The Role of Energy Models: Characterizing the Uncertainty of the Future Electricity System to Design More Efficient and Effective Laws and Regulations

Tara Righetti, Robert W. Godby, Dalia Patino-Echeverri, Temple Leigh Stoellinger, and Kipp A. Coddington*

"It is tough to make predictions, particularly about the future."
—Yogi Berra

When designing environmental protection and energy regulation policies, legislators and regulators rely upon the results of computer models that purport to forecast future conditions such as energy supply, demand, available technologies and market characteristics. In a perfect world, these energy models would prove to be reliable[1] and would, in turn, yield projections that would enable legislators and regulators to confidently enact regulations that advance societal energy and environmental goals.[2]

Unfortunately, it is impossible to predict or forecast with confidence all the variables that influence regulation and the effects of any regulatory choice.[3] Anticipating the impacts of future conditions and the effects of regulatory change on the power sector, for example, requires consideration of a complex mix of factors, including: (1) technology costs and performance; (2) macro-economic conditions; (3) fuel prices; (4) consumer preferences; (5) an ever-changing regulatory framework at the local and state levels of government; (6) the impact of naturally occurring events, such as adverse weather; (7) market impacts related to energy choice; (8) shifting balances of federalism; and (9) the fact that energy outcomes are intimately intertwined with the political process.[4] Box's statement "all models are wrong, some are useful," enunciated about statistical models, applies and will continue to apply

* *Tara Righetti is the SER Assistant Professor of Law and the Director of the program in Professional Land Management in the School of Energy Resources at the University of Wyoming. Robert Godby is the Director of the Center for Energy Economics and Public Policy ("CEEPP") and also an Associate Professor in the Department of Economics and Finance at the University of Wyoming. His main areas of research interest are energy economics, resource and environmental economics, and macroeconomic policy.* *His contributions to this Article were partially supported by a grant from the U.S. Department of Energy [DE-SC0012671].* *Dr. Dalia Patino-Echeverri is the Gendel Assistant Professor of Energy Systems and Public Policy at the Nicholas School of the Environment at Duke University. She has a Ph.D. in Engineering and Public Policy from Carnegie Mellon University and MSc and BSc degrees in Industrial Engineering from Universidad de los Andes. Her research focuses on the decisions that policy makers, private companies, and citizens face regarding alternatives to reduce air emissions from the U.S. electricity system, and in the methods available to analyze and improve these decisions. Her research group develops plan-level and power-system level computer models to explicitly account for the risk and uncertainty of the economic, environmental, and reliability performance of policy mechanisms, capital investment and operations decisions. Temple Stoellinger is an Assistant Professor in the Haub School of Natural Resources and Co-Director of the Center for Law and Energy Resources in the Rockies at the University of Wyoming. Professor Stoellinger is also the Co-Faculty Supervisor of the Energy, Environment and Natural Resources Law Clinic at the University of Wyoming ("UW"). Kipp Coddington is the Director of Energy Policy & Economics and the Director of the Carbon Management Institute at the School of Energy Resources, University of Wyoming. Prior to joining UW in 2015, Mr. Coddington worked on natural resource issues as a partner at Kazmarek Mowrey Could Laseter L.L.P.* *The authors wish to acknowledge the research assistants who contributed to this project, Lauren Johnson (J.D. 2016) and Casey Terrell (J.D. 2018), the School of Energy Resources at the University of Wyoming for its support of this research, and the editors of the* George Washington Journal of Energy and Environmental Law *for their excellent editorial assistance.*

1. Michael Wara, *Instrument Choice, Carbon Emissions, and Information*, 4 Mich. J. Envtl. & Admin. L. 261, 269 (2015).
2. *Id.* at 272–73.
3. This calls to mind the short story, first introduced to the authors by Danny Cullenward. *See generally* Jorge Luis Borges, *On Exactitude in Science*, *in* Collected Fictions (Andrew Hurley trans. 1658); *see also* Bezdek et al., *A Half Century of Long Range Energy Forecasts: Errors Made, Lessons Learned, and Implications for Forecasting*, 21 J. Fusion Energy, 155, 155–72 (2002).
4. *See generally* Wara, *supra* note 1.

to models of energy and other complex systems.[5] Hence, the outcomes of regulatory action are inevitably uncertain.[6]

Because energy forecasts are often wrong, they are regularly revised. However, the regulations and policies developed based upon earlier modeled forecasts are not often revised or updated alongside the models.[7] Modelers recognize that models are uncertain, but regulators and legislators rely upon models as if they are not. The result is the development of lasting regulations that are more or less inflexible and unable to account for new information.[8] Should the conditions of the regulated system deviate from the expected, rules enacted under conditions of uncertainty could be ineffective, or worse, cause unintended negative consequences. Thus, the acknowledgement of systematic uncertainty and the reliance on modeling, present a challenge: can laws and rules governing the electricity sector have adaptability and flexibility that are commensurate with the uncertain and volatile nature of the regulated activity?

In this Article, we suggest that principles of dynamic law can be used as guidance to design policy that is coherent with the highly uncertain context in which it operates. We explore the idea that the uncertainty surrounding the outcomes of a regulation can be taken into account and made part of the regulatory design. In so doing, we suggest that regulations can tackle uncertainty using the same methods by which the energy modeling community attempts to understand and bound uncertainty. The diverse set of projected regulatory effects produced by different models under different assumptions reveals risks and opportunities: The risk of ineffective regulation and unintended consequences; and the opportunity of making "dynamic regulations" that change with the pace of new information.

This Article is organized as follows; Section I provides evidence of the magnitude of the uncertainty surrounding regulatory outcomes and lists reasons for resisting the goal of forecasting. It argues that, despite the use of large and detailed computer based models, the enormous and persistent uncertainty surrounding the future of the U.S. power system needs to be embraced and tackled with rules that are predesigned to adapt to changing conditions of the regulated system. Section II describes three sources for the uncertainty surrounding the results of computer based energy models. Using the several models that have been used to evaluate the U.S. Environmental Protection Agency's Clean Power Plan ("CPP") as a case study, the section unpacks the way in which this uncertainty is understood and bound. Section III describes the concepts and different types of dynamic law, such as contingency rules, durational rules, and adaptive management, and provides broad observations on how dynamic provisions can be used to avoid unintended consequences that could result from the confluence of inflexible rules and unanticipated conditions, including a brief overview of dynamic approaches used in other sectors and opportunities for further experimentation. Section IV concludes by suggesting that the complexity of models and uncertain conditions in which rulemaking occurs creates fertile ground for the integration of dynamic systems in environmental regulation.

I. The Prevailing Irreducible Uncertainty Surrounding the Outcome of Regulations Affecting the Electricity Sector

The history of the use of computer-based quantitative energy models for informing policy and regulatory analysis in the U.S. spans at least half a century. In 1973, triggered by the energy crisis following the Arab Oil Embargo, the use of energy modeling systems for policy studies "exploded."[9] A decade later, in 1981, President Reagan's requirement that federal agencies perform Regulatory Impact Analysis of every major rule, spurred the development and use of models to understand the impact of changing world and regulatory conditions on the energy sector and the wider economy.[10] Since then, investment in energy models has continually increased.[11]

In the regulatory context, computer-based models are principally used to estimate the impacts of a proposed law, regulation, or agency decision on any number of variables.[12] Despite a proliferation of models, regulations are often developed based on the analysis resulting from a single or limited set of modeled outcomes using a single or limited set of models. For example, in developing its rules for carbon dioxide ("CO_2") emissions at existing power plants, the U.S. Environmental Protection Agency analyzed possible impacts

5. George E.P. Box, *Robustness in the Strategy of Scientific Model Building, in* Robustness in Statistics 201–02 (1979); George E.P. Box, *Science and Statistics*, 71 J. Am. Stat. Ass'n 791, 791–99 (1976).
6. Steve Yetiv & Lowell Field, *Why Energy Forecasting Goes Wildly Wrong*, J. Energy Security (2013), http://ensec.org/index.php?option=com_content&view=article&id=466:why-energy-forecasting-goes-wildly-wrong&catid=139:issue-content&Itemid=425 (noting that energy forecasting models are "almost always wrong and sometimes wildly mistaken."). Despite this uncertainty, investment decisions are made in part on the basis of regulatory conditions. As a result, capital-intensive and heavily regulated industries such as energy are subject to the whims of model-reliant rules—many of which are environmental—that tend to be inflexible and unfit to account for new information. This dilemma is particularly acute in the energy sector, given the long-lived nature of investments. A natural gas fired power plant, for example, may be in service for sixty years or more. *See* Wara, *supra* note 1, at 269; *see generally* Avinash K. Dixit & Robert S. Pyndick, Investment Under Uncertainty (1994) (defining the irreversibility of investment).
7. Yetiv & Field, *supra* note 6; *see also* Wara, *supra* note 1, at 272, 276, 300.
8. Wara, *supra* note 1, at 271–74.
9. William W. Hogan, *Energy Modeling for Policy Studies*, 50 Operations Res. 89, 89, 92–93 ((2002).
10. Exec. Order No. 12291, 46 Fed. Reg. 13,193 (Feb. 19, 1981).
11. Hogan, *Energy Modeling for Policy Studies*, *supra* note 9, at 89.
12. *See generally* Comm. on Models in the Regulatory Decision Process, Models in Environmental Regulatory Decision Making 40–75 (2007); Desmond Saunders-Newton & Harold Scott, *But the Computer Said!: Credible Uses of Computational Modeling in Public Sector Decision Making*, 19 Soc. Sci. Computer Rev. 47, 47 (2001).

based on the results of a single model—the Integrated Planning Model or IPM.[13] The inherent uncertainty present in such type of analysis suggests that the practice of designing regulations based on modelling outcomes could be greatly improved by widening the scope of models used.

The uncertainty surrounding the regulated systems and the outcomes of a regulation cannot be reduced, and hence must be acknowledged, characterized, and tackled with ex-ante regulatory provisions. The first step to identify opportunities for adding flexibility and adaptability into the design of a regulation affecting the electric power sector consists of predicting possible outcomes of such regulation under a wide set of future scenarios. In this exercise, projections from all corners of the private and public sectors should be considered.

Numerous government agencies around the world gather, analyze, and publish a wealth of energy data to inform decision-making and for other purposes. In the United States at the federal level, for example, that task largely falls to the Energy Information Administration ("EIA").[14] Internationally, organizations such as the International Energy Agency play a similar role.[15] These entities and others like them produce thoughtful and insightful analyses that are generally removed of any claim of real or perceived bias for or against any specific fuel source or technology.

However, it is often the case that not all the potential of these models is exploited. In general, baseline projections receive more attention and are more commonly used and cited than other alternative outcomes modeled in side cases. This presupposes that baseline projections are more likely, and side cases outcomes can be disregarded, when in fact both are needed for an accurate interpretation of modeling results. For example, due to EIA's goal to provide policy neutral projections, the agency's baseline projections assume existing U.S. laws and regulations as if the world was going to stay in a "business as usual" state. The EIA also provides a set of additional projections for alternative conditions to those assumed in the baseline case.[16] This practice makes baseline projections useful only as a benchmark to compare the effect of different assumptions, such as changes in fossil fuel resources, regulations on carbon emissions, or the expansion potential of renewable energy. The baseline case alone is understood to be a potentially and inherently inaccurate representation of future energy markets.[17] Given this limitation, any reliance on baseline EIA projections—the so-called Annual Energy Outlook ("AEO") reference case[18]—is questionable.[19] Yet, the EIA's data and projections from the baseline case are "used widely in regulatory proceedings, energy planning, scientific research, investment decisions, litigation, and legislation."[20] Greater use should be made of the EIA's AEO side-cases to better incorporate the uncertainty EIA acknowledges in the creation of its own projections.

Other forecasts and projections are also available. A number of other government agencies, think thanks, industry associations, non-governmental organizations, and firms project future energy outcomes to understand policy issues or current industry challenges, making predictions about what the future of energy holds.[21] The predictions made often differ, as it could be expected by the diversity of interests and sources of information of the analysts involved. Discrepancies may result due to the fact that the groups forecasting within specific industries possess data, sophisticated models, marketing/customer information, and technology assessments that are not otherwise in the public domain. While those projections may be sometimes biased by the commercial interests they represent, their credibility is often supported by the corporate disclosure and reporting requirements that limit, if not prohibit, the ability of publicly traded companies to engage in unsupported optimism about what the future holds for the products and services they offer.[22]

Far from being a problem, the diversity of projections is an opportunity. Conflicting forecasts can be used as inputs into an exercise to discern the outcomes of a regulatory mechanism. The varying size and scope of models available also suggests that a multiplicity of models may be necessary to understand the full scope and impact of a given regu-

13. U.S. Envtl. Prot. Agency, EPA-452/R-15-003, Regulatory Impact Analysis for the Clean Power Plan Final Rule 3–19 (2015) [hereinafter Regulatory Impact Analysis], https://www.epa.gov/sites/production/files/2015-08/documents/cpp-final-rule-ria.pdf.
14. *About EIA*, U.S. Energy Info. Admin, http://www.eia.gov/about/ (last visited Sept. 29, 2016).
15. Alan Neuhauser, *Wasted Energy: The Federal Agency Charged With Predicting the Nation's Energy Future Is Hamstrung by Its Attempt to Remain Objective*, U.S. News & World Rep., May 28, 2015, at *9, http://www.usnews.com/news/articles/2015/05/28/wasted-energy-the-pitfalls-of-the-eias-policy-neutral-approach.
16. *Id.*
17. *Id.*
18. U.S. Energy Info. Admin, Annual Energy Outlook 2016 Early Release: Annotated Summary of Two Cases, DOE/EIA-0383ER, at 2 (2016), http://www.eia.gov/forecasts/aeo/er/index.cfm.
19. Owen Comstock, *EIA's Annual Energy Outlook Is a Projection, Not a Prediction*, Today in Energy: U.S. Energy Info. Admin. (May 17, 2016), http://www.eia.gov/todayinenergy/detail.php?id=26272#.
20. T.J. Considine & F.A. Clemente, *Gas Markets: Betting on Bad Numbers; Why Predictions From the Energy Information Administration May Contain Systematic Errors*, Fort. Mag., July 2007, at 1, http://www.fortnightly.com/fortnightly/2007/07/gas-market-forecasts-betting-bad-numbers; Neuhauser, *supra* note 15 ("EIA models explore virtually every conceivable aspect of the energy industry: how the U.S. will generate its electricity, how Americans will heat their homes and fuel their cars, whether coal and oil will be viable . . . and how fast solar and wind power may expand."); Janet Peace & John Weyant, *Insights Not Numbers: The Appropriate Use of Economic Models*, Pew Ctr. on Global Climate Change 11, 13 (2008), http://www.c2es.org/docUploads/insights-not-numbers.pdf. Not all agencies rely on EIA's NEMS model, for example, EPA used the IPM model to project outcomes new emissions regulations on standing sources whereas EIA later used NEMS to determine the effects of the regulation. *See* Regulatory Impact Analysis, *supra* note 13, at 3–4, 3–23; Considine & Clemente, *supra* at 2.
21. *BP Energy Outlook*, BP, http://www.bp.com/en/global/corporate/energy-economics/energy-outlook-2035.html (last visited Sept. 29, 2016); *US Solar Market Set to Grow 119% in 2016, Installations to Reach 16 GW*, Solar Energy Indus. Ass'n (Mar. 9, 2016), http://www.seia.org/news/us-solar-market-set-grow-119-2016-installations-reach-16-gw (reporting findings from GTM Research). Certain participants within the oil and gas industry publish energy assessments that extend beyond their own traditional markets to cover, for example, coal and renewables. BP does this through its "Energy Outlook" publications. ExxonMobil publishes its "Outlook for Energy" assessments. Shell does something similar through its "Scenarios" analyses.
22. The U.S. Securities and Exchange Commission imposes disclosure requirements under numerous regulations. *See, e.g.*, 17 C.F.R. § 229.101 (2011) ("Description of business").

lation on the energy system. Models representing smaller systems may have a better chance of estimating ranges of possible outcomes in the short term that are reasonably narrow. These models make an effort to include more details, as if they are engineering models, whereas projections that examine different scenarios are unable to properly represent a "myriad of complex and generally uncontrollable variables."[23] Therefore, a multiplicity of projections is useful and may offer insights beyond what would be available through evaluation of a singular model or without the use of modeling altogether.

A. *Desisting From the Goal of "Predicting" Future Outcomes*

To understand why EIA and others from the energy modeling community do not attempt prediction or forecasting, and rather call the output of models "projections," it is useful to briefly discuss the meaning of "prediction" in the context of the natural sciences.[24] The notion of making predictions is rooted in the desire since ancient times to understand the past, predict the future, and therefore develop laws to explain observed natural phenomena with predictive force.[25]

> Scientific discoveries are sometimes verified through prediction: prediction of the planet Neptune's existence by Leverrier, prediction of deviation of light by Einstein, prediction of the helical structure of DNA by Watson and Crick, etc. Prediction [in these scientific contexts] has a very strong force of argument.[26]

Richard Feynman, in his famous lecture on the scientific method, described the process similarly.[27] In science, according to Feynman, the researcher first makes a guess.[28] She then runs experiments to determine if the guess was correct.[29] If the guess was correct based upon the experiments that were run, the scientist has a workable hypothesis that, in turn, may be applied again and again until the day comes—as it inevitably does—when it is proven wrong.[30] In Feynman's construct of the scientific method, the prediction is the initial "guess" about how a physical system operates.

Predictions have particular utility in scientific disciplines where repeated tests or observations may be conducted to check their validity. However, "the difficulty of prediction depends on the degree of freedom and complexity of the system; if too many parameters should be fixed, it is impossible to make a precise prediction."[31] Whereas the effects of gravity on a certain object may be possible to predict, in systems where multiple parameters "amplif[y] initial uncertainty too rapidly," prediction becomes impossible.[32] Where prediction is futile, projection is preferable.

The techno-economic system where electricity is generated, transmitted, and consumed consists of complex, interrelated and interdependent infrastructure, market participants, and institutions. A wide range of energy sources—some baseload, others intermittent, and each subject to market forces that impact both fuel availability and price—supply the power system.[33] Energy demand is created by millions of users. Weather happens. Federal, state and third-party energy and environmental regulators impose ever-changing obligations on the system. There is nothing about energy systems that is even remotely similar to making an initial "guess" about how a prism diffracts a beam of light. Accordingly, in contrast to physical or man-made systems, energy systems are better suited to projection across a wide arena of possible cases and combinations of events.

An evaluation of how well past predicative energy policy assessments have projected past or current outcomes provides insight into how accurately current modeling methods incorporate the various factors impacting energy models. The answer: not very well.[34] Recent history illustrates the challenges of reliance on baseline energy forecasts. For example, official forecasts did not foresee current oil price outcomes, or the "shale gas revolution." Yesterday's liquefied natural gas ("LNG") import terminals are now being converted to export terminals, and low natural gas prices are upending expectations and forecasts related to electricity generation and coal.[35] Other notable errors have occurred in the recent past with respect to model forecasts. For example, models in 1995 and 1996 predicted a contraction in the coal sector and loss of coal mining jobs due to fuel switching towards lower sulfur coal due to the imposition of non-climate environmental requirements such as the acid rain program.[36] Despite these projections coal usage increased in the United States.[37]

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23. Considine & Clemente, *supra* note 20, at 1.
24. Comstock, *supra* note 19.
25. Y. Matsuo & P. McBurney, *Chance Discovery—Prediction, Forecasting, & Chance Discovery*, *in* Chance Discovery 30–31 (2003), http://link.springer.com/chapter/10.1007%2F978-3-662-06230-2_3#page-1.
26. *Id.*
27. Nonstampcollector, *Feynman on Scientific Method,* YouTube (Feb. 18, 2011), https://www.youtube.com/watch?v=EYPapE-3FRw.
28. *Id.*
29. *Id.*
30. *Id.*
31. Matsuo & McBurney, *supra* note 25, at 30.
32. *Id.*
33. *See What Are the Major Factors Affecting Natural Gas Prices?*, U.S. Energy Info. Admin. (May 18, 2016), https://www.eia.gov/tools/faqs/faq.cfm?id=43&t=8; *What Is U.S. Electricity Generation by Energy Source*, U.S. Energy Info. Admin. (Apr. 1, 2016), https://www.eia.gov/tools/faqs/faq.cfm?id=427&t=3.
34. Yetiv & Field, *supra* note 6 ("Relying on [energy] forecasts, particularly long-term projections going out [ten] or [twenty] years, is largely a mistake because they are almost always wrong and sometimes wildly mistaken.").
35. Chris Cassar, *Nationwide, Electricity Generation From Coal Falls While Natural Gas Rises*, Today in Energy: U.S. Energy Info. Admin. (Oct. 7, 2015), http://www.eia.gov/todayinenergy/detail.cfm?id=23252; Clifford Krauss, *U-Turn for a Terminal Built in Texas to Import Natural Gas*, N.Y. Times, Sept. 29, 2014, http://www.nytimes.com/2014/09/30/business/energy-environment/a-u-turn-for-a-terminal-built-in-texas-to-import-natural-gas.html?_r=0.
36. U.S. Envtl. Prot. Agency, Impacts of the Acid Rain Program on Coal Industry Employment 23, 27, 28 (2001), https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=900O0600.txt; U.S. Envtl. Prot. Agency, EPA/430-R-96-012, 1995 Compliance Results (1996), https://www.epa.gov/sites/production/files/2015-08/documents/1995compreport.pdf.
37. U.S. Dep't. of Energy, Energy Info. Admin., DOE/EIA-0384, Annual Energy Review 2006, at 206 fig. 7.3 (2007), http://www.eia.gov/totalenergy/data/annual/archive/038406.pdf (entitled "Coal Consumption by Sector," 1949–2006); Nicolas Berghmans & Emilie Alberola, *The Power Sector in Phase 2 of the EU ETS: Fewer CO_2 Emissions but Just as Much Coal*, 42 Climate Rep. 15 (2013), http://www.cdcclimat.com/IMG/pdf/13-11_climate_report_no42_co2_emissions_in_the_power_sector.pdf (noting that "the use of coal-fired power plants increased in a number of States from 2011 onwards").

In Europe, the creation of cap-and-trade climate regulation under the European Union Emissions Trading System ("EU ETS") was predicted to slash demand for coal, and yet, at least in Sweden, no link has been demonstrated between the carbon pricing in the EU ETS and CO_2 emissions from Swedish Electricity Production, and overall demand for European coal has increased.[38]

The examples mentioned above illustrate several reasons for energy forecasting's poor record of divining the future. First, forecasts generally are based upon future projections of historic and current trends, an approach that is prone to missing the role that significant developments such as new technologies may play down the road.[39] Second, the impacts of shifting public attitudes and government policy are difficult to predict.[40] Third and finally, it has been noted that energy analysts, perhaps like their brethren on Wall Street, "tend to run in packs" out of fear of being the outlier with an obviously wrong assessment, leading to peer group and public scorn and ridicule.[41] As a result, forecasts are largely clustered around a mean of commercially or politically popular, and typically conservative, outcomes.

The dismal record of the accuracy of the forecasts produced by energy models demonstrates that the value of large and complex energy models is not in their products, but in the process they facilitate, and that their contribution is in the "insights [and] not in the numbers" they offer.[42] In line with this understanding, the EIA does not call the output of its models "forecasts" but "projections," and has in the last years made an effort to project ranges, rather than to offer point estimates.[43]

Although uncertainty is pervasive and irreducible, important features of the electricity sector are known with a reasonable degree of certainty. First, the system exhibits the properties of inertia and path dependency.[44] This is evident in the fact that energy sources have changed little over the centuries. Second, infrastructure generally is long-lived. Specific entrenched fuels possess physical and chemical attributes that make their displacement by an incumbent exceedingly unlikely.[45]

These intrinsic characteristics of the system can be well represented in energy models. Although any attempt to represent complex interactions of social, economic, technical and environmental factors that shape trends in energy consumption, production, or prices will be subject to inaccuracies; much can be learned from these models, and particularly from the discrepancies in model projections under different assumptions, or different modeling frameworks.

The growing demand for policy foresight combined with the enhanced scientific methods to detect risk, make it likely that the use of models to estimate policy impacts will become increasingly prevalent.[46] Given the inevitability of uncertainty and the futility of forecasting, there is room for attempting to consider this uncertainty ex-ante in the regulatory process. In this Article, we argue there is an opportunity for attempting to characterize the uncertainty on future system conditions, and to use such characterization to design contingent rules (explained in Section II) to react to system changes and new information. While both modelers and regulators are aware of the limits in modeling outputs, much more could be done to determine the bounds of the uncertainty facing the regulation and accomplish the goal of having stakeholders and regulators better informed today, rather than hypothesizing about the future.[47] Rather than designing regulation according to baseline or best guess projections of the future, and then subjecting those rules to multiple sequential reviews and updates as conditions in the regulated system change or emerge, we explore the idea of designing such contingent rules based on the outcomes of using multiple model runs exploring different future scenarios and conditions.

A close look at how modelers deal with uncertainty may offer insights towards improving regulatory and policy making processes to address future unknowns through the use of flexible and dynamic systems of law. First, more models should likely be used than is often the case under current regulatory practice to broaden the understanding of the wide variety of potential outcomes. Wider modeling through greater numbers of scenarios and the use of multiple model frameworks would also make clear the value of preserving the option to pursue alternative actions. Second, given the inherent uncertainty present in future conditions and resulting system outcomes, flexible and dynamic systems of law offer the potential benefits of both incentivizing regulated parties to take actions towards preferred outcomes, and offering opportunities to adjust the law to take into consideration new information and react to uncer-

38. Anna Widenberg & Markus Wråke, *The Impact of the EU Emissions Trading System on Co_2 Intensity in Electricity Generation* 1 (Univ. of Gothenburg, Dept. of Econ., Working Paper in Economics No. 361, 2009); Berghmans & Alberola, *supra* note 37. *But see* Tim Laing et al., *Assessing the Effectiveness of the EU Emissions Trading System* 24–26 (Ctr. for Climate Change Econs. & Policy, Working Paper No. 126, 2016) (noting attributable emissions savings from the EU ETS, despite the global recession and problems with initial over allocation).

39. John P. Weyant & Thomas Olavson, *Issues in Modeling Induced Technological Change in Energy, Environment, and Climate Policy*, 4 Envtl. Modeling & Assessment 67, 79–80 (1999).

40. *See* Darryl Read et al., *The Theory of Planned Behavior as a Model for Predicting Public Opposition to Wind Farm Developments*, J. Envt. Psychol. 36, 70–76 (2013).

41. *See* Kevin Walsh, *Challenging the Groupthink of the Guild*, Hoover Inst. (Mar. 8, 2016), http://www.hoover.org/research/challenging-groupthink-guild-0 ("The clustering of economic forecasts reveals conformity of views inside the Fed. The groupthink among policymakers may well deepen the groupthink among other stakeholders, including outside economists, Wall Street pros, and business leaders.").

42. Peace & Weyant, *supra* note 20, at 2; *see* Wara, *supra* note 1.

43. Comstock, *supra* note 19; Karl Mathieson, *Are Fossil Fuel Companies Using IEA to Talk Up Demand?*, Guardian, Oct. 23, 2015, https://www.theguardian.com/environment/2015/oct/23/are-fossil-fuel-companies-using-iea-reports-to-talk-up-demand.

44. Phillippe Aghion, Path Dependence, Innovation, and the Economics of Climate Change, Center for Climate Change Economics and Policy 6 (2014).

45. *Id.* at 8; Robert Bryce, *Don't Count Oil Out*, Slate (Oct. 14, 2011), http://www.slate.com/articles/technology/future_tense/2011/10/oil_and_gas_won_t_be_replaced_by_alternative_energies_anytime_so.html.

46. Jonathan Wiener & Daniel L. Ribeiro, *Impact Assessment: Diffusion and Integration*, *in* Comparative Law and Regulation 161 (Francesca Bignami & David Zaring eds., Elgar 2016).

47. Daniel Shostak, *Difference Between Prediction and Forecasting*, AnalyticBridge, http://www.analyticbridge.com/forum/topics/difference-between-prediction (last visited Sept. 29, 2016).

tainty. By focusing on the evolving roles of modeling in an ever increasing data-rich environment and the challenges of accurate electricity market modeling, it may be possible to draw insights to better frame our understanding of dynamic law as a response to uncertainty.

II. Uncertainty and the Role of Current Models in Policy-Making: A Case Study in the Use of Multi-Model Assessment

Insights from individual and comparative results of modeling efforts conducted by a multiplicity of stakeholders can help to characterize the uncertainty about the effects of the regulation in the techno-economic system in which the electric power sector exists. To evaluate the Clean Power Plan, modelers and policy-makers have had to grapple with uncertainty in several forms. For simplicity, these types of uncertainty might be classified under the following trichotomy: First, policy-makers have to deal with implementation uncertainty with respect to the policy change they consider.[48] This metric considers a variety of variables related to when and how a certain policy may be put into effect, and to what extent the *de facto* application differs from the *de jure* rule.[49] For example, given that the Clean Power Plan can be implemented in several different ways, none of which can be exactly foreseen, modelers are forced to assume a particular implementation, and hence it becomes uncertain how well the modeling results represent the potential outcome of the regulation.[50] Second, the outcomes are tempered by assumptions regarding inputs, or input uncertainty.[51] Some future outcomes must be assumed, for example with respect to the conditions assumed present during the time any policy in question is implemented. Assumptions regarding economic growth, fuel prices, and resource availability, for example, are unknown, and model results are contingent upon these assumptions.[52] Third, policy-makers have to deal with *model uncertainty*—even models that represent the same policy implementation, and make the same assumptions about key inputs, can result in different conclusions due to modelers' different representations of the energy economy, and their divergent descriptions of the world.[53] To understand modeling uncertainty, several communities engage in multi-model analyses[54] but refrain from ranking their outcomes.[55] Since policy implications of each model can differ, and it cannot be known which, if any, of the competing models is a better description of the "true" world, using a scenario based approach may result in a range of insights and inferences with respect to a particular policy question.[56]

The following section describes in more detail the sources of the uncertainty surrounding modeling results, and how they potentially confuse (or reinforce) the estimated impacts of the Clean Power Plan and the importance of particular regulatory choices, as well as how policy-makers often try to deal with such mixed sets of results and implications. The section then describes a selection of different models used to analyze various versions of the Clean Power Plan, ending with some broad conclusions regarding the results of these different models. Finally, more recent simulation results from two of these models, the EPA's IPM models, and the EIA's National Energy Modeling System ("NEMS") model (and an additional implementation used by Rhodium Group) are compared to describe how all three types of uncertainty, specifically, the changes from the 2014 to 2015 versions of the Clean Power Plan, changes in input assumptions, and context might be considered as examples of the dynamic modeling environment policy-makers must deal with in understanding and further developing regulations like the Clean Power Plan.

A. *Implementation Uncertainty*

Recent analyses of the potential impacts of the Clean Power Plan highlight the challenges policy-makers face in defining regulations, given policy goals and possible impacts of a given menu of policy choices they choose to consider. The Clean Power Plan, as it pertains to regulating existing power plants, is perhaps the most complex implementation of rule-making under section 111(d) ever created. The reason is that, given the multiplicity of compliance strategies, it is not clear exactly how it will be implemented by states as they devise their state implementation plans.[57] This has created a serious problem for modelers attempting to estimate the potential impact of the plan. Understanding the challenge first requires a description of how modelers have dealt with the

48. *See* Mary Hallward-Driemeier, *Deals Versus Rules: Policy Implementation Uncertainty and Why Firms Hate It* 2–5 (Nat'l Bureau of Econ. Research, Working Paper No. 16001, 2010).

49. *Id.*

50. Kate Konschnik & Ari Peskoe, *State Roles in the Clean Power Plan: A Primer for States*, Harv. Envtl. Pol'y Initiative (Aug. 19, 2015), http://environment.law.harvard.edu/wp-content/uploads/2015/08/State-Roles-Clean-Power-Plan.pdf.

51. *See* Shane G. Henderson, *Input Model Uncertainty: Why Do We Care and What Should We Do About It?, in* Proceedings of the 2003 Winter Simulation Conference 93–94 (S. Chick et al. eds., 2003).

52. *Id.*

53. Merlise Clyde & Edward I. George, *Model Uncertainty*, 19 Stat. Sci., 81, 81–94 (2004).

54. For examples of groups that use multi-model analyses, see generally *About*, Stan. Univ., https://emf.stanford.edu/about (last visited Sept. 29, 2016), and *Energy Modeling Forum*, Stan. Univ., https://emf.stanford.edu/ (last visited Sept. 2, 2016).

55. The use of non-hierarchically ranked models is not unique to the energy sector. *See* Jenee A. Colton, *Toxicity Extrapolation Models*, *in* Ecological Modeling in Risk Assessment: Chemical Effects on Populations, Ecosystems, and Landscapes 181 (Robert A. Pastorok et al. & CRC Press eds., 2016); George Casella & Elias Moreno, *Objective Bayesian Variable Selection*, 473 J. Am. Stat. Ass'n. 157, 158 (2006).

56. Stacy Langsdale, *Communiciation of Climate Change Uncertainty to Stakeholders Using the Scenario Approach*, 140 J. Contemp. Water Res. & Educ., 24–29 (2008).

57. Patrick Knight et al., *Multi-State Compliance Report With the Clean Power Plan in CP3T*, Synapse Energy Econ., Inc. (July 29, 2015), http://www.synapse-energy.com/sites/default/files/Multi-State-Compliance-Report-15-025.pdf; *see also* Robert Godby & Roger Coupal, *A Comparison of Clean Power Plan Forecasts for Wyoming: The Importance of Implementation and Modeling Assumptions*, 29 Electricity J. 53, 55, 61 (2015); Franz Litz & Brian Murray, *Mass-Based Trading Under the Clean Power Plan: Options for Allowance Allocation* 2–3 (Duke Nicholas Inst., Working Paper NI WP 16-04, 2016), http://nicholasinstitute.duke.edu/publications.

evolution of regulatory methods from centralized to decentralized frameworks prior to the Clean Power Plan.

Historically, most Clean Air Act-based regulations have relied on command and control regulation—that is the requirement and imposition of a specific set of performance requirements at all regulated facilities, which have been determined centrally by regulators.[58] Typically, these standards of performance requirements have been defined in terms of site-specific emissions permits.[59] Under the Clean Air Act, these permits have specified maximum emissions rates per unit of output (for example, tons of emissions per unit of electricity produced), and plants are permitted emissions rates up to the levels of their specific permit.[60] These requirements have been defined after consideration of available technologies, or "Best Systems of Emission Reduction" ("BSERs") choices available to firms.[61] In the past, the defined technologies that the EPA assumed could be used would normally be applied to plants "within the fence"—they implied specific changes to facilities, and in production techniques and inputs used by firms.[62] One example is the use of specific types of "scrubbers" in the control of power plant air emissions.[63] Accordingly, modeling such regulations and their impact in the electricity sector occurred by assuming the timing of implementation controls, their cost, and assumptions regarding improvements in technologies over time within economic and energy system models.[64] The interaction of these costs and market conditions over time—which were either assumed exogenously, or partially determined endogenously based on the model's internal structure[65]—would define the model's outcomes. These outcomes then provided estimates of the impact of such regulations on measures of policy interest such as emissions outcomes, electricity production, utility rates, primary energy production, and prices and economic growth, relative to projections using the same model when regulation is not implemented.[66]

The potential impacts of centralized regulation, while complex, are easier to forecast than decentralized or market-based regulations. For example, if a specific technology or production restriction is assumed to be implemented, it is often straightforward to use a mathematical optimization framework to describe how the adoption of such technologies will affect costs and production capacities, as well as the implications on power system outcomes, such as hourly electricity prices or longer term utility rates.[67] The regulatory impact of a particular policy is then defined by how these measures change relative to a no regulation baseline. Results become more complicated if dynamic economic models are combined with such simulations, allowing estimation of wider energy system and economic outcomes over time. Such models are referred to as partial equilibrium if they also estimate impacts on a limited set of additional market outcomes, or full equilibrium if they estimate impacts on the entire economy for regulatory changes in the power system.[68]

More recent regulations have moved away from command-and-control regulations, toward market-based approaches.[69] These decentralized approaches pose added complications to modeling potential policy-outcomes. The EPA's sulfur dioxide ("SO_2") trading market is one example of such a system, and the Clean Power Plan is another.[70] At the simplest level of explanation, decentralized "cap and trade" approaches like the SO_2 trading system begin by defining site-specific emission permits, but unlike earlier centralized approaches, such permits are transferable through trade.[71] Facilities may emit more than their original permitted levels only if they hold additional permits purchased from other regulated firms while selling firms would be obligated to emit less than they were initially permitted to.[72] Total emissions remain controlled as they would be under a centralized system and are defined by the total permits allocated across facilities, however, site specific emission-levels are allowed to vary based on the reallocation due to trade that occurs between firms.[73]

Market-based regulatory approaches attempt to take advantage of differences across firms regarding emission control costs to create incentives to minimize the cost of emission reduction.[74] Such permit trading systems effectively commodify emissions reductions, creating incentives for firms with lower control costs to finance additional reductions through sales of their emission permits.[75] Similarly,

58. 42 U.S.C. § 7411(d) (2012); Samuel D. Eisenberg et al., *A State Tax Approach to Regulating Greenhouse Gases Under the Clean Air Act*, Brookings 1, 3 (May 22, 2014), https://www.brookings.edu/wp-content/uploads/2016/06/state_approach_regulating_ghgs_morris.pdf.
59. *Id.* at 3.
60. *Id.*
61. *Id.*
62. Ohio EPA Comments on "Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units; Proposed Rule" [79 FR 34830], Ohio Envtl. Protection Agency 11, http://www.epa.ohio.gov/portals/27/111d/CPP_2014-12-01_Final_Tech_Comments.pdf; Marlo Lewis, *How Unlawful Is EPA's Clean Power Plan* (Oct. 6, 2014), http://www.globalwarming.org/2014/10/06/how-unlawful-is-epas-clean-power-plan/.
63. *Id.* ("Although even here the analogy is strained. Previous 111(d) rules based ESPS on particular control technologies (e.g., scrubbers for fluoride emissions from phosphate fertilizer plants).").
64. U.S. Envt'l Prot. Agency, The Benefits and Cost of the Clean Air Act, 1970 to 1990 app. B (1997).
65. U.S. Envt'l Prot. Agency, EPA No. 450R13002, Documentation for EPA Base Case v.5.13, Using the Integrated Planning Model 2–2 (2013).
66. *Id.* at 2–13.
67. Timothy Lawrence Johnson, *Energy Models, in* Encyclopedia of Geography (SAGE Publications, 2016), http://sk.sagepub.com.proxygw.wrlc.org/reference/geography/n347.xml.
68. Lisa M.H. Hall & Alastair R. Buckley, *A Review of Energy Systems Models in the UK: Prevalent Usage and Categorisation*, 169 Applied Energy 619, 623 (2016).
69. Winston Harrington & Richard D. Morgenstern, Resources for the Future, Economic Incentives Versus Command and Control 13–14 (2004).
70. *See generally* 40 C.F.R. §§ 72–78 (2016); Gabriel Chan et al., *The SO_2 Allowance-Trading System and the Clean Air Act Amendments of 1990: Reflections on 20 Years of Policy Innovation*, 65(2) Nat'l Tax J. 419, 421–26 (2012).
71. Dallas Burtraw & Sarah Jo Szambelan, *U.S. Emissions Trading Markets for SO_2 and No_x* 5 (Res. for the Future, Discussion Paper No. RFF DP 09-40, 2009); Robert N. Stavins, *Market-Based Environmental Policies* 1, 4 (Res. for the Future, Discussion Paper No. 98-26, 1998).
72. Stavins, *supra* note 71, at 1, 3. Permits may be defined on the basis of total emissions or for emissions rates. *See* Burtraw & Szambelan, *supra* note 71, at 5.
73. Inter-firm trade of emissions permits can be further controlled, for example to avoid "hotspots" by specific regulations restricting possible trade, or by applying trading ratios to avoid excessive local emissions levels. *See, e.g.*, W. David Montgomery, *Markets in Licenses and Efficient Pollution Control Programs*, 5 J. Econ. Theory 395, 403 (1972).
74. Stavins, *supra* note 71, at 1, 3.
75. *Id.* at 4–5.

high emission-cost firms and facilities will willingly purchase such permits as long as the prices paid are lower than the costs faced at their own plants to reduce emissions by a similar amount. Permit market outcomes (price and quantity traded) adjust to reflect the equilibrium between total permit market supply, defined by the permits made available for trade, and total market demand to purchase permits.

The advantages of market-based systems over command-and-control ones are several and well demonstrated by recent programs such as EPA's Acid Rain program. First, they can create incentives to minimize the total cost of emission control across all regulated firms, something centralized approaches do not achieve.[76] They can also reduce informational burdens for regulators and create additional incentives to develop new control technologies that lower future emissions control costs.[77] Additionally, by leaving to firms the decision of when, where, and how to reduce emissions, the bureaucracy required to administer, monitor, and enforce pollution regulations can be reduced relative to centralized methods.

Modeling the impacts of such decentralized systems, however, becomes much more complicated in part because decentralized methods rely on incentives and assumed behavior of regulated agents. Power system models that assume estimates of emissions-control costs as part of the electricity generation costs to project power plant investment, dispatch, and prices, are no longer adequate as they do not endogenously incorporate feedbacks between market outcomes and firm decisions. Instead, firm investment choices and costs must be modeled explicitly, along with the emission permit markets to endogenously determine the control costs that result from the imposition of a given emissions limit. These can then be input into optimization/simulation models intended to represent power system operations and its outcomes. Optimally, associated input and production markets would also be modeled to demonstrate the impact of regulations on emissions and the economy, as well as on electricity prices. Modeled outcomes, however, are inherent to the assumptions made regarding agent behavior.[78]

The Clean Power Plan utilizes neither a market-based approach such as a tax or a traditional cap and trade program, nor purely a centralized "command and control" approach. Instead, it employs a unique decentralized approach that makes possible multiple compliance alternatives to firms and to the states regulating affected firms within their borders.[79] Eschewing defined actions "inside the fence" at regulated sites, facilities do not have site-specific permitted levels of emission. Instead, annual emissions targets are defined at unique state-wide levels utilizing a unique "building block" approach.[80] The BSER assumed relevant to meet the regulation at existing plants does not define any specific technologies, but instead a set of actions that a state could potentially enforce at and across sites.[81] Specifically, to reduce greenhouse gases ("GHGs"), states may employ a combination of energy efficiency improvements at plants, recommitment decisions between fossil-fueled and renewable and zero-emissions sources across the state power sector, and recommitment from fossil-fueled plants to less intensive GHG emitting sources (e.g. from coal to natural gas) across the state power sector.[82] States could choose any combination of these (or in the 2015 rules, the first three choices), or undefined alternative means of reducing GHG emissions, such as the use of carbon capture technologies to meet their emissions requirements.[83]

State implementation plans can also include regional trading schemes in which groups of states can create cooperative arrangements such as permit trading programs to meet their collective emissions targets.[84] While both the 2014 and 2015 rules contemplated state trading programs, in the 2014 rules, no specific rules were assumed regarding how these trading systems would be organized.[85] In contrast, the 2015 rule promised "model rules" to hasten and help state cooperation and coordination in developing regional emission control

76. Theoretically, a competitive market creates the incentive for all firms to choose emissions levels such that the cost of making an additional emission reduction equivalent to the amount one permit would allow to be avoided, is equal to the market price of acquiring an emission permit. If control costs differ but are rising across all regulated firms in the market, the resulting competitive market outcome results in all firms buying or selling permits until the control costs across firms are equal. When this outcome occurs, no additional reallocation of control effort, which reduces total control costs across all firms, is possible, and the cost of emission control across the market has been minimized. The potential for such a cost-minimizing decentralized regulatory outcomes was first described in seminal papers by Thomas D. Crocker, *The Structuring of Atmospheric Pollution Control Systems*, *in* The Economics of Air Pollution 234 (Wolozin, ed. 1966), John H. Dales, Pollution, Property and Prices 6 (1968), and Montgomery, *supra* note 73, at 396. Outcomes in emission trading markets under uncompetitive conditions have been described in Robert Hahn, *Market Power and Transferable Property Rights*, 99 Q. J. Econ. 753–65 (1984), and William S. Misiolek & Harold W. Elder, *Exclusionary Manipulation of Markets for Pollution Rights*, 16 J. Envtl. Econ. & Mgmt. 156, 156–66 (1989), and were demonstrated in artificial markets by Robert Godby, *Market Power in Laboratory Emission Permit Markets*, 23 Envtl. & Resource Econ., 279–318 (2002). The actual success of such decentralized approaches over alternative centralized ones (in which permits are allocated and no trade is allowed) has been documented by many authors. *See, e.g.*, Richard Schmalensee et al., *An Interim Evaluation of Sulfur Dioxide Emissions Trading*, 12 J. Econ. Persp. 53, 64–65 (1998). More recently, Richard Schmalensee and Robert N. Stavins commented on these results and the additional impacts other contemporary changes (such as railroad deregulation) had on these original cost estimates, as well as the recent challenges such regulatory methods have faced politically and in the courts. *See* Richard Schmalensee & Robert N. Stavins, *The SO_2 Allowance Trading System: The Ironic History of a Grand Policy Experiment*, 27 J. Econ. Persp. 103 (2013).

77. U.S. Envtl Prot. Agency, Guidelines for Preparing Economic Analyses 4–5 (2010).

78. Peace & Weyant, *supra* note 20, at 2. Specifically, models assume both how agents perceive the choices they face, and they usually assume agents optimize perfectly. Neither is necessarily consistent with how agents will actually make choices for a wide variety of reasons.

79. 42 U.S.C. § 7410(a)(1) (2012).

80. Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units, 80 Fed. Reg. 64,662, 64,667, *passim* (proposed Oct. 23, 2015) (to be codified at 40 C.F.R. pt. 60).

81. *Id.*

82. Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units, 80 Fed. Reg. 64,662, 64,666 (proposed Oct. 23, 2015) (to be codified at 40 C.F.R. pt. 60). The original 2014 rules also permitted reductions through the use of end-user energy efficiency measures to reduce total electricity demand.

83. *Id.* at 64,884.

84. Knight et al., *supra* note 57, at 15–16, 23–30.

85. Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units, 80 Fed. Reg. 64,662, 64,833 *passim* (proposed Oct. 23, 2015) (to be codified at 40 C.F.R. pt. 60).

plans.[86] Finally, the 2015 version of the CPP permits states to choose how their emissions target will be defined—as a mass-based (total mass of CO_2 emissions) or rate based (amount of CO_2 emissions per megawatt-hour of generation).[87] Choice of target definition then limits potential cooperative efforts only with states choosing to define emissions in a similar manner.[88] Overall, the CPP leaves responses to the regulation to firms and states.

The unprecedented latitude by which regulated states, and the firms within them, can meet the requirements of the CPP creates significant complexity for energy modelers.[89] This latitude and resulting complexity can be used to consider the possible limitations of relying on too few models to consider future impacts of a regulation, and therefore the need and utility of using a wider multi-model assessment of a proposed regulation.[90] A study by the National Association of Clean Air Agencies (2015) included twenty-six chapters of individual and separate ways the CPP could be implemented by states and firms under the proposed 2014 rules.[91] These choices are shown in Table 1. Not only does the CPP define specific performance outcomes across facilities, it also includes the potential choice to have states define how the grid operates.[92] The multiplicity of choices the regulation could include, and the far-reaching implications these choices could have, not only on the grid but also on related sectors of the economy (and potentially on the entire economy), calls for the use of larger models that incorporate multiple inter-related sectors. Further, longer-term, larger, and more complex models seem necessitated by the regulation, given that state emissions targets may take place according to the EPA's suggested timetable, or outside of it, provided average emissions levels are achieved in the interim period prior to the final target year of 2030.[93]

Exercises to bound modeling uncertainty would optimally include several model outcomes with identical implementation assumptions. Unfortunately, due to modelers' preferences, possibly with respect to the questions and potential choices and impacts they wish to address, the complexity of the modeling problem, or a mix of both, different CPP studies have assumed alternative implementation assumptions.

Further, the CPP itself has been released in two iterations: the proposed rules released in June 2015, and the final rules released August 2015.[94] Between these two releases, additional potential choices were made available, for example the choice to regulate on the basis of mass or rate-based targets.[95] Accordingly, policy-makers considering the implications of the rule have a wide range of potential projection outcomes to contemplate depending on which model and implementation rules they consider, creating uncertainty as to the scale of potential impacts of various aspects of the CPP.

Since there may be many possible combinations of policy implementations, studies are often designed as an experiment in which end-points of policy choices are modeled such that a "bracket of truth" is created.[96] Policies are modeled in isolation to other choices, creating what is called a "polar type"—a case study involving extreme or unique characteristics—and which can yield theoretical insights.[97] While policies are seldom implemented in manner that mimics a polar case, polar cases are often used in models.[98] Such an approach allows the range of outcomes to be described between the polar cases and allows an inference regarding the degree to which a policy choice might affect model outcomes.

For example, the Clean Power Plan allows states to meet their individual CO_2 targets through actions within their respective borders, or through working together to meet collective state targets.[99] In both the 2014 and 2015 versions of the CPP, emissions trading was presumed to be a primary mechanism under which such regional cooperation could occur. The scope of such cooperation could range from regional state efforts to a national trading model, depending on if, or how, states choose to work together. It may be less likely that all states choose to coordinate in a national plan, however, modelers unwilling to assume specific regional combinations will often model a national trade outcome and compare it to one with no state cooperation (no trade). Policy-makers can use such an approach even if the modeled outcomes are not exactly like those they are specifically considering, inferring that wider trading outcomes including more states are more likely to be similar to the modeled national trade outcomes, while limited trade may result in outcomes closer to the no-trade results.

86. *Id.*
87. *Id.* at 64,832; 79 Fed. Reg. 34,830, 34,833 (proposed June 18, 2014); Godby & Coupal, *A Comparison of Clean Power Plan Forecasts for Wyoming*, *supra* note 57, at 2; Martin T. Ross et al., *The Clean Power Plan: Implications of Three Compliance Decisions for U.S. States*, NI WP 15-02, 2 (Duke Univ., Working Paper NI WP 15-02, 2015), https://nicholasinstitute.duke.edu/sites/default/files/publications/ni_wp_15-02_full_pdf.pdf.
88. Godby & Coupal, *A Comparison of Clean Power Plan Forecasts for Wyoming*, *supra* note 57, at 4.
89. *See* William W. Hogan, *Electricity Markets and the Clean Power Plan*, 28.9 Electricity J. 9, 11 (2015) (explaining that the Clean Power Plan is only a rule that sets emissions standards, and not a prescription for how to meet standards).
90. *Id.*
91. Nat'l Ass'n of Clean Air Agencies, Implementing EPA's Clean Power Plan: A Menu of Options ES-1 (2015), http://www.4cleanair.org/NACAA_Menu_of_Options.
92. Hogan, *Electricity Markets and the Clean Power Plan*, *supra* note 89, at 12, 17.
93. *Id.* at 3.
94. Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units, 80 Fed. Reg. 64,832 (proposed Oct. 23, 2015) (to be codified at 40 C.F.R. pt. 60); Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units, 79 Fed. Reg. 34,830 (proposed June 18, 2014) (to be codified at 40 C.F.R pt. 60).
95. *See* Hogan, *Electricity Markets and the Clean Power Plan*, *supra* note 89, at 9.
96. An example of such a methodology being employed is found in John Larsen et al., Remaking American Power, Ctr for Strat. and Int'l Studies and Rhodium Group 57–64 (2014), https://csis-prod.s3.amazonaws.com/s3fspublic/legacy_files/files/publication/141107_Ladislaw_RemakingAmerPower_Web.pdf.
97. Kam Jugdev & Lisa N. LaFramboise, *Polar Types*, *in* Encyclopedia of Case Study Research (SAGE Publications, 2016), http://sk.sagepub.com/reference/casestudy/n257.xml.
98. It may be impossible to know the precise linear combination for any continuous variable, and accordingly polar cases are used to illustrate important ideas about how the models work and to frame the range of possibilities dependent on that variable. For example, economics models usually consider markets that are either monopolistic or perfectly competitive, although modelers know that the actual effect is somewhere in the middle (monopolistic competition) on a possible continuous spectrum. *See* N. Gregory Mankiw, Principals of Economics 346 (5th ed. 2008).
99. *See* Hogan, *Electricity Markets and the Clean Power Plan*, *supra* note 89, at 9.

Table 1: Possible Implementation Choices Under the CPP

Optimize Power Plant Operations	Implement Combined Heat and Power in the Electric Sector
Implement Combined Heat and Power in Other Sectors	Improve Coal Quality
Optimize Grid Operations	Increase Generation From Low-Emission Resources
Pursue Carbon Capture and Utilization or Sequestration	Retire Aging Power Plants
Switch Fuels at Existing Power Plants	Reduce Losses in the Transmission and Distribution System
Establish Energy Savings Targets for Utilities	Foster New Markets for Energy Efficiency
Pursue Behavioral Efficiency Programs	Boost Appliance Efficiency Standards
Boost Building Energy Codes	Increase Clean Energy Procurement Requirements
Encourage Clean Distributed Generation	Revise Transmission Pricing and Access Policies
Revise Capacity Market Practices and Policies	Improve Integration of Renewables Into the Grid
Change the Dispatch Order of Power Plants	Improve Utility Resource Planning Practices
Improve Demand Response Policies and Programs	Adopt Market-Based Emissions Reduction Programs
Tax Carbon Dioxide Emissions	Consider Emerging Technologies and Other Important Policies

Source: William W. Hogan, *Electricity Markets and the Clean Power Plan*, 28.9 Electricity J. 9, 12 (Nov. 2015).

B. *Input Uncertainty*

Input uncertainty, or the assumptions regarding exogenous factors in any model (for example, the initial starting conditions), can have a tremendous impact on projected outcomes. Input uncertainty arises not only with respect to unexpected changes in model inputs, such as economic growth trends, technological change, production costs, energy prices, or resource availability, but also due to context assumptions, such as additional regulatory conditions. Projections of new policy impacts will often be dependent on the other policies that may be in place, especially in the energy sector where a multiplicity of regulations exist.[100] The existence of previously implemented policies could reinforce or counteract impacts of the specific policy under consideration. Model results are contingent upon both types of input assumptions, and violations of these assumptions are inevitable as time passes after a particular modeling effort is completed, and can occur even while a modeled analysis is being prepared.[101] For example, regulations or a set of energy prices can change during the preparation of an analysis, but contemporary estimates of economic growth may not be available for some additional period of time. Including new conditions in the model without including a set of consistent economic conditions can be problematic. Therefore, to meet a research or contract deadline, or in the interest of generating results, modeling may proceed despite the fact that some assumptions or assumed conditions are already known to violate reality.[102] Users of such results then face uncertainty regarding whether model results are due purely to policy conditions or are driven in part by the assumed model context.

There are numerous examples of the impacts that assumption changes over time can have on model projections.[103] Some modeling organizations even document these changes and the failures over time of projections to match reality as well as overall impacts of changes to assumed conditions.[104] For example, past projections of United States coal production have been impacted by unexpected developments in natural gas production.[105] As a result of the development of shale gas resources and the implementation of new technologies to extract gas from previously undevelopable "tight gas" formations domestic production of natural gas has increased since 2005.[106] The result has been dramatically lower natural gas prices, and reduced coal demand as cheaper natural gas has displaced it in electricity generation.[107] Figures 1 and 2 compare the EIA's NEMS-derived AEO projections for coal production and natural gas prices in the electricity sector from 1994 to 2014, as well as actual coal production and natural gas prices over this period.[108] Coal use projections prior to 2008 tended to increase year over year beginning around 2000 as unanticipated natural gas price increases

100. Elizabeth Doris et al., Energy Efficiency in the United States: Overview of Trends at Different Levels of Government, National Renewable Energy Laboratory 2 (2009).
101. Peace & Weyant, *supra* note 20, at 3.
102. For example, recent modeling of the Clean Power Plan by Rhodium-CSIS (January 2015), which is referred to in more detail in the next section, was conducted using AEO2015 assumptions to be consistent with previous modeling, with the exception of Production and Investment tax credit conditions. The AEO2015 assumptions were known to be outdated, in particular regarding oil and natural gas prices, but, because new AEO2016 conditions were not yet available, to maintain consistency with previous modeling efforts and to highlight the impact of the tax credit changes within the National Energy Modeling system, they were used anyway. Robert Godby & Roger Coupal, The Potential Impact of Rate-Based or Mass-Based Rules on Coal-Producing States Under the Clean Power Plan, 29 Electricity J. 42, 42–51 (2016).
103. Note that the changes discussed here are assumed to have been unexpected and often outside the normal variation of such variables. As will be discussed, normal variations in many variables can be in part addressed by sensitivity analyses.
104. For example, the EIA's AEO2015 report included an appendix comparing reference case conditions to those in the previous report. *See* U.S. Energy Info. Admin., Annual Energy Outlook 2015, DOE/EIA-0282, at app. E (2016), http://www.eia.gov/forecasts/aeo/appendixe.cfm.
105. Am. Petroleum Inst., Understanding Natural Gas Markets 2–3 (2014).
106. U.S. Energy Info. Admin., Natural Gas, Annual Energy Outlook 2015, at 6–7 (2015), https://www.eia.gov/forecasts/aeo/section_energyprod.cfm#naturalgas.
107. Cassar, *supra* note 35.
108. Data for figures come from U.S. Energy Info. Admin., Annual Energy Outlook Retrospective Review, DOE/EIA-0640, at tbls. 7(a) & 13 (2015), https://www.eia.gov/forecasts/aeo/retrospective/.

took place.[109] After 2008 the opposite occurred; annual projections of coal use shifted downward as unexpected natural gas price declines continued.[110] These outcomes have had significant impacts on CO_2 emissions from the electric power sector since 2008, as coal's share of total electricity generation fell from approximately 50% to 39% by 2014.[111]

Figure 1: AEO Coal Production Projections vs. Actual[112]

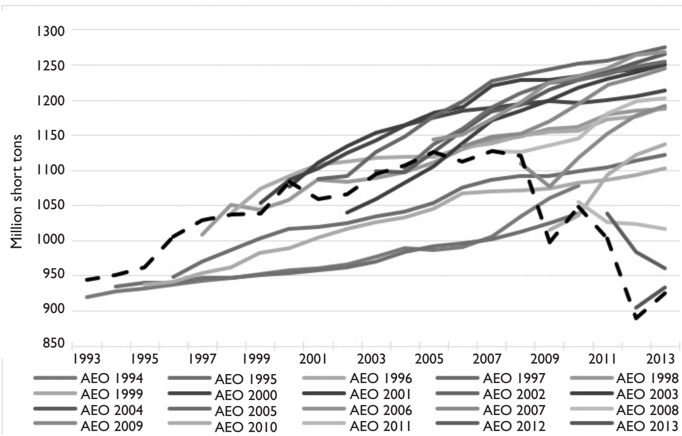
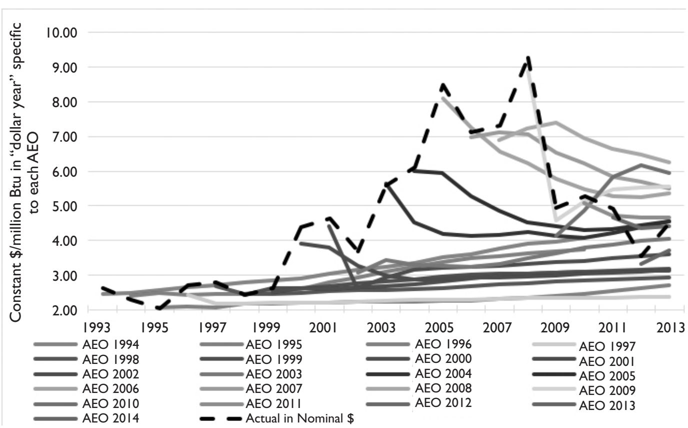


Figure 2: AEO Natural Gas Projections vs. Actual[113]



Figures 1 and 2 illustrate how unanticipated changes in market outcomes can affect model results. The primary input assumption that changed between both was a resource assumption regarding availability of natural gas. The source of the change was technology and the implicit assumption in early forecasts that production costs for natural gas would not change due to new technological developments in its production.

With respect to more recent Clean Power Plan modeling, projected use of coal in generation is very sensitive not only to natural gas assumptions, but also to oil price and coal productivity (production cost) assumptions and how they change over time. Godby and Coupal illustrate the impacts these changes have on the potential impacts of the Clean Power Plan on Wyoming, the nation's largest coal producing state.[114] They compare estimated impacts of the 2014 proposed CPP rules on Wyoming coal production by considering two NEMS-based simulations, one using the AEO2014 modeling assumptions and one using updated 2015 assumptions.[115] A major difference in the input assumptions between the two simulations is the dramatic and unexpected change in oil prices that occurred in mid-2014. These lower oil prices result in the assumed time-path of world oil prices shifting downward from 2015 through 2040.[116] The result is higher natural gas prices.[117] These, along with revisions to the previously assumed rate of decrease in coal productivity resulting in lower Wyoming coal production costs, and downward revisions to assumed wind generation costs over the projection period, cause Wyoming coal production to rise by as much as 100 million tons per year (approximately 33%) relative to the 2014 estimates under the CPP.[118] Nationally these changes have wider impact, causing natural gas to be displaced by wind as the "bridge fuel" to the more stringent carbon-emission standards.[119] Overall, the change in input assumptions results in complex dynamics playing out across energy markets, and significant changes to how the country accommodates more stringent GHG emissions standards. While models are necessary for policy-makers to understand and estimate these complexities, these results are indicative of the sensitivity modeled outcomes have to input assumptions.

To understand and characterize what has been called input uncertainty, a first step is to assume several future scenarios within a specific model, in order to test the sensitivity of outcomes to changes in assumptions. For example, EIA in its AEO modeling always includes several side cases. These side cases are used to account for input variables that are historically volatile or *a priori* judged to be most likely to change. The AEO2014 projections included 30 side cases, including ones for both higher and lower natural gas and oil prices than assumed in the baseline case.[120] The natural gas cases were included because of the volatility and relative unpredictability of natural gas outcomes over the recent past,

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109. *Id.*
110. *Id.*
111. *Id.*; Ass'n of Am. R.Rs., Railroads and Coal (2016), https://www.aar.org/BackgroundPapers/Railroads%20and%20Coal.pdf.
112. U.S. Energy Info. Admin., Annual Energy Outlook Retrospective Review, *supra* note 108, at tbl. 13.
113. *Id.* at tbl. 7(a).
114. *See* Godby & Coupal, *A Comparison of Clean Power Plan Forecasts for Wyoming: supra* note 57, at 53–62.
115. *Id.* at 54.
116. *Id.* at 57.
117. Some natural gas production is a byproduct of oil production, and lower oil prices result in lower oil production, which results in lower natural gas production nationally and therefore higher natural gas prices.
118. Robert Godby & Roger Coupal, The Potential Impact of Rate-Based or Mass-Based Rules on Coal-Producing States Under the Clean Power Plan: Implications for Wyoming 17 (2016), http://www.uwyo.edu/cee/_files/docs/wyoming-cpp-impact-2016-state%20report.pdf.
119. Reduced use of natural gas in generation due to higher fuel costs results in greater coal use in the EIA simulations of the proposed 2014 CPP rules. *See* U.S. Energy Info. Admin., Analysis of the Impacts of the Clean Power Plan 47–48 (2015), https://www.eia.gov/analysis/requests/powerplants/cleanplan/. The resultant increase in coal emissions is accommodated under the emissions regulations through greater electricity generation from wind, which is enabled by the lower costs assumed in the 2015 technology assumptions for this fuel relative to 2014 assumptions.
120. U.S. Energy Info. Admin., Annual Energy Outlook 2014, DOE/EIA-0383, at E6–8 (2014) [hereinafter AEO2014], http://www.eia.gov/forecasts/aeo/pdf/0383(2014).pdf.

and oil cases were included to allow users to understand the potential impacts of the historic volatility in these prices.[121]

Furthermore, such side cases can be used to account for alternative regulatory scenarios. Again, EIA's AEO2014 side cases included three carbon tax scenarios to allow the impacts of such a policy to be identified.[122] The use of several side cases within the same model (i.e., *sensitivity analysis*) facilitates a single consistent framework for understanding the potential relative changes caused to the overall system for a specific change in assumptions. As such, sensitivity analyses not only allow for reduced input uncertainty by offering a wide range of projections through changed assumptions, but also greater understanding of how model outcomes occur when assumed conditions change. These insights are indeed the most valuable benefit of modeling.[123]

C. A Multiplicity of Models: Model Uncertainty

Models reduce a complex system of relationships in the actual world to a subset that can be represented by a set of mathematic equations. Models are simplified abstractions of reality, and, as such, they will differ in design and structure, depending on what modelers feel most appropriate to describe the aspect of the world they wish to abstract.[124] In the energy space, this creates competing representations of the energy economy and generates divergent descriptions of the world. Model differences can be driven by structure, but further, even in similar structures, they can be driven by parameter uncertainty—for example, differences in assumptions about productivity and cost relationships, parameter stability over time, and the dynamics of technological change.[125] Model differences may also be fundamental, due to their representation of whether agents have perfect foresight. Facing choices under uncertainty, do agents look ahead to anticipate future conditions, or act myopically? Models may also be limited to describing a narrower or wider set of outcomes and/or may be constrained by limiting assumptions, or the level of technical detail.[126] Models may also be partial equilibrium systems which may describe power systems only—that is, fuels and output relationships in the generation sector alone, or the larger energy sector that describes how policy decisions impact use of all forms of energy; or they may be general equilibrium systems describing the energy sector and its relationship to wider economic outcomes, and how these economic outcomes in turn determine the demand for the use of energy to begin with.

To deal with modeling uncertainty—that is, to understand how much of the discrepancy in modeling results is due to the models structure and policies implemented—policy-makers will often turn to a meta-analysis of model outcomes.[127] Such multi-model assessments allow a combination of qualitative and quantitative approaches. Models outcomes are compared for similar policy choices to determine a range of outcomes.[128] The actual model outcomes can define a quantitative range of impacts while also describing a qualitative response to the policy choice considered. These can further be described and compared for changes in inputs and policy implementations assumed. The overall results can then be used to describe the probable outcomes that policy-makers may expect to occur for a specific policy given the current state of collective knowledge over energy systems (and the wider economy where appropriate) as described and embodied within the models considered.[129]

In addition, to deal with the input and implementation uncertainties already described, each model considered in a multi-model assessment may include alternative scenarios to account for model sensitivity to changes in input and implementation assumptions. They will also usually include a baseline (no-policy) case to allow comparison of scenarios to a "business as usual ("BAU") condition in which the policy is not implemented at all.[130] Comparison of scenarios to the BAU-case allows modelers to quantify estimates of impacts due to changes in input and implementation assumptions within a model-consistent framework.

D. How Multi-Model Assessment Can Be Used: CPP Outcomes as Predicted by Various Modeling Efforts

The Clean Power Plan provides an example of how models are used by policy-makers in their attempt to assess the potential impact a regulatory program may have on the energy sector and the wider economy. Table 2 describes a collection of analyses of the Clean Power Plan since 2014, delineating the agency conducting the study, the model used, the input

121. *Id.* at CP–3, CP–9. The low oil price case was fortunate as the low oil resource (high oil price case) considered an outcome in which oil prices were similar to what they actually were at the end of 2014 when they unexpectedly fell on world markets. Unfortunately, oil prices continued to fall, and by 2015 even the low oil prices relative to recent history assumed in the high oil resource case were significantly higher than those that actually occurred.

122. AEO2014, *supra* note 120, at D–1.

123. Peace & Weyant, *supra* note 20, at 2.

124. *Id.* at 1–3.

125. Recent research on integrated climate models and related parameter uncertainties can be found in Kenneth Gillingham et al., *Modeling Uncertainty in Climate Change: A Multi-Model Comparison* (Yale Univ., Cowles Found. Discussion Paper No. 2022, 2015), http://www.nber.org/papers/w21637. While not directly relevant to energy models, some of the models considered include integrated economic and power sector relationships. The dynamics of technical change has been an area of recent research. Technological change and innovation are historically assumed exogenous to many models; however, since policy often directs or incentivizes technological development, specific policy choices may change the path of technological innovation. In such cases, technological change becomes endogenous and such feedbacks may also be included in economic policy models. *See* Kenneth Gillingham et al., *Modeling Endogenous Technological Change for Climate Policy Analysis*, 30 Energy Econ. 6, 30 (2008).

126. Such assumptions could include imperfectly versus perfectly mobile capital or the inclusion of backstop technologies.

127. *See* Daniel A. Farber, *Modeling Climate Change and Its Impacts: Law, Policy, and Science*, 86 Tex. L. Rev. 1655, 1669 (2007).

128. Stanford Univ., *About*, Energy Modeling F., https://emf.stanford.edu/about (last visited Oct. 2, 2016).

129. A more formal analysis of collective model outcomes is also possible beyond the simple aggregation of a range model outcomes as described. Gillingham et al., *supra* note 125, at 25–28, suggests a quantitative meta-analysis to deal with model and parameter uncertainties more formally, introducing a Monte Carlo framework for such multi-model assessments. Such methods, however, are uncommon.

130. Johns Hopkins Ctr. for Climate and Energy Sol., Modeling EPA's Clean Power Plan: Insights for Cost-Effective Implementation 4 (2015) [hereinafter Hopkins], http://www.c2es.org/publications/modeling-epas-clean-power-plan-insights-cost-effective-implementation.

and implementation assumptions, as well as the additional scenarios considered, and illustrates the three forms of uncertainty discussed as they pertain to analyzing the CPP. Information regarding inputs for current and assumed economic conditions, energy prices, technology improvement and production cost time-paths, etc. has been updated as new forecasts have become available. The 2014 CPP proposal and the 2015 CPP final rule changes necessitated an additional round of modeling. Specifically, increases in the stringency of CO_2 reductions in the new rule (from a 30% reduction from 2010 levels in the 2014 proposal to a 32% reduction by 2030 in the final rules), changes in BSER used in the final rule which eliminated energy efficiency, changes to final state emissions targets, the required state choice of mass and rate-based emissions standards, and changes to the timing of emissions limits being implemented from 2020 to 2022, as well as additional rules changes, would all have resulted in the estimated impacts of the CPP changing even without changes to initial input assumptions. Summaries of all study outcomes would be beyond the scope of this paper, however, a summary of the first six studies can be found in Hopkins (2015).[131]

Overall, modeling of the 2014 proposed CPP rules using AEO 2013 and 2014 input assumptions led to some broad conclusions. As outlined in Hopkins (2015), a qualitative summary of the results of the first six models in Table 2 prompts the following observations:

- Energy efficiency is the most cost-effective means to reduce emissions and resulted in lower power consumption. Studies, however, differed in how energy efficiency was considered, the degree of energy efficiency implementation assumed, and the cost savings this choice entailed.
- Switching from coal to natural gas was the primary means of meeting the regulation requirements from a generation perspective. The degree to which energy efficiency was employed could potentially offset or minimize the degree that natural gas prices rise due to the CPP.
- Forecasted cost impacts to U.S. households were relatively low, averaging an increase of $87/year (in 2012 dollars). Total increases in power spending were estimated to be less than $10 billion/year in five of the six studies.
- Renewable generation and nuclear power growth remained at business as usual levels despite the imposition of the CPP. In the case of renewables this growth remained robust.
- In all but one scenario modeled in the first six studies, annual average CO_2 emissions were between 1514 and 1774 million metric tons ("MMT") between 2020 and 2030.[132]

In addition to the results reported in Hopkins (2015), the Rhodium-CSIS 2014 study, utilizing a version of the EIA's NEMS model, considered the impact of expanded state cooperation through the use of permit trading as permitted by the CPP rules.[133] Their study indicated that in addition to exploiting energy efficiency, widened trade opportunities could both reduce emissions more quickly and reduce the cost of compliance nationally.[134]

In June 2015, prompted by a request from Congress,[135] the EIA released the most extensive analysis of the proposed 2014 CPP rules to date.[136] In this study the EIA updated its input assumptions to be consistent with those in the AEO2015. As previously discussed, some significant effects were caused by this change, as well as the modeling methods the EIA undertook. The EIA modeling considered states engaging in various levels of electricity trade as a proxy for state cooperation. In addition, the EIA model allowed states to choose a minimum-cost time-path of emissions reduction, as opposed to explicitly meeting the schedule of proposed targets in the 2014 proposal.[137] Results of their modeling in the baseline case were generally consistent with the previous results. However, there were some significant differences[138]:

- The degree of energy efficiency utilized was much lower than some past studies predicted, in part because an alternative set of estimated costs for implementing energy efficiency were used.
- Previously discussed changes to the assumed cost of renewable generation in the future, as well as natural gas price and coal production cost assumptions caused renewable energy to play a much larger role in the transition towards the final CPP target in 2030. This was further enabled by the alternative glide-path that states were allowed to use in meeting final emissions targets under the CPP.[139] Initial compliance is achieved through greater natural gas use. However, later in the CPP compliance period, renewables become much more important and renewable generation deployment is higher than in the BAU case.[140] Nuclear generation is also expanded if treated in the same manner as renewable generation with respect to CPP compliance.

131. *Id.* at 1.
132. Hopkins, *supra* note 130, at 15.
133. Larsen et al., *supra* note 96, at vii–viii, 2.
134. *Id.* at 17, 46.
135. U.S. Energy Info. Admin., Analysis of the Impacts of the Clean Power Plan 74 (2015) [hereinafter EIA 2015 Analysis], https://www.eia.gov/analysis/requests/powerplants/cleanplan/pdf/powerplant.pdf.
136. *See* Hopkins, *supra* note 130, at 4.
137. *See* EIA 2015 Analysis, *supra* note 135, at 75–76. Previous studies assumed states met the time path of target reductions outlined in the 2014 CPP proposal. The 2014 rules, however, allowed states to emit higher levels of CO_2 in the early years of the implementation period if in later years they exceeded targets such that the average annual emissions rate defined by the CPP targets for each state was met from 2020 to 2029.
138. *See* Hopkins, *supra* note 130, at 8–10.
139. *See* Godby & Coupal, *A Comparison of Clean Power Plan Forecasts for Wyoming*, *supra* note 57, at 58. Due to greater use of renewables and delayed implementation of emissions reductions between 2020 and 2029 under the alternative emissions time path that states are presumed to use, the EIA study also projected a reduced impact on coal generation.
140. Hopkins, *supra* note 130, at 12.

Table 2: Selected CPP Analyses

Study	Model	Sectors Included	Policy Modeled	CPP Rules	Initial Conditions Assumed	Sensitivity Cases	BSER Range Considered
EPA (2014)	IPM	Power Sector Only	State-based emissions rates	2014 Proposal	AEO 2013	N.A.	All 2014 building blocks
CATF	Northbridge	Power Sector Only	Mass-budget, inter-state trade allowed	2014 Proposal	AEO 2013	N.A.	Did not include energy efficiency
EVA	AuroraXMP	Power Sector Only	State emission rate, inter-state trade allowed	2014 Proposal	AEO 2013	N.A.	Did not include heat rate improvements
NERA	NewERA	Power Sector Only	State emission rate, inter-state trade allowed	2014 Proposal	AEO 2013	No energy efficiency	All 2014 building blocks
NRDC	IPM	Power Sector Only	State emission rate	2014 Proposal	AEO 2014	Limited energy efficiency	All 2014 building blocks
Rhodium-CSIS (2014)	RHG-NEMS	Power and Energy Sectors	Regional emissions rate, inter-state trade allowed	2014 Proposal	AEO 2014	No energy efficiency, national trading.	Did not include heat rate improvements
EIA (2015)	EIA-NEMS	Power and Energy Sectors	State emission rate, inter-state trade allowed	2014 Proposal	AEO 2015	No CPP, 15 side cases including no EE,	All 2014 building blocks
EPA (2015)	IPM	Power Sector Only	State-based emissions rates and mass-based limits	2015 Proposal	AEO 2015	Rate-based, mass-based stds.	All 2015 building blocks
Rhodium-CSIS (2015)	RHG-NEMS	Power and Energy Sectors	State-based emissions rates and mass-based limits, inter-state trade allowed	2015 Proposal	AEO 2015	Rate-based, mass-based stds., national trade, renewable tax extension	Did not include heat rate improvements

Source: Johns Hopkins Ctr. for Climate and Energy Sol., Modeling EPA's Clean Power Plan: Insights for Cost-Effective Implementation 1 (2015).

- Average annual CO_2 emissions in this study were between 1553 and 1727 MMT by 2030, depending on the scenario.
- Trade and wider state cooperation benefits, as the EIA modeled them, were reduced relative to those modeled in the Rhodium-CSIS study. However, they still potentially improved systems cost and emissions outcomes relative to a no cooperation outcome.[141]
- Electricity expenditure outcomes by end-users are consistent with earlier studies summarized in Hopkins (2015).[142]

Representation of the final CPP rules in August 2015 required yet more modeling. Based on previous study findings, policy analysis had not focused on the benefits of wider trade and state cooperation. Earlier findings indicating the benefits of such efforts were likely some of the impetus for the 2015 rules clarifying trade and cooperation rules, and the inclusion of "model trading rules" developed by the EPA to facilitate state implementation plans including such efforts.[143]

In addition to changes in the methodology, probably one of the most significant impacts of the new rules on states was the requirement that states select the type of regulatory standard by which they wish to be governed.[144] Among the first decisions states must make to comply with the new rules is whether they wish to have their state emissions targets defined by a rate or mass-based standard.[145] The EPA 2015 modeling utilized a "bracket of truth" methodology to compare the impacts of either choice on power sector outcomes, including scenarios for both rate and mass-based outcomes, under the assumption that regulated states all choose one or the other option while utilizing limited state cooperation.[146]

141. *See* Larsen et al., *supra* note 96, at 10–11, 29. The EIA modeled state cooperation on the basis of expanded power flows across the transmission system. They did not model expanded cooperation as a permit system in the way the Rhodium-CSIS studies did.

142. *See* Hopkins, *supra* note 130, at 2; EIA 2015 Analysis, *supra* note 135, at 87.

143. *See generally* U.S. Envtl. Prot. Agency, Factsheet: Clean Power Plan Proposed Federal Plan and Proposed Model Rules 1 (2015), https://www.epa.gov/sites/production/files/2015-10/documents/fs-cpp-proposed-federal-plan.pdf.

144. *See* Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units, 80 Fed. Reg. 205, 64,664 (proposed Oct. 23, 2015) (to be codified at 40 C.F.R. pt. 60); Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units, 79 Fed. Reg. 117, 34,830, 34,833 (proposed June 18, 2014) (to be codified at 40 C.F.R. pt 60).

145. *See* 80 Fed. Reg. 205, at 64,664 ((proposed Oct. 23, 2015) (to be codified at 40 C.F.R. pt. 60).

146. *Id.* at 64,927–29. In reality, it is highly unlikely states will coordinate in this

EPA's emissions results under the new rules projected higher estimated emissions from the power sector than previous studies, ranging from 1812 MMT in the rate-based case to 1814 MMT in the mass-based case by 2030.[147] Incremental costs from the EPA's BAU base case were also consistent with previous studies, ranging from $5.1 billion under a mass-based approach to $8.4 billion under the rate-based approach.[148] Despite these costs, the EPA estimated that the average consumer's electricity bill would decrease by between 7% and 7.7% by 2030 due to reduced power consumption through energy efficiency measures, while retail electricity rates were nearly unchanged from their BAU projections.[149] Unlike EIA's results under the 2014 proposed rules, but using the same AEO2015 input assumptions, renewable generation would increase only moderately under the 2015 rules. By 2030, all non-hydro renewables are projected to rise by 8% under a mass-based regime, and increase by 9% in a rate-based setting.[150] Natural gas generation at existing plants (existing when the rules are implemented) was the generation source projected to increase the most under the new rules—by 5% and 18% under a mass-based and rate-based system, respectively.[151] Both renewable and natural gas generation are projected to increase despite an 8% reduction in total generation under both mass and rate-based rules.

Rhodium-CSIS also consider two scenarios describing outcomes under rate and mass-based rules using their version of the NEMS model. Their study assumed unrestricted nationwide trading, unlike EPA's study. While complete results of the modeling—including cost and generation details of their analysis—were not released by Rhodium, the emissions reduction in 2030 achieved 34% to 35% relative to 2005 levels.[152] This compared to EPA's projection of 32% in their study.[153]

Rhodium released a companion study later that repeated their original analysis of the 2015 rules, but included the impact of Congress' decision to extend renewable production and investment tax credits through 2020 and 2021, respectively.[154] Production tax credits for wind had expired in 2014, and investment tax credits for solar were scheduled to fall to 10% from 30% of project costs in 2016.[155] They reported that under their modeling, the primary change in power generation mix to meet the new CPP rules was in the share of natural gas, however, the impact of Congress' decision was to significantly increase renewable build-out in their projections.[156] With the tax-extensions, they projected under mass-based rules that the new CO_2 rules would be met almost exclusively with renewable energy. This newer study did not include details of emissions and cost impacts either.

Taking stock of the combined modeling results from the exercises presented in Table 2, it becomes clear how modeling uncertainty might be at least reduced by the use of multi-model assessments and scenario analysis. Considering the exercises cited, clear areas of convergence and divergence arise. Overall, the model outcomes are generally consistent with their projections of emissions outcomes and program costs under both the 2014 and 2015 rules. In those models where it is considered, clear benefits can be achieved with greater cooperation among states, such as through the use of permit trading programs. These results likely had some influence on the additional accommodations and efforts in the 2015 rules to encourage such plans. Convergence over model outcomes occurred despite differences in input assumptions and policy implementation.

Divergence, where it exists, appears to be created when modelers' assumptions regarding how states will achieve emissions targets are changed as illustrated in the EIA's study. Unlike other studies, EIA's analysis allowed states to delay implementation of emissions standards early in the compliance period of the CPP to access greater cost savings as new technologies developed later in the compliance period.[157] Such actions also reduced the impact on natural gas prices and therefore reduced the cost of complying with the rules. This study, and Rhodium-CSIS's are the only studies that find renewables playing the most significant role in meeting the CPP emissions limit. All other studies conclude that natural gas generation will be the primary means of achieving emissions targets.[158] This suggests that changes in technology and market conditions could significantly alter how firms and states comply with the CPP.

The later Rhodium-CSIS study also indicates the potential for other changes in the regulatory environment to affect program outcomes. Changes in legislation and tax treat-

fashion and it is unclear if there is a cost to a lack of coordination. The EPA study comments on this possibility but gives no potential cost estimates of uncoordinated state choices regarding rate or mass-based regulation.

147. 80 Fed. Reg. 64,924 (Oct. 23, 2015).

148. *Clean Power Plan Fact Sheet: Energy Efficiency in Mass-Based Plans*, All. to Save Energy, https://www.ase.org/sites/ase.org/files/cpp_fact_sheet_-_ee_in_mass-based_plans.pdf (last visited Sept. 1, 2016).

149. Stephen D. Eule, *Shocking! Electricity Bills Will Rise Under EPA's Clean Power Plan*, Energy XXI, http://www.energyxxi.org/shocking-electricity-bills-will-rise-under-epa's-clean-power-plan; *FACT SHEET: Clean Power Plan Benefits*, U.S. Envtl. Protection Agency, https://www.epa.gov/cleanpowerplan/fact-sheet-clean-power-plan-benefits#affordable-reliable (last visited Oct. 2, 2016) ("In 2030 when the plan is fully implemented, electricity bills would be expected to be roughly 8 percent lower that they would been without the actions in state plans"); Ari Phillips, *Obama's Clean Power Plan Will Actually Lower Your Energy Bill, According to New Study,* Think Process (July 30, 2015), https://thinkprogress.org/obamas-clean-power-plan-will-actually-lower-your-energy-bill-according-to-new-study-141cad0314cd#.vgmbplhm3.

150. 80 Fed. Reg. 64,695 (Oct. 23, 2015).

151. *Id.*

152. John Larsen et al., Assessing the Clean Power Plan 7 (2016), https://csis-prod.s3.amazonaws.com/s3fs-public/legacy_files/files/publication/160106_Larsen_AssessingCleanPowerPlan2_Web.pdf.

153. *Id*. Rhodium noted that differences in the emissions estimates between the two studies could be due to modeling different models, different implementations of the CPP assumed, or due to EPA's use of their own emissions data, which differs from that reported by the EIA, which Rhodium used. *Id.*

154. John Larsen et al., *What Happens to Renewable Energy Without the Clean Power Plan?*, Rhodium Group (Feb. 25, 2016), http://rhg.com/notes/renewable-energy-without-the-clean-power-plan.

155. *Renewable Electricity Production Tax Credit (PTC)*, U.S. Dep't of Energy, http://energy.gov/savings/renewable-electricity-production-tax-credit-ptc (last visited Oct. 23, 2016); *Solar Investment Tax Credit (ITC)*, Solar Energy Indus. Ass'n, http://www.seia.org/policy/finance-tax/solar-investment-tax-credit (last visited Oct. 2, 2016).

156. *See* Larsen et al., *supra* note 154.

157. Larsen et al., *supra* note 96, at 7.

158. *Id*. at 47.

ments, as well as other regulations, could have a significant impact on how emissions reductions are achieved. Given that states are required to make early decisions regarding how to comply with the current and proposed new regulations like the CPP, and these decisions then commit states to future costs which may eventually be seen in hindsight as sub-optimal, are there ways to design regulation that avoid such potential costs?

III. Accounting for Uncertainty in Law

Despite the fact that large and complex models seeking to project long term, global trends in energy generation and consumption, resulting prices, emissions and reliability will always be wrong in their projections, the exercises of sensitivity analysis and multi-model comparisons can offer useful information about the magnitude of the uncertainty, and suggest ways in which the law can be designed to be effective under changing and unforeseen conditions. In fact, increased understanding about the uncertain effects of proposed regulations reveals an opportunity for enlarging the box in which models operate.[159] Modeling offers the benefit of identifying which inputs, if changed, will have material impacts on the efficacy of the regulation—for example, the availability of tax credits for renewables such as wind, or the price of natural gas. This, in turn, provides an opportunity to deal with certain contingencies prospectively by incorporating them directly into the rule in an if-then format.

Recent scholarly contributions in the area of dynamic law suggest that rules that account for uncertainty and anticipate new information and a changing regulatory landscape are not only possible but also may offer incentives towards desired behavior and overcome certain issues with passive law such as inertia and path-dependency.[160] Dynamic law is designed to account for uncertainty in the system it intends to regulate.[161] Recognizing that lawmakers are forced to regulate with imperfect information, dynamic law seeks to build responsiveness to emerging information and changing norms into the law itself. For example, having tested the sensitivity of outcomes to changes in assumptions during modeling, dynamic rules would provide for subsequent revision, repeal, or learning based processes depending on evolving understandings of these baseline assumptions. This view of law has taken hold among scholars advocating for regulation that acknowledges the metamorphic nature of ecological systems.[162] As J.B. Ruhl has written: "[t]o manage the impact of human society on the inherently chaotic, adaptive environment, the environmental law system itself must possess those dynamical qualities."[163]

Dynamic law can take a variety of forms, but all relate to the notion that rules should themselves acknowledge and be responsive to the uncertainties inherent in the systems the rules are designed to regulate. Importantly, dynamic rules must be distinguished from flexible rules. Flexible rules are those that provide discretion in the means to achieve compliance. Examples of flexible rules in the electricity regulation sector are state implementation programs and the Acid Rain programs under the Clean Air Act, including the CPP.[164] These rules are helpful in that they can promote innovation and reduce compliance costs. However, they are not necessarily, in and of themselves, dynamic as the ultimate standard that must be achieved is static—and is not subject to repeal, change, or reconsideration upon the happening of any specific event, whether it be the passage of time, receipt of new information, or the occurrence (or non-occurrence) of a predetermined outcome. Dynamism requires that the standard itself be responsive to new information, not solely the method of achieving the standard.

Justin Pidot, in his exploration of the topic, categorizes the forms of dynamic law as durational, adaptive, and contingent.[165] As Pidot acknowledges, even static law has some dynamic elements, taking into consideration changing community standards, for prurience for example, and congressional authority to "exit" from static regimes through subsequent repeals.[166] The next section describes durational and contingent categories of dynamic law, and discusses how lawmakers can apply insights from models to better address uncertainty through dynamic legal rules.

A. Durational Rules

Durational rules are those that provide opportunities to lawmakers to consider new information by "facilitating periodic opportunities for amendment or repeal of existing rules" with the goal of considering new information and encouraging responsiveness.[167] These rules can take a variety of forms including sunset provisions[168] and retrospective review.[169] Deadline-based measures have been praised for their ability to create pressure to adapt to evolving standards and new

159. Attributed to Dwight D. Eisenhower "if you cannot solve a problem, enlarge it." Russ Linden, *Reframe, Broaden a Problem*, Governing (May 4, 2011), http://www.governing.com/columns/mgmt-insights/reframe-broaden-problems.html.
160. *E.g.*, Justin R. Pidot, *Governance and Uncertainty*, 37 Cardozo L. Rev. 113, 118, 139–41 (2015).
161. *Id.* at 118.
162. *See id.* at 125–27.
163. J.B. Ruhl, *Thinking of Environmental Law as a Complex Adaptive System: How to Clean Up the Environment by Making a Mess of Environmental Law*, 34 Hous. L. Rev. 933, 940 (1997).
164. *See* Dalia Patino-Echeverri, *Feasibility of Flexible Technology Standards for Existing Coal-Fired Power Plants and Their Implications for New Technology Development*, 61 UCLA L. Rev. 1896, 1907–08 (2014). Other examples of flexible standards can be found in a review of CAFÉ, see, e.g., Carley et al., Rethinking Auto Fuel Economy Policy: Technical and Policy Suggestions for the 2016-17 Midterm Reviews 10–11 (2016).
165. Pidot, *supra* note 160, at 141.
166. There are challenges with these mechanisms in static law. As Pidot notes, "Even when lawmakers agree that a static law regime needs to be amended or abandoned altogether, it may nonetheless persist because lawmakers lack resources or attention to the matter." *Id.* at 139 (citing Hannah Wiseman, *Remedying Regulatory Diseconomies of Scale,* 94 Boston L. Rev. 235, 272 (2014)).
167. Pidot, *supra* note 160, at 142.
168. In actuality it has been hard for lawmakers to consider changes or exit due to political and economic considerations, *see* Rebecca Kysar, *Lasting Legislation*, 159 U. Pa. L. Rev. 1007, 1007–08 (2011).
169. Cary Coglianese, *Moving Forward With Regulatory Lookback*, 30 Yale J. on Reg. 57, 57–66 (2013).

information, but have been derided for their high economic and political costs.[170]

Although most durational rules incorporate a deadline in the form of a term of years, there is nothing *per se* that requires use of a standard increment of time. Durational rules can also be structured so that they sunset upon the occurrence or non-occurrence of a specified, foreseeable event.[171] Modeling can help identify which inputs would have a material impact on the rule, and help design a response accordingly. The downside of this approach is that rules that adopt such an approach could require constant or periodic monitoring to determine whether such an event had occurred. Further, tying durational rules to other outcomes may compound the regulatory uncertainty associated with other potential agency or actions. While not without costs, this approach may offer benefits—particularly where initial major points of divergence are foreseeable.

Another category of durational rules is experimental, or multi-stage durational rules.[172] These rules consist of an experimental stage prior to the sunset and a more permanent stage after the agency takes regulatory action in response to the experimental results.[173] Implementing a rule in a controlled setting on a representative sample population provides an opportunity to collect data about the costs and benefits in response to the regulation.[174] Carefully designed experiments will incorporate prior knowledge and provide insights where the policy maker or modeler needs information most.[175] While there is a potential that the structure of the experimental rule could in fact create behavioral anomalies, the benefit of this approach is that it allows policy makers to test a theory before creating a final rule.[176] This approach may offer the most benefits where the costs and benefits of a given policy are highly uncertain.[177]

An understanding of the sources of modeling uncertainty may provide an opportunity for a more efficient use of durational rules or help scope use of retrospective review. This may ultimately yield an iterative process of review and response that provides a pathway for "careful systematic research that addresses . . . benefits and costs that can actually be attributed to a regulation after it has been implemented[.]"[178] In a multi-stage experimental rule the mechanism for retrospective review, at least after the initial implementation, would be crafted into the structure of the rule itself.[179] As such, these rules provide options for subsequent learning and evaluation. By structuring rules so that experimentation and subsequent evaluation is achievable, it is possible to improve understanding of costs and benefits, inform future lawmaking, and increase the public's trust in government.[180]

Rules enacted based on benefit and cost estimates subject to high levels of uncertainty, or that rely on common assumptions, may be particularly suited to this type of review.[181] For example, multi-stage durational rules inherently require a new final agency decision to be made at a specified point in the future; at the specified time, or upon occurrence or non-occurrence of the pre-determined event, the rule will be cancelled, revised or extended. The Administrative Procedure Act's "hard look review" requires that an agency considers information reasonably available to it in the process.[182] Accordingly, any data gathered during the initial stage of the rule would therefore be required to be considered in any decision whether to extend, modify, or terminate the rule.[183] This information, in turn, could be used to update and refine models and to generate new model runs—taking earlier, simplified models incorporating long-term projections and adding new information to make projections of the rule outcomes more narrow and specific, "identify[ing] both real successes and real problems that need fixing" and thus better informing future promulgations of the rule.[184]

B. *Adaptive Rules*

Adaptive rules are those that focus on flexible decision making and learning through process-based mechanisms, such as periodic reviews, that allow an agency or other party to modify rules based on the availability of new information.[185] Recognizing the benefits that adaptive management principals offer towards species and land management, the Department of the Interior ("DOI") encourages agencies to incorporate adaptive management principals wherever possible.[186] The DOI's technical guide[187] and Applications Guide[188] identify eight main conditions that should be met

170. Pidot, *supra* note 160, at 128 (citing Roberta Romano, *Regulating in the Dark*, *in* Regulatory Breakdown: The Crisis of Confidence in U.S. Regulation 86, 87 (Cary Coglianese, ed., 2012), Zachary J. Gubler, *Experimental Rules*, 55 B.C. L. Rev. 129, 134 (2014), and Rebecca M. Kysar, *Lasting Legislation*, 159 U. Pa. L. Rev. 1007, 1067 (2011)).
171. Pidot, *supra* note 160, at 113, 118, 142–43.
172. Gubler, *supra* note 170, at 130, 134–35 (2014) (describing two examples of multi-stage rules in the context of the SEC: the proxy rule and the rules regulating short sales).
173. *Id*. at 131.
174. *See id*. at 136–38.
175. Jens Ludwig et al., *Mechanism Experiments and Policy Evaluation*, 25-3 J. Econ. Persps. 17, 19 (2011).
176. Gubler, *supra* note 170, at 148–49.
177. *Id*.
178. Coglianese, *supra* note 169, at 61 (citation omitted).
179. *Id.* at 60–61.
180. Michael Greenstone, *Toward a Culture of Persistent Regulatory Experimentation and Evaluation*, *in* New Perspectives on Regulation 111, 119 (David Moss & John Cisternino eds., 2009), http://www.tobinproject.org/sites/tobinproject.org/files/assets/New_Perspectives_Ch5_Greenstone.pdf.
181. Coglianese, *supra* note 169, at 65.
182. Gubler, *supra* note 170, at 144.
183. *See* 5 U.S.C. § 557(c)(3)(A) (2012).
184. Coglianese, *supra* note 169 (citation omitted).
185. Robin Kundis Craig & J.B. Ruhl, *Designing Administrative Law for Adaptive* Management, 67 Vand. L. Rev. 1, 1 (2014) ("Adaptive management is a structured decision-making method, the core of which is a multi-step, iterative process for adjusting management measures to changing circumstances or new information about the effectiveness of prior measures or the system being managed.").
186. Melinda Harm Benson, *Adaptive Management Approaches by Resource Management Agencies in the United States: Implications for Energy Development in the Interior West*, 28 J. Energy & Nat. Resources L. 87, 88 (2010).
187. Byron K. Williams et al., The U.S. Department of the Interior Technical Guide v (2009) [hereinafter Technical Guide], http://www2.usgs.gov/sdc/doc/DOI-%20Adaptive%20ManagementTechGuide.pdf.
188. *See* Byron K. Williams & Eleanor D. Brown, The U.S. Department of the Interior Applications Guide vi–vii (2012), http://www2.usgs.gov/sdc/doc/DOI-Adaptive-Management-Applications-Guide-27.pdf.

before adaptive management is implemented.[189] Adaptive management is justified when: (1) there must be a mandate to take action in the face of uncertainty; (2) there must be the institutional capacity and commitment to undertake and sustain an adaptive program; (3) there are consequential decisions to be made; (4) there is an opportunity to apply learning; (5) the objectives of management are clear; (6) the value of reducing uncertainty is high; (7) uncertainty can be expressed as a set of competing, testable models; and (8) a monitoring system can be put in place with a reasonable expectation of reducing uncertainty.[190]

These parameters make clear the potential benefits of using adaptive management in rules such as the Clean Power Plan, that are designed to regulate the highly uncertain impacts of the electricity sector. Examples of inclusion of adaptive management principles, or planned adaptation, provide insight as to where "induced-learning" mechanisms in law have been successful to reduce or re-characterize underlying uncertainties over time.[191] In addition to examples in land management, McCray, Oye, and Petersen identify five cases, including EPA's program for ambient air standards, where planned adaptation has been implemented towards adoption of more open-ended policy.[192] This approach may help overcome the inertia and path dependency that characterize static rules by permitting requirements to evolve in response to new information over time.[193]

It is difficult to characterize the impacts of adaptive rules on investments in technology. On one hand, open-endedness can increase uncertainty as to final impacts on the regulated community, thus making long-term investment in compliance technology more risky. However, adaptive rules also have the nearly unique capacity for rules to keep pace with the accelerated development of new technologies.[194] Rather than "locking in" inferior technology choices, adaptive rules acknowledge an opportunity for the role of new technologies in a flexible and changing regulated environment.[195] One could surmise, for example, that technological developments such as Big Data[196] and the Internet of Things[197] will have beneficial and likely unanticipated impacts on future electricity markets. Big Data, for example, may drive remarkable improvements in energy efficiency as utilities gain more information about how their systems—and customers—make use of energy. Likewise, the Internet of Things—which for starters is expected to arm consumers with more information about how they use energy—may result in decreases in energy demand as the public becomes more educated about what a kilowatt is, how it is generated, and how much it costs.

Although issues remain, the concept of adopting learning rules is growing across multiple sectors and industries. Incorporated into rules, adaptive management principals may present an opportunity for rules themselves to evolve based on changing sets of inputs and as questions of implementation are resolved, thereby becoming ever more refined towards accomplishing a set of fluid goals.

C. *Contingency Rules*

Unlike the durational rules and adaptive rules that encourage incorporation of new information at a later date for modification, renewal, or repeal, contingency regulation includes predetermined substantive outcomes. Contingency rules provide for an alternate set of rules that will automatically spring into effect upon the occurrence or non-occurrence of a predetermined, foreseeable event, the occurrence of which would impact the efficacy of the rule.[198] This method provides an ideal opportunity to deal with divergent expectations of parties and information asymmetries: it permits parties to agree to disagree about how the future will look and instead to focus efforts on what should happen in either scenario. As a result, contingent regulation may encourage information sharing and signaling via disclosure.[199]

Contingent regulation also has potential to address what Hanna Wiseman calls diseconomies of scale.[200] Diseconomies of scale refer to the "disproportionately negative effects sometimes associated with the expansion of a long regulated activity" rendering the balance struck by earlier static rules inadequate.[201] The same diseconomies can occur where the scale of a regulated activity contracts, possibly to the point where it is no longer needed.[202] Wiseman offers several examples of diseconomies of scale, including the inability of regulations to keep pace with the rapid increase in scale of hydraulic fracturing and the possibility that increases in numbers of vehicles driven may render fuel economy and pollution control standards under the Clean Air Act ineffective for achieving emissions reductions.[203] Similarly, a rule

189. Technical Guide, *supra* note 187, at 9.
190. *Id.*
191. L. McCray et al., *Planned Adaptation in Risk Regulation: An Initial Survey of US Environmental, Health, and Safety Regulation*, 77 Tech. Forecasting & Social Change 951, 951–59 (2010) (citing Warren E. Walker et al., *Adaptive Policies, Policy Analysis, and Policymaking*, 128(2) Eur. J. Oper. Res. 282–89 (2001)).
192. *Id.* at 958.
193. *Id.*
194. *See* Gary E. Marchant, The Growing Gap Between Emerging Technologies and Legal-Ethical Oversight ch. 2 (2011) (discussing the growing gap between pace of technology and law).
195. David Grover, *Do Flexible Instruments Really Induce More Environmental R&D?* (Jan. 2012), http://www.webmeets.com/files/papers/EAERE/2012/1026/Do%20flexible%20instruments%20really%20induce%20more%20environmental%20R&D.pdf; David Kline, *Positive Feedback, Lock-In, and Environmental Policy*, 34 Pol'y Sci. 95-107, 95 (2001), www.nrel.gov/docs/gen/fy01/28513.pdf; Ryan Plummer et al., *Adaptive Comanagement and Its Relationship to Environmental Governance*, 18 Ecology & Soc'y *1 (2013).
196. "Big Data" can be defined as "datasets whose size is beyond the ability of typical database software tools to capture, store, manage and analyze." *See* James Manyika et al., *Big Data: The Next Frontier For Innovation, Competition, and Productivity*, McKinsey Global Inst. (2011).
197. "The Internet of Things" is the interconnection between physical devises and other items embedded with electronics, software, sensors, and networks that enable devises and products to interact, collect, and exchange data. *See* Michael Chiu et al., *The Internet of Things*, McKinsey Q. (Mar. 2010), http://www.mckinsey.com/industries/high-tech/our-insights/the-internet-of-things.
198. Pidot, *supra* note 160, at 117, 164.
199. *Id.* at 168–69.
200. *See* Wiseman, *Remedying Regulatory Diseconomies of Scale, supra* note 166, at 246–49.
201. *Id.* at 236.
202. *Id.* at 241; J.B. Ruhl & James Salzman, *Regulatory Exit*, 68 Vand. L. Rev. 1295, 1300 n.13 (2015).
203. Wiseman, *Remedying Regulatory Diseconomies of Scale, supra* note 166, at 244–46.

that requires "massive simultaneous investment that either replaces or retrofits coals plants" could have the effect of reducing the size of the market for new plants, thus stifling incentives for research, development, and implementation of new path breaking electricity-generation technologies.[204] Each of these examples demonstrates potential failures for static regulation achieving its objectives when scale of regulated activity, or where independent "small harms," increase beyond initial estimates.[205]

As Wiseman suggests, one way to remedy these diseconomies is through use of harm thresholds.[206] Harm thresholds impose more stringent controls on a regulated activity as it moves closer to a predetermined harm threshold or thresholds. If the threshold is not reached, "industry can continue growing and innovating without burdensome regulation."[207] If it is reached, new rules determined at the outset would spring into place. By way of example, Wiseman describes the health-based standards in the Clean Air Act. When pollution exceeds a designated level in a specified region, new, more stringent controls on industrial activities in that region spring into effect.[208] This is a form of contingency rule.

One of the benefits of contingent regulation is that the existence of a contingency can itself drive behavior towards a desired result. Because contingent regulation is static in the sense that it requires that lawmakers make choices about the optimal regulation under an anticipated set of circumstances at the outset, contingent regulations communicate precise eventualities to the regulated community. This in turn, reduces regulatory uncertainty and its associated costs[209] and motivates those regulated to consider scientific or market uncertainty. As such, a contingent rule may drive behavior among participants in the regulated activity to achieve or avoid the triggering factor that would result in the contingent rule.

The efficacy of contingent rules in driving behavior may depend on the causal relationship between the regulated activity and the triggering event. One can surmise that the stronger the causal relationship—and therefore the more control a participant has over the ultimate outcome of the rule—the greater incentive it provides. For example, a trigger based on a set amount of temperature or sea level rise would likely have nominal incentive effects because the ability of any one market participant, or even a consortium of them, to meaningfully influence the result is minimal. For example, a potential that an unforeseen event such as a volcanic eruption[210] or the Aliso Canyon[211] gas leak could completely reverse positive efforts by industry to avoid the trigger established by the harm threshold. The stronger the perceived inevitability of the triggers' occurrence, the less the rule would be anticipated to incentivize innovation, early adoption, or compliance.

Returning to Wiseman's example of the Clean Air Act, the harm trigger is unlikely to incentivize the owners of industrial sources to take proactive action to avoid reaching the harm threshold. While the established threshold may advance the public policy of preventing harmful public health outcomes, it is unlikely to spur individual investment in new emissions control technologies. Given the multiple contributors to air quality in any given region unrelated to industrial sources—including weather, wood burning, and vehicle emissions, each of which may accumulate to trigger the harm threshold—action by any one industrial source or even a group of them would not guarantee preventing the imposition of more stringent rules. While this method may be effective in terms of creating an immediate response to the health-based harms the Act attempts to avoid, the rule itself does not encourage individuals to take actions to avoid harms.

As an alternative to harm threshold rules, we propose rules that focus instead on achieving a minimum level of participation through the creation of a compliance threshold. Rather than concentrating on prevention of an externality related to the regulated activity, a compliance threshold rule would focus on achieving a minimum level of participation in a desired activity. By tying the resultant regulation to the decisions of the regulated community, rules developed according to this design would incorporate a strong causal relationship to incentivize individuals in the regulated communities to make choices directed towards achieving a predetermined result and would encourage private ordering among participants in the regulated community. Returning to the example of the Clean Power Plan advanced earlier in this Article, and leaving aside all discussion of the legality or likelihood of implementation of that rule, a regulation could be structured so that industry would have to achieve a quantified reduction in air emissions from industrial sources or offsets from mitigation, and to meet a minimum level of industry participation within a specified period of time—thus creating a compliance threshold. The failure to meet the threshold would result in the application of more stringent and broad-based rules than were initially proposed. Importantly, the rule would provide maximum flexibility to the regulated community: it would not require

204. Dalia Patino-Echeverri, *Feasibility of Flexible Technology Standards for Existing Coal-Fired Power Plants and Their Implications for New Technology Development*, 61 UCLA L. Rev. 1896, 1899–900 (2014). For example, policy decisions that have driven disinvestment in coal generation could result in disincentive to develop commercially viable technologies for coal carbon capture and geologic sequestration. Ironically, it may have made more sense to pursue these technologies ten years ago than it does now.

205. Wiseman, *Remedying Regulatory Diseconomies of Scale, supra* note 166, at 245–46 (citing William E. Odum, *Environmental Degradation and the Tyranny of Small Decisions,* 32 Bioscience 728, 728–29 (1987), and Dave Owen, *Critical Habitat and the Challenge of Regulating Small Harms*, 64 Fla. L. Rev. 141, 195 (2012)).

206. *Id.* at 279.

207. *Id.* at 241 n.12.

208. *Id.* at 247 (citing 42 U.S.C. §§ 7408(a), 7502(a)(1)(A) (2006)).

209. *See generally* Dalia Patino-Echeverri et al., *Econ. and Envt'l Cost of Regulatory Uncertainty for Coal-Fired Power Plants*, 43 Envtl. Sci. & Tech. 578, 581–83 (2009).

210. Terry Gerlach, *Volcanic Versus Anthropogenic Carbon Dioxide*, 92(24) Eos Trans. AGU 201, 201 (2011) (noting that present-day volcanoes emit relatively modest amounts of CO_2, about as much annually as states like Florida, Michigan, and Ohio).

211. The leak from the Aliso Canyon gas storage facility was estimated (as of October 21, 2016) to have emitted 109,500 tons of methane. *Aliso Canyon Natural Gas Leak*, Cal. Envtl. Protection Agency: Air Resources Board (Oct. 25, 2016), http://www.arb.ca.gov/research/aliso_canyon_natural_gas_leak.htm.

participation by all market participants, require equal distribution across geographic areas, or specify the means of compliance. Theoretically, the potential imposition of more stringent regulation would encourage compliance, facilitate transfers from holdouts to early adopters, and incentivize investment in R&D and innovation oriented towards the development of new technologies. As such, the structure of the rule itself could contribute to the likelihood of it achieving its stated goals.[212]

Contingent regulation is the form of dynamic law that perhaps offers the greatest opportunity for law to address the issues of model uncertainty.[213] A contingency rule would start with a baseline rule based off the status quo and then provide a series of alternative rules that would come into play at a later date based on new information indicating the occurrence or non-occurrence of a specified event. Models can be the basis for assessing which events have potentially disruptive impacts on baseline assumptions. For example, a contingency rule based on the Clean Power Plan could allow for later assessment of state implementation plans and actions, as well as certain key inputs such as the price of natural gas, and provide for predetermined adjustments in the rule based on those findings, which in turn may improve outcomes and reduce compliance costs.

While requiring more extensive effort on the front end, contingent regulations are attractive because they require fewer resources for monitoring.[214] Contingent rules achieve this ease of implementation precisely because the substantive result has been determined in advance and thus has been subjected to the process-based review of rulemaking. Careful design of thresholds should make the monitoring relatively painless by incorporating publicly available metrics already subject to consistent monitoring by the EIA or other agencies. If a threshold were met, the agency would issue a declarative order (which of course would be subject to challenge), and the contingency rule could go into effect immediately without additional rulemaking.[215]

Despite a rich body of literature in this area, actual use of dynamic law is relatively rare.[216] There are a number of possible explorations for why they are not used more often, including path dependence, capital intensive demands on front end, opposition from interest groups, and a perception that dynamic rules may be more susceptible to legal challenge.[217] As Pidot argues, contingency rules may be best suited to resolve some of these issues,[218] and present the added benefit of communicating expected outcome to the regulated community.

D. *An Example: The Flexible Technology Standards Re-Conceptualized as a Contingent-Durational Adaptive Rule*

The flexible technology standard, proposed by Patino-Echeverri of Duke University, attempts to address the highly uncertain conditions under which owners of power plants must decide how and whether to retrofit or replace a plant to comply with new and proposed EPA rules.[219] Among the variables at play are the characteristics of the coal plant and the state's implementation of such rules, but also variables affecting the cost and profitability of any alternative, including "future fuel prices, costs and performance of future technologies, future regulations," and assumptions about the economic life of the new or retrofitted plant.[220] Faced with these uncertain conditions within which to make a decision, investors may desire to defer decision-making until more information or potential new "path breaking" technologies are available.[221]

A flexible technology standard is a performance standard that would permit owners of older coal-fired plants to defer installation of pollution controls in order to wait for new information or potential breakthrough technologies.[222] Building upon existing source performance emissions standards, the flexible mandate would permit plant owners to either install conventional pollution controls or to make alternative payments for each unit of emissions in excess of the standard during a set flexible period. The payment and the duration of the flexibility period would be chosen by regulators based on expectations about the likelihood of arrival of path-breaking technologies and their performance to ensure that on expectation, the total emissions over the lifetime of the regulated plant would not exceed those that would have been permitted under existing traditional source performance standards.[223] If a new technology capable of achieving greater emissions reductions was not proven successful during the flexible period, the plant would be retrofitted with conventional emissions control equipment.[224] Alternative payments could, in turn, be used to subsidize early adoption of pollution controls on other plants, to support future capital costs of retrofits, or could be invested in research to support successful realization of the path breaking technology during the flexibility period.[225] This invest-

212. There is a possibility that some within the regulated community could try to arbitrage the possibility that the rule would be overturned prior to enforcement of stricter controls.
213. *See* discussion *supra* notes 124-130 and accompanying text ("A Multiplicity of Models").
214. Pidot, *supra* note 160, at 7 ("Such efforts currently face stiff obstacles because governing bodies often fail to provide ongoing resources necessary to successfully revisit existing rules and, where such revisitation occurs, interest group politics appear to obstruct meaningful change.").
215. *Id.* at 164.
216. McCray et al., *supra* note 191, at 958.
217. Gubler, *supra* note 170, at 132–36; McCray et al., *supra* note 191, at 951; Pidot, *supra* note 160, at 149.
218. Pidot, *supra* note 160, at 119 ("Contingent regulation in particular may ameliorate thorny problems that are endemic to previous attempts at dynamic law.").
219. Patino-Echeverri, *Feasibility of Flexible Technology Standards for Existing Coal-Fired Power Plants and Their Implications for New Technology Development*, *supra* note 204, at 1901–02.
220. *Id.* at 1909–15.
221. *Id.* at 1916–17.
222. *Id.* at 1920.
223. *Id.* at 1921.
224. Patino-Echeverri, *Feasibility of Flexible Technology Standards for Existing Coal-Fired Power Plants and Their Implications for New Technology Development*, *supra* note 204, at 1922.
225. Dalia Patino-Echeverri et al., *Flexible Mandates for Investment in New Technology* 15 (Res. for the Future, Discussion Paper No. RFF-DP 12-14, 2012), http://www.rff.org/files/sharepoint/WorkImages/Download/RFF-DP-12-14.pdf.

ment could increase the possibility of success and superior emissions reductions by not only supporting research but by also assuring the availability of a market for such new technologies were they to prove successful.[226]

The flexible implementation permitted by the standard can be combined with elements of adaptive planning and contingency regulation to create a more dynamic rule that strives to craft incentives for development and implementation of new technologies, while reducing overall emissions. As proposed, the rule resembles a multi-stage experimental rule with only one significant variable—whether new technology capable of achieving greater emissions reductions will become feasible during the experimental period. In this example, the method and timing by which companies must achieve emissions reductions to comply with EPA rules is flexible, but the actual levels of emissions reductions enforced by EPA are static.[227] Accordingly, to introduce elements of dynamism, EPA's emissions standards for companies not installing pollution control technology at the outset should be open-ended. For example, instead of requiring companies that fail to realize new technologies to outfit plants with conventional emissions control equipment available at the beginning of the period, the rule could be revised to provide periodic opportunities for learning the potential of improved technologies in order to revise the emissions compliance standards. Accordingly, plant owners facing the decision whether to retire or retrofit older coal-fired power plants could, at the end of the flexible period, be subject to new sets of standards that take into account new information about factors both related (such as compliance rates and the availability and efficacy of new technology) and unrelated (such as generation fuel prices). Additionally, the rule could incorporate a contingency mechanism, with a new standard or standards, predetermined at the outset, which would then spring into effect if program participants failed to reach certain total emissions reductions over the flexible period. Drafted as such, the flexible technology standard would present an opportunity to address two sources of uncertainty including implementation (availability and use of new technologies) and inputs (fuel prices and demand).

E. Opportunities for Integration of Dynamic Principles of Law in the CPP

The modeling of the CPP suggests that decisions to comply may result in considerable costs to society if key uncertainties are resolved differently than what is assumed by decision makers. For example, if states *ex ante* assume the use of greater natural gas technologies is optimal based on what later turn out to be inaccurate assumptions regarding renewable technology options, the result could be a higher cost and sub-optimal response to the legislation *ex post*.

It is unclear if and when key uncertainties such as the cost of renewables and the prices and environmental implications of natural gas will resolve, or whether such uncertainties justify delaying the CPP or any CPP-like regulation. However, it is clear that a regulatory approach that could allow states to adapt to the unfolding of uncertainty before committing to what could be sub-optimal investment decisions could save society significant cost in meeting its regulatory goals. It is also clear that, given the long economic lives of power plants, natural gas pipelines, and other energy relevant infrastructure, a policy affecting investment in the electric sector must look at the goals of the CPP of reducing CO_2 emissions by 30% as interim goals, and incentivize investment alternatives that do not conflict with the more ambitious decarbonization objectives that may be pursued in the near future.[228]

Crafting a rule that accounts for potential revisions of carbon abatement goals, new technological developments that would improve the performance and costs of electric power generation alternatives, and new knowledge about the environmental impacts of coal, gas and renewables, could avoid costly investment in inferior technology choices.[229] While proposing a specific rule to address these issues is beyond the scope of this Article, given the multiple forms of uncertainty and opportunities for future learning, adaptive and dynamic forms of regulation based on projections from energy models that characterize and account for relevant uncertainties, may offer attractive solutions.

IV. Conclusion

Generous budgets, and tremendous increases in computational power may produce more complex—and sometimes—more realistic models, but the causes of the impossibility of forecasting will remain.[230] Despite this limitation, large and complex energy models have a lot to offer to the policy and regulatory processes. They represent an unparalleled opportunity to document current knowledge about the system they represent,[231] and can be used in research for identifying and prioritizing knowledge gaps. The same reasons that originated the field of system dynamics and the development of controversial models persist: using models to project systems performance under a set of assumptions offers insights that the limited ability of the human brain would probably miss on its own. The system's emergent properties resulting from relations between causes and effects that are removed

226. *Id.* at 20–21 (discussing how rational investors who seeks profit under a surcharge-based regime will shop in a market that forces investors to choose whether to devote resources toward new emission control technology, existing technology, or new facility construction).

227. Patino-Echeverri, *Feasibility of Flexible Technology Standards for Existing Coal-Fired Power Plants and Their Implications for New Technology Development*, *supra* note 204, at 1921.

228. Consider for example the announcement of a historic goal for North America to strive to achieve 50% clean power generation by 2025 made by Prime Minister Justin Trudeau, President Barack Obama, and President Enrique Peña Nieto on June 2016. *See* Press Release, White House, Leaders' Statement on a North American Climate, Clean Energy, and Environment Partnership (June 29, 2016), https://www.whitehouse.gov/the-press-office/2016/06/29/leaders-statement-north-american-climate-clean-energy-and-environment.

229. *See* Hopkins, *supra* note 130.

230. *See id.*; Vaclav Smil, *Against Forecasting*, *in* Energy at the Cross-Roads: Global Perspectives and Uncertainties 121–80 (2012).

231. M. Granger Morgan et al., Uncertainty: A Guide to Dealing With Uncertainty in Quantitative Risk and Policy Analysis 289–90 (1990).

in time and space, are likely to involve many moving pieces of information hard to process without a quantitative computer model.

Current regulatory processes utilize modeling, however, the impact analysis used to define anticipated regulatory outcomes when developing such rules usually involves the use of only a single model and limited set of scenarios. The Environmental Protection Agency's use of its IPM model provides such an example.[232] Shortcomings of this approach include lack of consideration modeling uncertainties and this could be improved through best practices already identified in the energy modeling community, including the use of multi-model assessments.

Although nobody knows with precision what the electricity market and its various components—generation and transmission, for example—will look like next year, let alone 20 or 30 years in the future, it is possible to identify the factors likely to influence that outcome. IEA forecasts that even in the face of the 2015 Paris Agreement, global energy consumption, and thus demand, will continue to grow with varying regional outcomes.[233] We also know that, domestically, without regulations such as the Clean Power Plan, the generation mix is expected to be little changed through 2030, and that the Clean Power Plan, if enacted as currently defined, might primarily impact the market through fuel-switching from coal to natural gas.[234] Undeniably, the relative prices of fuels will be essential to forecasting and regulating future electricity markets.

An investigation of these factors and acknowledgement of the uncertainties inherent in energy projections, provides an opportunity to identify windows of expansion for the use of dynamic systems of law. A systematic evaluation of a regulation's effects under varied sets of assumptions—including extreme scenarios—can help determine the range of possible outcomes. Using these outcomes, it may be possible to design backstop provisions, contingent rules, and "insurance policies" that discourage sub-optimal investment actions, reduce the social cost of regulation, and make the regulation's effectiveness resilient to the volatile environment in which it operates. Contingent rules, combined with imbedded processes of adaptive management, may harmonize the adaptability and flexibility of the regulated sectors with the need to meet regulatory goals.

232. *Power Sector Modeling*, U.S. Envtl. Protection Agency (Nov. 23, 2015), https://www.epa.gov/airmarkets/power-sector-modeling.

233. *World Energy Outlook 2015—Executive Summary*, Int'l Energy Agency 1 (2015), http://www.iea.org/publications/freepublications/publication/world-energy-outlook-2015---executive-summary---english.html ("Energy use worldwide is set to grow by one-third to 2014 . . . driven primarily by India, China, Africa, the Middle East, and Southeast Asia.").

234. Regulatory Impact Analysis, *supra* note 13, at fig. 3–4 (Oct. 23, 2015), https://www.epa.gov/sites/production/files/2015-08/documents/cpp-final-rule-ria.pdf). Natural gas, however, faces its own suite of environmental challenges, and thus whether it will remain the low cost option for fuel switching is unknown.