to AEO 2013 in the Reference case	Approximately 0.9% national
Rhodium Group	May 2016	AEO 2015	0.7% national
EIA	April 2015 (AEO 2015)	Endogenous	0.7% national
EIA	July 2016 (AEO 2016)	Endogenous	0.7% national
U.S. EPA	August 2015	AEO 2015	0.7% national

Table 6: Summary of Rate-Based Specifications

Organization	Date of Report Publication	Model State-Specific Blended Goals	Model Technology-Specific Goals
Bipartisan Policy Center	June 2016	Yes	Yes
EPRI	February 2016	Yes	Yes
FACETS	April 2016	Yes	Yes
Georgia Tech	June 2016	Yes	No
MJ Bradley	June 2016	No	Yes
Nicholas Institute	July 2016	No	Yes
MISO	July 2016	Yes	Yes
PJM	September 2016	Yes	Yes
RFF	June 2016	No	Yes
Rhodium Group	May 2016	Yes	No
U.S. EIA	April 2015 (AEO 2015)	CPP not modeled	CPP not modeled
U.S. EIA	July 2016 (AEO 2016)	Yes, by EMM region	No
U.S. EPA	August 2015	Yes	No

Table 7: ERC Trading Regions in Rate-Based Policy Cases

Organization	Date of Report Publication	Model Intrastate-Only ERC trading?	Model Regional ERC trading?	Model National ERC trading?
Bipartisan Policy Center	June 2016	Yes	Yes	No
EPRI	February 2016	Yes	Yes, as part of patchwork cases	Yes
FACETS	April 2016	Yes	Yes	Yes
Georgia Tech	June 2016	No	Yes, within modeling regions	No
MJ Bradley	June 2016	No	No	Yes (CA and RGGI use mass-based compliance in all policy runs)
Nicholas Institute	July 2016	No (ran but no results reported)	Yes	Yes
MISO	July 2016	Yes	Yes	No
PJM	September 2016	Yes (with interstate trading of renewable energy ERCs)	Yes	No
RFF	June 2016	No	Not reported	Yes
Rhodium Group	May 2016	No	No	Yes
U.S. EIA	April 2015 (AEO 2015)	Did not model CPP	Did not model CPP	Did not model CPP
U.S. EIA	July 2016 (AEO 2016)	No	Within EMM regions	No
U.S. EPA	August 2015	Yes	EE and RE ERC trade within interconnects	No

Table 8: Allowance Trading Regions in Mass-Based Policy Cases

Organization	Date of Report Publication	Model Intrastate-Only Allowance trading?	Model Regional Allowance trading?	Model National Allowance trading?
Bipartisan Policy Center	June 2016	Yes	Yes	No
EPRI	February 2016	Yes	Yes, as part of patchwork cases	Yes
FACETS	April 2016	Yes	Yes	Yes
Georgia Tech	June 2016	No	Yes, within modeling regions	No
MJ Bradley	June 2016	Yes	No	Yes
Nicholas Institute	July 2016	Not Reported	Yes	Yes
MISO	July 2016	Yes	Yes	No
PJM	September 2016	Yes	Yes	No
RFF	June 2016	No	Not reported	Yes
Rhodium Group	May 2016	No	No	Yes
U.S. EIA	April 2015 (AEO 2015)	Did not model CPP	Did not model CPP	Did not model CPP
U.S. EIA	July 2016 (AEO 2016)	No	Yes (at interconnect and regional level)	No
U.S. EPA	August 2015	Yes	No	No

Table 9: Allowance Allocation Assumptions

Organization	Date of Report Publication	Model Allowance Auctioning	Model Grandfathering of Allowances	Model Updating Output Based Allocation
Bipartisan Policy Center	June 2016	Yes	Yes	Yes
EPRI	February 2016	Yes	Yes	Yes
FACETS	April 2016	Yes	No	Yes
Georgia Tech	June 2016	No	No	No
MJ Bradley	June 2016	Yes	Yes	No
Nicholas Institute	July 2016	No	No	Yes
MISO	July 2016	No	No	No
PJM	September 2016	Implicit within the model	No	No
RFF	June 2016	Not reported	Yes	Yes
Rhodium Group	May 2016	Yes	No	No
U.S. EIA	April 2015 (AEO 2015)	Did not model CPP	Did not model CPP	Did not model CPP
U.S. EIA	July 2016 (AEO 2016)	No	Yes (assumed allocated to load-serving entities)	No
U.S. EPA	August 2015	Yes (restructured states)	No	No

Table 10: Allowance Banking Assumptions

Organization	Date of Report Publication	Allows Banking of Allowance in Core Runs	Allows Banking of Allowance in a Sensitivity Run
Bipartisan Policy Center	June 2016	No	Yes
EPRI	February 2016	No	No
FACETS	April 2016	Yes	No
Georgia Tech	June 2016	No	No
MJ Bradley	June 2016	No	No
Nicholas Institute	July 2016	Yes	No allowance banking sensitivity
MISO	July 2016	No	No
PJM	September 2016	No	No
RFF	June 2016	No	No
Rhodium Group	May 2016	No	No
U.S. EIA	April 2015 (AEO 2015)	Did not model CPP	Did not model CPP
U.S. EIA	July 2016 (AEO 2016)	No	No
U.S. EPA	August 2015	No	No

Table 11: Treatment of New Units in Mass-Based Compliance Policy Cases

Organization	Date of Report Publication	Model Existing + New Mass Goals	Model Existing—Only Mass Goals	Model a "Leakage" Fix [16]
Bipartisan Policy Center	June 2016	Yes	Yes	Yes
EPRI	February 2016	Yes	Yes	Yes
FACETS	April 2016	Yes	Yes	Yes
Georgia Tech	June 2016	Yes	Yes	No (examined the ability of EE to reduce leakage)
MJ Bradley	June 2016	Yes	Yes	No
Nicholas Institute	July 2016	Yes	Yes	Yes
MISO	July 2016	Yes	Yes	No
PJM	September 2016	Yes	Yes	No
RFF	June 2016	Yes	Yes	Yes
Rhodium Group	May 2016	Yes	No	No
U.S. EIA	April 2015 (AEO 2015)	Did not model CPP	Did not model CPP	Did not model CPP
U.S. EIA	July 2016 (AEO 2016)	Yes	No	No
U.S. EPA	August 2016	No	Yes	Yes (modeled the RE set aside from the proposed model rule)

16. This column captures whether analyses model a potential leakage fix other than modeling the new source complement.

Table 12: Summary of Patchwork Cases Modeled

Organization	Date of Report Publication	Model Patchwork Cases	Description of Patchwork Cases
Bipartisan Policy Center	June 2016	Yes	2 patchwork cases: 1) All states comply with a mass-based policy covering new and existing sources except for six rate-based states 2) All states comply with mass-based policy covering existing sources only except for six rate-based states
EPRI	February 2016	Yes	2 patchwork cases: 1) New nuclear states (Georgia, South Carolina, Tennessee) comply with a rate-based policy, California & RGGI states[17] comply with a mass-based policy that covers new and existing sources, and all other states comply with a mass-based policy covering existing sources only 2) Colorado, Georgia, Iowa, Kansas, South Carolina, Tennessee, Wisconsin comply with a rate-based policy, California & RGGI states comply with a mass-based policy covering new and existing sources, all other states comply with a mass-based policy covering existing sources only
FACETS	April 2016	No	
Georgia Tech	June 2016	Yes	1 patchwork case where Southern regions comply with blended rates, all other regions comply with a mass-based policy covering new and existing sources
MJ Bradley	June 2016	No	
Nicholas Institute	July 2016	Yes	5 patchwork cases in Eastern Interconnect and Texas: NJ and states with new nuclear units (Georgia, South Carolina, Tennessee) comply with a rate-based policy, then adding plains states, Mid-Atlantic States, and Southeast
MISO	July 2016	Yes	2 patchwork cases: 1) Half of the states modeled opt for rate-based compliance and half opt for mass-based compliance 2) Assigns states into rate- or mass-based compliance based on economics
PJM	September 2016	Yes	2 patchwork cases: 1) Assumes a group of coal-heavy states in the western part of PJM complies with a rate-based policy and all other PJM states comply with a mass-based policy. 2) Switches those assumptions

[17] The Regional Greenhouse Gas Initiative (RGGI) is a regional cap-and-trade program to reduce greenhouse gas emissions. Nine states in the northeast are members of RGGI: Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont.

Table 12: Summary of Patchwork Cases Modeled (Continued)

RFF	June 2016	Not reported	Over 75 scenarios with various regional configurations and policy choices
Rhodium Group	May 2016	No	
U.S. EIA	April 2015 (AEO 2015)	Did not model CPP	Did not model CPP
U.S. EIA	July 2016 (AEO 2016)	Yes	Hybrid case assumes California and New York/New England regions comply with a mass-based policy and all other regions comply with a rate-based policy
U.S. EPA	August 2015	No	

Table 13: Summary of Reported Cost Metrics

Organization	Date of Report Publication	Allowance Prices	ERC Prices	Total System Costs	Compliance Costs	Wholesale Electricity Prices	Retail Prices
Bipartisan Policy Center	June 2016	Yes	Yes	No	Yes	No	No
EPRI	February 2016	Yes	Yes	No	No	No	No
FACETS	April 2016	Yes	Yes	Yes	Yes	No	No
Georgia Tech	June 2016	No	No	Yes	Yes	No	Yes
MJ Bradley	June 2016	Yes	No	No	No	No	Bill impacts
Nicholas Institute	July 2016	Yes	Yes	Yes	Yes	No	No
MISO	July 2016	Yes	Yes	No	Change in production costs (no capital costs)	Yes	No
PJM	September 2016	Yes	Yes	Yes	Yes	Yes	No
RFF	June 2016	Yes	Yes	Yes	No	No	Yes
Rhodium Group	May 2016	No	No	Yes	Yes	No	Bill impacts
U.S. EIA	April 2015 (AEO 2015)	Did not model CPP	Did not model CPP	No	Did not model CPP	Did not model CPP	Yes
U.S. EIA	July 2016 (AEO 2016)	No	No	No	No	No	Yes
U.S. EPA	August 2015	No	No	Yes	Yes	No	Yes

Works Cited

Bipartisan Policy Center. "Modeling the Evolving Power Sector and Impacts of the Final Clean Power Plan." 2016. Available at: http://cdn.bipartisanpolicy.org/wp-content/uploads/2016/06/BPC-Energy-Clean-Power-Plan-Modeling.pdf.

Electric Power Research Institute. "State-Level Modeling of Clean Power Plan Compliance Pathways with EPRI's US-REGEN Model."2016. Available at: http://www.rff.org/files/document/file/160211__CPPModelingForStrategicInsights__Niemeyer__0.pdf.

Framework for Analysis of Climate-Energy-Technology Systems. "Emissions Sensitivities and Incentives to Generation under Clean Power Plan Compliance Pathways: An Analysis in FACETS." 2016. Available at: https://static1.squarespace.com/static/51755f0fe4b05f51bd7872f7/t/5712d2d64c2f851448f7943e/1460851417053/FACETS+CPP+analysis__April2016.pdf.

Georgia Institute of Technology. "The Clean Power Plan and Beyond." 2016. Available at: https://cepl.gatech.edu/sites/default/files/attachments/NEMS_CPP_Paper_06-24-2016.pdf

M.J. Bradley & Associates, LLC. "EPA's Clean Power Plan Summary of IPM Modeling Results With ITC/PTC Extension." 2016. Available at: http://www.mjbradley.com/sites/default/files/MJBA__CPP__IPM__Report__III__2016-06-01__final__0.pdf.

Nicholas Institute for Environmental Policy Solutions. "Ongoing Evolution of the Electricity Industry: Effects of Market Conditions and the Clean Power Plan on States." 2016. Available at: https://nicholasinstitute.duke.edu/sites/default/files/publications/ni__wp__16-07__final.pdf.

Midcontinent Independent System Operator, "MISO's Analysis of EPA's Final Clean Power Plan Study Report." 2016. Available at: https://www.misoenergy.org/Library/Repository/Meeting%20Material/Stakeholder/PAC/2016/20160720/20160720%20PAC%20Item%2002a%20Clean%20Power%20Plan%20Study%20Report.pdf.

PJM. "EPA's Final Clean Power Plan Compliance Pathways Economic and Reliability Analysis." 2016. Available at: http://www.pjm.com/~/media/documents/reports/20160901-cpp-compliance-assessment.ashx.

Resources for the Future. "Lessons for Reducing Leakage to Uncovered Sources under the Clean Power Plan." 2016. Available at: http://www.rff.org/files/document/file/Burtraw__CPP%20Leakage%20160823__dis.pdf.

Rhodium Group and Center for Strategic & International Studies. "Assessing the Final Clean Power Plan Energy Market Impacts." 2016. Available at: http://rhg.com/wp-content/uploads/2016/05/AssessingCleanPowerPlan__EMI.pdf.

U.S. Energy Information Administration. "Annual Energy Outlook 2015." 2015. Available at: http://www.eia.gov/forecasts/archive/aeo15/.

U.S. Energy Information Administration. "Annual Energy Outlook 2016." 2016. Available at: http://www.eia.gov/forecasts/aeo/.

U.S. Environmental Protection Agency. "Regulatory Impact Analysis for the Clean Power Plan Final Rule." 2015. Available at: https://www.epa.gov/sites/production/files/2015-08/documents/cpp-final-rule-ria.pdf.

Appendix B: Frequently Asked Questions about Clean Power Plan Modeling

1. Can modeling results tell me how much Clean Power Plan compliance will cost my state?
To learn more about what models do well and what limits modeling analyses have, see "What Can Economic Models Tell Us," on page 5. To learn more about the range of cost and price data that models can produce see "How Do Models Shed Light on the Economic Impacts of the Clean Power Plan," on page 23.

2. Different organizations are using different economic models to analyze the Clean Power Plan. How are the models different?
To learn more about the types of models being deployed to model the Clean Power Plan, and examples of these modeling platforms, see "What are some of the modeling platforms being used to model the Clean Power Plan" on page 8.

3. How important are input assumptions about end-use energy efficiency in Clean Power Plan modeling?
To learn more about the range of energy efficiency assumptions and how these input assumptions help shape results, see "What key input assumptions help drive Clean Power Plan modeling results" page 11. To see what energy efficiency assumptions some recent Clean Power Plan analyses adopted, see Table 1 in Appendix A.

4. How do assumptions about the future price of natural gas impact modeling results?
To learn more about the impact of different gas price assumptions, see "What key input assumptions help drive Clean Power Plan modeling results" page 13. To see what some recent Clean Power Plan analyses assumed about gas prices, see Table 2 in Appendix A.

5. How do models factor in the uncertainty about the aging nuclear power fleet?
To learn more about the importance of nuclear retirement assumptions, see "What key input assumptions help drive Clean Power Plan modeling results" page 14. To see what nuclear retirement assumptions some recent Clean Power Plan analyses adopted, see Table 3 in Appendix A.

6. How important are input assumptions about renewable energy costs and generation?
To learn more about the range of renewable energy assumptions and how these input assumptions help shape results, see "What key input assumptions help drive Clean Power Plan modeling results" page 14. To see what renewable energy assumptions some recent Clean Power Plan analyses adopted, see Table 4 in Appendix A.

7. Are modeling analyses capturing the impact of technology innovation when they make projections about the future?
To learn more about the importance and difficulty of capturing technology innovation in modeling analyses, see "What key input assumptions help drive Clean Power Plan modeling results" page 16.

8. What are some of the key impacts of modeling rate-based Clean Power Plan compliance differently?
To learn more about key modeling assumptions that impact modeling of rate-based compliance, see "How do models capture Clean Power Plan compliance" page 18. To see how different groups have modeled rate-based compliance see Tables 6 and 7 in Appendix A.

9. What are some of the key impacts of modeling mass-based Clean Power Plan compliance differently?
To learn more about key modeling assumptions that impact modeling of mass-based compliance, see "How do models capture Clean

Power Plan compliance" page 19. To see how different groups have modeled mass-based compliance see Tables 8, 9, 10, and 11 in Appendix A

10. What happens to state-level and national trends when states vary compliance pathways instead of selecting uniform policies?
To learn more about key modeling assumptions that impact modeling of a patchwork of rate- and mass-based compliance, see "How do models capture Clean Power Plan compliance" page 21. To see how different groups have modeled a patchwork of compliance see Table 12 in Appendix A

Appendix C: Glossary of Key Terms

Allowances
Allowances represent the right to emit CO_2. Under mass-based compliance, covered sources are required to hold one allowance for each ton of CO_2 emitted in a given compliance period.

Allowance Allocation
The process by which a state that adopts mass-based compliance distributes allowances.

Banking
The saving of allowances from one compliance period for use in a future compliance period.

Capacity
The maximum amount of electricity an electric generating unit can produce. This is typically represented in kilowatts (kW), megawatts (MW), gigawatts (GW), or terawatts (TW).

Capital Costs
This represents the cost of building a new power plant.

Clean Power Plan (CPP)
The Clean Power Plan is a regulation that limits CO_2 emissions from existing power plants under Section 111(d) of the Clean Air Act. The U.S. Environmental Protection agency published the final regulation in October 2015. The U.S. Supreme Court issued a stay of the rule in February 2016 while it makes its way through the legal system.

Compliance Costs
As modeling output, this represents the difference in costs between a Reference case, where there is no Clean Power Plan obligation, and a policy case, where states must comply with the Clean Power Plan.

Emission Rate Credits (ERCs)
The Clean Power Plan allows for the creation of ERCs under rate-based compliance. ERCs represent one megawatt hour (MWh) of emissions-free generation. They can be produced by a variety of sources, including qualified renewable energy sources and energy efficiency sources. Affected sources, such as coal and gas plants, can purchase emission reduction credits to adjust their emission rates and help bring them into compliance.

End-Use Energy Efficiency (EE)
EE measures are technology-based solutions, beyond the power plant, that reduce the energy use required to perform tasks. This includes efforts such as light bulb replacement programs, where inefficient incandescent light bulbs are replaced with more efficient LED or compact fluorescent bulbs.

Endogenous
In economic modeling, endogenous choices are selections made within the model as it solves for the least-cost solution

Exogenous
In economic modeling, exogenous choices are selections specified outside of the modeling framework.

Generation
The amount of electricity that an electric generating unit produced during a given period of time. This is commonly represented in kilowatt hours (kWh), megawatt hours (MWh), or terawatt hours (TWh).

Henry Hub
Henry Hub is a major natural gas distribution hub located in Louisiana. Henry Hub gas prices are often seen as the primary gas price in the North American gas market.

Investment Tax Credit (ITC)
The ITC is a tax credit for qualified renewable energy resources including some solar, wind, and geothermal systems. Congress has extended the tax credit several times, most recently in December 2015.

Leakage
The Clean Power Plan requires states that adopt mass-based plans that cover existing sources only to account for leakage. The regulation defines leakage as the possibility of shifting generation from existing fossil units that are covered by the policy to new fossil units that are not covered by the policy.

Legacy EE
The Clean Power Plan allows states that adopt rate-based policies to issue ERCs to EE investments made as early as 2013 that are still generating emission reductions in 2022 or beyond. Legacy EE refers to EE investments made between 2013 and the present, which are often hard to account for within modeling analyses.

Mass-Based Compliance
The Clean Power Plan allows states to select from several compliance pathways. Under mass-based policies, affected units must meet mass-based goals starting in 2022. The EPA provides state-specific mass-based goals denoted in total tons of CO_2 emissions per year. The EPA provides mass goals that cover existing fossil units only or both new and existing fossil units.

New Source Complement
States that opt to cover both new and existing units under their mass-based compliance plan are given a larger mass-based budget than states that opt to cover existing units only. The incremental difference between the two mass budgets is the new source complement.

Patchwork Case
In Clean Power Plan modeling, Patchwork cases are a type of policy case in which states are assumed to adopt different compliance pathways. For example, these modeling cases may assume a portion of states adopt rate-based compliance and a portion of states adopt mass-based compliance.

Policy Case
In Clean Power Plan modeling, policy cases are identical to the Reference case except for the inclusion of the Clean Power Plan. Many analyses include a several different policy cases that explore different compliance pathways, such as rate-based trading or mass-based trading.

Production Tax Credit (PTC)
The PTC is a tax credit for qualified renewable energy resources, including wind. Congress has extended the tax credit several times, most recently in December 2015.

Rate-Based Compliance

The Clean Power Plan allows states to select from several compliance pathways. Under rate-based compliance, affected, existing units must meet emission-rate goals starting in 2022. The goals are denoted in pounds of CO_2 per megawatt hour (lb/MWh). The regulation provides a state-specific uniform rate that each state could adopt. By doing so, the state would require all affected units in the state to comply with the same emission-rate goal. In addition, the Clean Power Plan provides national, technology-specific emission-rate targets, a standard often referred to as the dual-rate standard or subcategory rate standard. Here, affected units would have different emission-rate standards depending on whether they are fossil steam or NGCC units.

Reference Case

The Reference case is intended to capture a business-as-usual projection without the Clean Power Plan. While it is business-as-usual, it is not intended to be static. Reference cases include assumptions about the future, such as fuel cost and capital build cost projections.

Retail Price

This is the price of electricity paid by retail customers to utilities or other suppliers of electricity. Retail prices differ from the wholesale price based on state-specific retail rate policies. For example, retail pricing structures may differ by customer class, including residential, industrial, and commercial classes. Prices may also reflect the cost of moving electricity over local distribution lines.

Sensitivity Case

Sensitivity cases are identical to either Policy cases or Reference cases, except for an isolated difference in input assumptions. These cases allow analysts to explore how sensitive results are to changes in the electricity sector beyond the Clean Power Plan. For example, sensitivity cases may explore different input assumptions about gas price projections or renewable energy costs.

Total System Cost

This represents the costs faced by the electric generators as they generate electricity, including variable and fixed costs. Variable costs change depending on how much electricity is produced. This includes fuel costs and operating and maintenance costs. Fixed costs do not change based on output. This includes capital build costs

Variable Renewable Energy (VRE)

Variable renewable energy sources, such as wind and solar, fluctuate in their ability to produce electricity. For example, wind generation depends on the wind blowing and solar generation depends on the sun shining. These sources are often supported by dispatchable generation sources, such as gas turbines, that can be utilized when the variable renewable energy source is not generating.

Wholesale Electricity Prices

This is the price generators receive for producing electricity.

BIPARTISAN POLICY CENTER

2017 marks the Bipartisan Policy Center's 10th Anniversary. For a decade, BPC has worked to find actionable solutions to America's major policy changes.

Celebrating ten years of productive partisanship.

The Bipartisan Policy Center is a non-profit organization that combines the best ideas from both parties to promote health, security, and opportunity for all Americans. BPC drives principled and politically viable policy solutions through the power of rigorous analysis, painstaking negotiation, and aggressive advocacy.

bipartisanpolicy.org | 202-204-2400
1225 Eye Street NW, Suite 1000 | Washington, D.C. 20005

@BPC_Bipartisan
facebook.com/BipartisanPolicyCenter
instagram.com/BPC_Bipartisan
flickr.com/BPC_Bipartisan

BPC Policy Areas

Economy

Energy

Finance

Governance

Health

Housing

Immigration

Infrastructure

National Security

1225 Eye Street NW, Suite 1000
Washington, D.C. 20005

202-204-2400
bipartisanpolicy.org

P.O. Box 90335
Durham, North Carolina 27708

919-613-8709
nicholasinstitute.duke.edu