LETTER

Capacity at risk: a metric for robust planning decisions under uncertainty in the electric sector

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Abstract

Many decision contexts are characterized by deep uncertainty where there is disagreement about values and probabilities such as policy and technological uncertainties for energy sector investments. Although there are methods for decision analysis in these contexts, there are few simple metrics to guide analysts and decision-makers on whether more sophisticated methods are appropriate, to highlight aspects of robust decision-making, and to prioritize information gathering on uncertainties. Here, we introduce a screening metric called ‘capacity at risk’ and two complementary metrics—robust capacity and risk ratio—for identifying the most decision-relevant uncertainties and for understanding which investments could be robust and which are more uncertain across a range of different futures. The use of deterministic model runs in calculating capacity at risk metrics can lower barriers to entry for modelers and communications with stakeholders. These metrics are applied to an illustrative example of electric sector decarbonization in the United States using a detailed capacity planning and dispatch model. Scenario results demonstrate the importance of climate policy targets and timing on decisions, while uncertainties such as natural gas prices and renewable costs have more moderate impacts on planning. We also apply the capacity at risk framework to other prominent U.S. electric sector scenario analysis. These comparisons suggest that commonly used scenarios may understate uncertainty, giving decision-makers a misleading sense of portfolio risk and understating the value of frameworks that explicitly assess decisions under uncertainty.

1. Introduction

Many decision contexts are characterized by deep uncertainty, where there is disagreement about values, system dynamics, and probabilities (Hall et al. 2012, DeCarolis et al. 2017). Electric sector investments are a domain with a range of policy and technological unknowns. Declining costs and improved performance of solar, battery storage, and wind power have altered projections for how and where electricity is generated (Mai et al. 2018). At the same time, other promising supply-side technologies (e.g., advanced nuclear, hydrogen, long-duration energy storage, carbon-capture-equipped capacity) and demand-side trends (e.g., electrification, distributed energy resources) introduce uncertainties about future planning (Bistline 2021, EPRI 2021a, 2021b). These dramatic changes are amplified by policy-related uncertainties at federal and subnational levels on climate and clean energy policies, including renewable portfolio standards, clean electricity standards, carbon pricing, emissions caps, and tax credits (Peng et al. 2021). In this context of deep uncertainty, single pathways that may be cost-effective under a given set of assumptions about the future may perform poorly under other plausible states-of-the-world, hence the goal of identifying robust strategies that make sense under a range of possible futures (Lempert et al. 2006).

Although there are decision analysis approaches in these contexts of deep uncertainty (Kann and Weyant 2000, Baker et al. 2020), many approaches present challenges with selecting uncertainties, assessing probabilities, and communicating insights to stakeholders, which to some degree reflects unavoidable features of the decision contexts themselves (Fischhoff and Davis 2014, Morgan 2015). Existing metrics such as the expected value of information and
the value of the stochastic solution typically assume the availability of a stochastic model (Birge 1982, Bistline 2015). There are sensitivity frameworks based on deterministic model runs to guide decision-makers, analysts, and other stakeholders on whether more sophisticated methods are appropriate and to prioritize information gathering on uncertain factors (Herman et al 2015, Pianosi et al 2016, Quinn et al 2019, Wagener et al 2022). However, these approaches have largely been neglected in energy systems context in favor of stochastic optimization approaches. Additionally, a key consideration in factor prioritization is the selection of a metric that captures aspects of system performance (Saltelli et al 2008, Reed et al 2022), which begs questions about which dynamics and aspects of robustness should be captured for energy systems decisions.

The objective of this paper is to develop a framework that uses deterministic sensitivity analysis to help stakeholders think about which uncertainties materially impact decisions in an energy systems context, which can help to prioritize model development, more detailed risk analysis, and probability assessments. This study introduces three metrics—capacity at risk, robust capacity, and risk ratio—to help analysts assess decision-relevant uncertainties before applying advanced stochastic methods. These metrics and proof-of-concept analysis are first steps toward systematically exploring uncertainty in energy systems and determining which uncertainties require additional effort to quantify (and the value of using frameworks that explicitly evaluate decisions under uncertainty such as stochastic planning or robust portfolio analysis). The use of deterministic model runs can lower barriers to entry for modelers and communications with stakeholders, and these metrics can be better-suited for accommodating portfolio problems than other approaches in the literature (e.g., tornado diagrams), which are important features in energy systems decisions. These metrics are applied to an illustrative example of electric sector decarbonization in the United States using a detailed capacity planning and dispatch model.

In our analysis, we aggregate the scenarios into various categories (e.g., climate policy targets, fuel prices, technology costs). Scenario results demonstrate the importance of climate policy targets and timing on electric sector investment decisions, while uncertainties such as natural gas prices and renewable costs have more moderate impacts on planning. On average, capacity at risk for climate policy targets and timing is 750 GW (nearly 70% of current installed utility-scale generating capacity), compared to 175 GW for natural gas prices, and 245 GW for renewable costs uncertainties. We also apply the capacity at risk framework to other prominent U.S. electric sector scenario analysis. These comparisons suggest that commonly used scenarios may underestimate uncertainty, giving decision-makers a misleading sense of portfolio risk and understating the value of frameworks that explicitly assess decisions under uncertainty.

2. Methods

2.1. Defining capacity at risk
Suppose \( z^*_g(i, \omega) \in \mathbb{R}^{G_i} \) is the vector of optimal capacity investment in generator \( g \) (with \( G \) possible generator types) that solves the capacity planning problem to minimize the cost of supplying electricity subject to technical and policy constraints. The set of uncertainties \( i = 1, \ldots, I \) has corresponding realizations \( \omega_i = 1, \ldots, \Omega_i \) (which alter parameter values in the objective function and the constraints), and the cost-minimizing investment mix varies based on the outcomes of these uncertainties.

Robust actions are ones that are shared across expansion plans. Here, the minimum amount of capacity investment across scenarios provides a conservative lower bound on ‘robust capacity’ \( \rho \) for a particular uncertainty. \(^1\) This measure provides confidence that at least this much capacity of a given technology will be part of the least-cost portfolio for a given set of scenarios regardless of which state-of-the-world obtains:

\[
\rho^g_i = \arg \min_{\omega} z^*_g(i, \omega) \quad \forall \ g, i
\]  

For each uncertain variable and its realizations (i.e., all outcomes or states-of-the-world), ‘capacity at risk’ \( \kappa \) is defined as the technology-specific difference between investment \(^2\) in that state and the minimum investment across all states over a specified time horizon:

\(^1\) Alternate definitions of robustness are possible depending on the decision context. For instance, robust actions could be ones that are shared by a specified percentile of expansion plans rather than across all scenarios. Here, the definition of robustness provides a conservative lower bound for specified uncertainties, which should provide confidence that, at a minimum, this much capacity of a specific technology will be in the least-cost portfolio regardless of how the uncertainty resolves.

\(^2\) Note that we are not addressing methods for selecting which sensitivities to run in the first place and whether the choice of uncertain variables and their possible outcomes is adequately covering the appropriate space (Saltelli et al 2008).

\(^3\) Given the application to electric sector capacity planning, this exposition is framed in terms of capacity investments. The specific metric used in later sections is the cumulative capacity investments through 2035 in units of gigawatts (GW). Other metrics or units could be substituted without loss of generality. For instance, investments could be expressed in dollar terms to facilitate comparisons not only over generation capacity but also over other resources such as transmission and carbon dioxide removal technologies.
The 'upper threshold for capacity at risk' \( v \) for a given uncertainty is the maximum technology-specific variation across all states for a given uncertainty, which again provides a conservative upper bound on capacity risk:

\[
\kappa_g(i, \omega_i) = \left( \max_{g} H_g(i, \omega_i) \right) \left( \min_{g} H_g(i, \omega_i) \right) \forall g, i, \omega_i
\]

(2)

The overall risk ratio can be calculated by dividing the upper threshold by the minimum robust additions \( v_g(i) / \mu_g(i) \), which provides an aggregate risk metric than can be compared across uncertainties and across studies. The lower the robust additions, the greater the potential risk (and capacity at risk).

Comparing capacity at risk across different uncertainties as well as robust capacity, upper threshold, and risk ratio across different categories of uncertainties provides a screening tool for identifying the most decision-relevant uncertainties, understanding which investments could be robust, and assessing at-risk capacity across a range of different futures. These metrics can identify possible candidate resources for robust portfolios, stranded asset risks, and uncertainties that should be considered for more detailed risk analysis (i.e., where probabilities are assessed and then incorporated into a framework that explicitly evaluates decisions under uncertainty).

Note that the definitions of these metrics mean that they can be sensitive to the inclusion of extreme scenarios and thus require care in screening for reasonably plausible states-of-the-world. This dependence on selected uncertainties and their possible realizations is similar to other metrics such as minimax regret, which have literatures dedicated to techniques to ex-ante sorting states-of-the-world for inclusion (McPhail et al 2018). Moreover, our framework is not intended to make decisions directly based on these metrics but instead to identify which uncertainties could change decisions and should be considered for more in-depth risk assessments. Given that role, it seems reasonable to err on the side of including lower-probability, higher-impact possibilities so that these states are not disregarded from the more formal risk analysis if they can materially alter decisions. However, appropriate contextualization of such scenarios is important, especially before they have been explicitly assigned probabilities. Scenario generation has important implications for the interpretation of these scenarios and subsequent decision-making (Morgan and Henrion 1990), so this step in the analysis process should be given commensurate attention. Importantly, scenario generation should be undertaken with a thorough understanding of cognitive heuristics and biases when making judgments about uncertainties (Kahneman et al 1982, Morgan 2014).

2.2. Framework for applying capacity at risk: electric sector modeling

To provide an illustrative example of capacity at risk in a decision-relevant domain, a numerical analysis is conducted for electric sector decarbonization in the United States. This analysis applies a linked model of end-use technology adoption and a power sector capacity planning and dispatch model with temporal, spatial, and technological detail. The model—EPRI’s Regional Economy, Greenhouse Gas, and Energy (REGEN)—is documented in detail in EPRI (2020), and summaries are provided here and in Appendix A.1. The electric sector model in REGEN simultaneously optimizes capacity investments and retirements, energy storage, hourly system dispatch, inter-regional transmission capacity, CO2 transport and storage, and carbon removal given assumptions about policies and technologies. Like many capacity planning models, REGEN is an intertemporal optimization model that minimizes the net present value of system costs with deterministic inputs, and future uncertainties are addressed through discrete scenario or sensitivity analysis. Investment and retirement decisions are made in five-year timesteps through 2050, but the focus here is on decisions through 2035.

The following uncertainties are considered in this analysis:

- **Climate policy target definition**: Proposed climate and emissions reductions policy can vary in terms of their detailed policy design, but one central element is which technologies are eligible (Blanford et al 2021). There are four possible outcomes associated with climate policy that are investigated here: A ‘Reference’ scenario (i.e., with on-the-books state and federal policies and incentives as of June 2021), a ‘Net-Zero’ scenario (i.e., net national CO2 emissions in the power sector are zero so that any emissions produced are balanced by an equivalent amount of removals), a ‘Carbon-Free’ scenario (i.e., electricity generation does not use fossil fuels and does not emit CO2), and ‘100% Renewables’ (i.e., the narrowest choice set where 100% of electricity generated must come from eligible renewables).

- **Climate policy timing**: Although many announced utility net-zero goals target a 2050 timeframe (Godefyskaya et al 2021), the recent U.S. nationally determined contribution as part of the Paris Agreement sets a goal to reach ‘100 percent carbon pollution-free electricity by 2035’ (U.S. Government 2021). The analysis looks at both 2035 and 2050 zero emissions targets for the power sector across the three definitions of zero emissions in the previous uncertainty. The baseline policy target and timing is Net-Zero by 2035 given
the policy focus on this goal, though we also conduct cross-sensitivities with other climate policy scenarios to illustrate how the risk metrics and insights can change (Appendix A.3 and appendix A.4).

- **Renewables and storage costs**: Capital cost trajectories for onshore wind, offshore wind, solar photovoltaic (PV), and battery storage vary assumptions from their reference levels to low- and high-cost cases, based on an assessment of projections in the literature (Bistline et al. 2022). Capital cost ranges are shown in appendix figure A2.

- **Natural gas prices**: The analysis considers three natural gas price trajectories over time (low, reference, and high), which come from the U.S. Energy Information Administration’s *Annual Energy Outlook*. Gas price trajectories are shown in appendix figure A3.

- **Other technological costs**: The analysis also examines lower cost sensitivities for direct air capture (DAC), hydrogen electrolyzers, new nuclear, and battery storage as well as higher cost sensitivities for bioenergy with carbon capture.

Additional scenario assumptions are described in appendix A.1. We apply the metrics from section 2.1 to scenarios within each uncertainty and then compare across uncertainties to identify the most decision-relevant ones.

### 3. Results

In this section, we first present results of various electric sector decarbonization scenarios using the REGEN model (described in section 2.2), focusing on net capacity additions through 2035. In section 3.2, we then apply capacity at risk and other risk metrics to these scenario results. In section 3.3, we apply these same risk metrics to the commonly used U.S. Energy Information Administration’s *Annual Energy Outlook 2021* (U.S. EIA 2021) to compare and contrast with the REGEN results.

#### 3.1. Scenario results from the REGEN model

The results from the capacity expansion suggest that climate policy target definitions and timing have large impacts on near-term investments (figure 1) and the generation mix (Appendix figure A5). Under a Net-Zero emissions policy, carbon removal from bioenergy with carbon capture (BECCS) enables natural gas to balance variability from wind and solar (roughly 40 GW of BECCS creates a negative flow of 250 Mt-CO$_2$ annually). The Carbon-Free scenario exhibits rapid builds of nuclear and energy storage (including both short-duration batteries and long-duration hydrogen) to balance larger solar and wind expansions. The 100% Renewables scenario shows higher wind and solar generation, hydrogen use, and battery storage deployment. Common elements of decarbonization pathways include phasing out coal generation, maintaining existing hydropower and nuclear, and much higher wind and solar deployment (Bistline et al. 2022). The net capacity additions of all the scenarios are provided in appendix figures A6–A9.

Across all zero-emissions scenarios, there is a significant acceleration of investments, especially with a 2035 target. The Net-Zero scenario has the broadest technological portfolio by construction with high wind and solar deployment combined with negative emissions from bioenergy with carbon capture to enable gas to balance renewable variability. Carbon removal also provides a hedge against transition risk, especially with accelerated decarbonization schedules. The Carbon-Free scenario entails a rapid build out of nuclear and storage (including batteries and hydrogen) to balance larger solar and wind expansions. The 100% Renewables scenario has nearly double the capacity investment requirements of the Net-Zero scenario. Shifting the target from 2035 to 2050 (including a 2035 interim cap of 80% CO$_2$ reductions relative to 2005) lowers magnitudes of near-term investments and makes Net-Zero and Carbon-Free builds more similar in the near term.

As the next section illustrates, these cumulative changes in capacity across scenarios have implications for capacity at risk, both for the climate policy target and timing uncertainties as well as the others considered in this analysis. While the climate policy sensitivity exhibits the largest range of outcomes for near-term investments, changes across other uncertainties can be considerable. Variable renewables become the largest producer under many scenarios, though shares exhibit considerable variation based on policy and technology assumptions (Bistline et al. 2022).

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4 Additional detail on generation, capacity, and costs under these climate policy scenarios can be found in Blanford et al. (2021).
3.2. Capacity at Risk Metrics from the REGEN Analysis
For the climate policy target and timing uncertainties, figure 2 summarizes technology mixes for scenario-specific capacity at risk, robust capacity, and upper threshold for capacity at risk. The portfolio for robust capacity additions encompasses wind, solar, and energy storage technologies, which totals roughly 150 GW of capacity. These technologies are ‘robust capacity,’ irrespective of the climate policy targets and timing. The highest capacities at risk are also solar and wind technologies, because of significant expansions in near-term Carbon-Free and 100% Renewables scenarios by 2035 beyond cost-minimizing levels for the Reference and Net-Zero scenarios. Capacity at risk varies across climate policy outcomes, varying between 200 GW (in the Reference, which is primarily gas-fired capacity) to 1,500 GW (in the 100% Renewables by 2035 scenario, which is largely solar and wind). The difference between the upper threshold of capacities and minimum robust capacity is 1,900 GW, indicating the large dispersion of outcomes across the climate policy uncertainties. The overall risk ratio—the upper threshold divided by minimum robust additions—is 15, which indicates higher levels of risk associated with climate policy target definitions and timing. Since the risk ratio is a function of

Figure 1. Capacity additions and retirements by technology for the climate policy target and timing scenarios. Historical values come from Form EIA-860 data. The horizontal axis represents scenarios for the climate policy target and timing uncertainties, and the vertical axis represents net capacity additions (in GW). Monetary investments in generation and bulk transmission are shown above each bar and include cumulative capital expenditures through 2035. (Note the potential for deviations between projected and actual costs for the required capacity investments).

Figure 2. Capacity at risk values across different realizations of the climate policy target and timing uncertainties. The horizontal axis represents scenarios, and vertical axis represents capacity investments between 2020 and 2035 (in GW). Dates above targets refer to the target year in which emissions reach (net-)zero. The colors represent different technologies.
minimum robust additions and maximum values, the inclusion of extreme scenarios can drive higher risk ratios, and thus requires care in screening for reasonably plausible states-of-the-world (similar to the minimax criterion).

Overall, these metrics highlight the importance of climate policy targets and timing on investment decisions, which is also reflected in the different generation mixes across these sensitivities (figure A5, appendix A.2). The minimum robust capacity is higher and capacity at risk lower for other sensitivities considered in this analysis, including renewable costs and natural gas prices.

For the natural gas price uncertainties, figure 3 summarizes technology mixes for scenario-specific capacity at risk, robust capacity, and upper threshold for capacity at risk. The portfolio for robust capacity additions (i.e., regardless of the natural gas prices) encompasses wind, solar, energy storage, BECCS, and natural gas, which totals roughly 650 GW of capacity. The highest capacity at risk is solar, which is most significant under high natural gas prices. Capacity at risk (50–300 GW) does not vary as much as climate policy outcomes (200–1,500 GW). The difference between the upper threshold of capacities and minimum robust capacity is 350 GW, indicating relatively smaller dispersion of outcomes across the natural gas price uncertainty compared with climate policy. The overall risk ratio—the upper threshold divided by minimum robust additions—is 1.6, ten times lower than the risk associated with climate policy target definitions and timing.

For the renewable cost uncertainties, figure 4 summarizes technology mixes across the three-risk metrics. The portfolio for robust capacity additions again is dominated by wind and solar capacity, which totals 600 GW of capacity and is similar in magnitude and composition to the natural gas price uncertainty. The highest capacity at risk is solar under the low renewables cost state-of-the-world, as investments are lower under other realizations. The difference between the upper threshold of capacities and minimum robust capacity (450 GW) and the overall risk ratio (1.8) are more similar to the gas price uncertainty than to the climate policy uncertainty.

Figure 5 summarizes technology mixes for the additional technology cost uncertainties. Wind and solar dominate the portfolio for robust capacity additions, totaling 580 GW of capacity. Capacity at risk varies between 150–300 GW. The difference between the upper threshold of capacities and minimum robust capacity is 480 GW, similar to natural gas price uncertainty and renewable cost uncertainty. The overall risk ratio is 1.84, similar to renewable cost uncertainty.

Table 1 summarizes the risk ratio and capacity at risk values across all the uncertainties. The highest risk ratio and capacity at risk values for policy timing/targets demonstrate that climate policy actions or inactions have more significant impacts on future expansion plans, as compared to other uncertainties related to fuel prices or technology costs.

Results thus far assume that each uncertainty holds others constant at their baseline values. The baseline policy target and timing is Net-Zero by 2035 given the policy focus on this goal, though we also conduct cross-sensitivities with other climate policy scenarios to illustrate how the risk metrics and insights can change, which are summarized in Appendices A.3 and A.4. Relative to robust capacity additions under a Net-Zero by 2035 policy, robust capacity under a ‘current policies’ Reference scenario entails higher natural gas investments and
lower additions of renewables and energy storage (figure 1), which leads to a higher risk ratio for the natural gas price uncertainty (1.85, table A2). On the other hand, the Net-Zero by 2050 policy scenario has a lower risk ratio for the gas price uncertainty (1.18, table A3), and even though the total robust capacity is similar to the Net-Zero by 2035 scenario, the composition is notably different—a later net-zero target leads to greater near-term investment in gas-fired capacity. The risk ratio is similarly lower for the technological cost uncertainty under the Net-Zero by 2050 policy (1.18, table A3). The lower sensitivity of the portfolio composition to these technological uncertainties under the Net-Zero by 2050 policy reflects that many of these options (e.g., new nuclear, direct air capture, bioenergy with carbon capture) are not deployed until the system is closer to net-zero levels (Bistline and Blanford 2021). As a result, lower costs of these options do not accelerate investments to 2035 when net-zero emissions are not targeted until 2050. Overall, these sensitivities illustrate how magnitudes and compositions of these risk metrics can be sensitive to the specification of baseline values and how the carbon policy uncertainties have the largest impacts on investment mixes.
3.3. Application to other analyses

We also apply capacity at risk metrics to the commonly used Annual Energy Outlook 2021 (EIA 2020). Results from the Annual Energy Outlook are widely applied by policymakers, industry, and other stakeholders for planning and policy. The number and variety of sensitivities (also referred to as ‘side cases’) varies by year, and the 2021 edition includes sensitivities related to the following uncertainties:

- **Renewable costs**: A lower-cost case assumes higher endogenous technical learning for capital costs of renewable technologies, which leads to cost reductions of 40% by 2050 relative to the reference. A higher-cost case assumes no cost reductions from learning.

- **Economic growth**: High and low economic growth sensitivities assume compound annual growth rates for U.S. gross domestic product of 2.6% and 1.6%, respectively, compared with 2.1% per year in the reference scenario.

- **Oil and gas supply**: High and low supply scenarios for oil and gas reflect alternate assumptions about domestic costs and resource availability relative to the reference.

- **Oil prices**: Sensitivities to higher and lower oil prices, which are assumed to be driven by global factors, assume $173 per barrel in 2050 and $48/b, respectively, compared with $95/b in the reference scenario.

Figure 6 compares robust capacity additions across scenarios for the AEO 2021 and results from the REGEN analysis in the previous section. In this section, we do not intend to compare the output decisions from two different studies directly but use the risk-based metrics to compare the portfolio risk from two different studies.

AEO robust capacity shows lower variation across uncertainties relative to the REGEN analysis, lower wind and energy storage deployment, and greater natural-gas-fired capacity, especially gas peaking units. Capacity at risk comparisons for individual uncertainties in AEO 2021 are shown in appendix A.2.

Figure 7 compares upper threshold capacities across scenarios for the AEO and REGEN analyses. REGEN sensitivities generally point to more wind and energy storage in the robust additions, except when climate policy...
uncertainty is considered. AEO indicates that more gas-fired capacity is in the robust portfolio, which REGEN analysis suggests has higher asset-specific risks under more stringent climate policy. Overall, this comparison suggests that the selected uncertainties for the AEO 2021 do not lead to as much variation in investment-related outputs relative to those in this analysis. Upper threshold capacities are generally larger for the uncertainties considered in the REGEN analysis, which indicates greater portfolio risk. This higher risk is also reflected by comparing overall risk ratios: Ratios in REGEN ranged from 1.5 to 15.2, whereas the AEO risk ratios are between 1.2 and 1.8 (summarized in table 2).

Overall, these results suggest that decision-makers may be underestimating risk if they rely on scenarios that omit uncertainties such as climate policy design and timing and instead focusing on uncertainties related to fuel prices, technology costs, and demand growth. Overlooking these important uncertainties may give decision-makers a misleading sense of portfolio risk and understate the value of frameworks that explicitly assess decisions under uncertainty.

There are several caveats with these comparisons. We focus on near-term electric sector decisions (operationalized through the metric of cumulative capacity investments through 2035), but uncertainties could materially impact other decisions. Examples include oil prices altering industrial fuel choice and renewable costs impacting post-2030 investments. Additionally, scenario selection may be politically constrained, which may present institutional limitations on the types of uncertainties considered in an analysis and which extremes are explored (McCollum et al 2020).

4. Discussion and conclusions

This work introduces a new metric—capacity at risk—and companion metrics to identify strategic decision points and uncertainties that could materially alter near-term decisions. Deterministic sensitivities combined with the capacity at risk metric can help to identify and prioritize future research. The use of deterministic model runs can lower barriers to entry for modelers and communications with stakeholders. These metrics can help analysts focus on uncertainties that matter for more detailed uncertainty quantification and stochastic analysis, where the ‘curse of dimensionality’ applies not only to solving complex stochastic models but also to constructing them in the first place and to communicating results to decision-makers. Such analysis is also valuable for considering which sensitivities to conduct to stress test thinking across a range of possible future,
including extremes that may materially alter decisions (McCollum et al. 2020). This capacity at risk framework could be applied in the context of other normative models used in policy analysis, strategic planning, and technology assessment.

The capacity at risk metric is analogous to the commonly used ‘value at risk’ metric for understanding the risk of loss for investments under uncertainty (Duffie and Pan 1997; Sadeghi and Shavvalpour 2006). A broad benefit of both frameworks is the ‘imposition of a structured methodology for critically thinking about risk’ (Jorion 1997). Capacity at risk is also rooted in the decision analysis notion that information only has value if it has the potential to change near-term decisions (Howard 1966). Our metrics also are conceptually similar to tornado diagrams used by decision analysts to vary each parameter between its minimum and maximum values and then plot variations across outputs of interest. The broad similarity may help to increase adoption of our approach, but note that an important extension of our framework is the ability to accommodate portfolio problems, which are important features in energy system decisions (e.g., the electric sector capacity planning application in section 3) and other domains.

The illustrative electric sector decarbonization example indicates that the timing of climate policy and its technology eligibility materially impact near-term decisions and costs. The capacity at risk metric can help to future-proof investments by deploying transition-ready technologies. Future work should link the analysis to models of decisions under uncertainty to evaluate hedging strategies, should explicitly quantify probabilities associated with important uncertainties, and should investigate capacity at risk for a broader range of sensitivities. Additionally, results focused on national-level insights, but given the heterogeneity in regional circumstances (e.g., due to policy, existing capacity mixes, renewable resource quality), new analysis should examine capacity at risk metrics from a regional perspective.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Appendix

A.1. Additional model and scenario information

EPRI’s U.S. Regional Economy, Greenhouse Gas, and Energy (REGEN) model finds intertemporally cost-optimal electric sector pathways given exogenous assumptions about technology costs, markets, and policies. The variant of REGEN used for this analysis includes full 8,760 hourly capacity investments and operations to represent the unique characteristics of variable renewables and energy storage, especially with deeper decarbonization. Regional aggregation and reporting regions for this analysis are shown in figure A1.

Cost and performance assumptions for other technologies come from the literature and EPRI’s Integrated Technology Generation Options report (EPRI 2018). Capital cost projections are shown in figure A2. Annual electricity demand and hourly load shapes come from REGEN’s end-use model.

Natural gas price assumptions come from the U.S. Energy Information Administration’s Annual Energy Outlook 2020 ‘Reference’ case (EIA 2020), as shown in figure A3. Low and high gas price sensitivities come from the Annual Energy Outlook 2020 ‘High Oil and Gas Supply’ and ‘Low Oil and Gas Supply’ scenarios, respectively.

The reference scenario captures on-the-books federal and state electric sector policies and incentives as of June 2021, including federal tax credits (including the production tax credit for wind, investment tax credit for solar, and 45Q for captured CO₂), state-specific renewable portfolio and clean electricity standards, and state-specific CO₂ policies (e.g., California’s economy-wide emissions targets, Regional Greenhouse Gas Initiative cap-and-trade). Electric sector policy scenarios are layered on top of these existing policies and incentives. Comparisons of historical electric sector CO₂ emissions and reductions under the policy scenarios are shown in figure A4.

Table A1 shows a table of scenarios used in this analysis. Descriptions are provided in section 2.2.2.

Time-synchronized hourly load comes from the REGEN end-use model, which characterizes the economic and behavioral incentives for end-use technology adoption and captures heterogeneity across households, industries, and regions. To reflect the deep decarbonization context of the power sector sensitivities for the
Net-Zero and Carbon-Free scenarios, the end-use model assumes federal CO$_2$ pricing of $50$/t-CO$_2$ in all sectors and regions beginning in 2025, escalating at seven percent per year.

A.2. Additional results

Figure A5 shows how assumptions about policy targets and policy timeframes alter the national generation mix. Note that cost-minimizing mixes differ by region with higher wind and solar shares in the West and Midwest (Blanford et al 2021). Electrification in the zero-emissions scenarios increases load, but higher prices from more restrictive target definitions can offset this growth by discouraging electrification and increasing energy efficiency.

Figure A6 through figure A9 shows the net capacity additions by technology across the four uncertainties considered in the REGEN analysis. Net capacity additions represent cumulative investments through 2035 less retirements of existing capacity from 2020.

Figure A10 through figure A13 shows the net capacity additions by technology across the four uncertainties considered in the AEO analysis.
A.3. Capacity at risk metrics for reference case

The capacity at risk and other metrics are evaluated for a reference case scenario, which is a ‘business-as-usual’ scenario with no additional decarbonization technologies or policy mandates. This scenario includes major confirmed federal, regional, and state environmental and climate policies. The following uncertainties are considered in this analysis:

- Natural gas prices over time, including historical prices and projections. Projections come from the U.S. Energy Information Administration’s Annual Energy Outlook.
- Electric sector CO₂ emissions. Historical emissions are shown alongside model projections in the reference scenario and zero emissions scenarios by 2035 and 2050.
- Summary of scenarios. Detailed descriptions in section 2.2.
Renewables and storage costs: Capital cost trajectories for onshore wind, offshore wind, solar photovoltaic (PV), and battery storage vary assumptions from their reference levels to low- and high-cost cases, based on an assessment of projections in the literature (Bistline et al 2022). Capital cost ranges are shown in appendix figure A2.

Natural gas prices: The analysis considers three natural gas price trajectories over time (low, reference, and high), which come from the U.S. Energy Information Administration’s Annual Energy Outlook. Gas price trajectories are shown in appendix figure A3.

Additional scenario assumptions are described in appendix A.1. We apply the metrics from section 2.1 to scenarios within each uncertainty.

For the natural gas price uncertainty, figure A14 summarizes technology mixes for scenario-specific capacity at risk, robust capacity, and upper threshold for capacity at risk. The portfolio for robust capacity additions (i.e., regardless of the natural gas prices) encompasses natural gas, solar, energy storage, wind, and storage, which totals roughly 225 GW of capacity. Relative to robust capacity additions under a net-zero by 2035 policy (figure 3), robust capacity under current policies entails much higher natural gas investments and lower additions of renewables and energy storage. The highest capacity at risk are gas and wind with natural gas price

Figure A5. National generation by technology and scenario in 2035. 'Storage Discharge' refers to gross discharge. 'Total Load' refers to energy for load (i.e., consumption plus transmission/distribution losses).

Figure A6. Net Capacity Additions by Technology in 2035. Scenario: Carbon Policy Target/Timing.
uncertainty. The difference between the upper threshold of capacities and minimum robust capacity is 190 GW, indicating relatively smaller dispersion of outcomes across the natural gas price uncertainty compared with the climate policy target and timing. The overall risk ratio—the upper threshold divided by minimum robust additions—is 1.85 (table A2), higher than the net-zero scenario cases.

For the renewable cost uncertainty, figure A15 summarizes technology mixes across the three-risk metrics. The portfolio for robust capacity additions again is dominated by gas and solar capacity, which totals 270 GW of capacity and is similar in magnitude and composition to the natural gas price uncertainty. The highest capacity at risk is wind under the low renewables cost state-of-the-world, as investments are lower under other realizations. The difference between the upper threshold of capacities and minimum robust capacity (125 GW) and the overall risk ratio (1.46) are slightly lower than the gas price uncertainty (table A2).

A.4. Capacity at risk metrics for net-zero by 2050 case
The capacity at risk, and other metrics are evaluated for Net-Zero by 2050 climate policy scenario. In this case, the emissions produced are balanced by an equivalent number of removals in 2050 with an interim target of 80% CO2 reductions below 2005 in 2035 (figure A4). Additional scenario assumptions are described in appendix A.1, and we apply the metrics from section 2.1 to scenarios within each uncertainty.
For the natural gas price uncertainty, figure A16 summarizes technology mixes for scenario-specific capacity at risk, robust capacity, and upper threshold for capacity at risk. The portfolio for robust capacity additions (i.e., regardless of the natural gas prices) encompasses natural gas, wind, solar, and energy storage, which is higher than the reference case and similar in magnitude to the Net-Zero by 2035 case (figure 1). Although the magnitude of robust capacity is similar between the Net-Zero by 2035 and 2050 scenarios, their composition is notably different, with increased natural-gas-fired capacity with the 2050 target and decreased renewables and storage. The difference between the upper threshold of capacities and minimum robust capacity is 125 GW, and the overall risk ratio is 1.18 (table A3), lower than all the other scenarios, which reflects that the portfolio composition is less sensitive to natural gas price variations under this policy timing and stringency.

Figure A17 summarizes technology mixes for the additional technology cost uncertainties. Wind and solar dominate the portfolio for robust capacity additions, similar to Net-Zero by 2035 case, totaling 700 GW of capacity. Capacity at risk varies between 40–80 GW. The difference between the upper threshold of capacities and minimum robust capacity is 126 GW, and the risk ratio is 1.18 (table A3). The lower sensitivity of the portfolio composition to these technological uncertainties under the Net-Zero by 2050 policy reflects that many
of these options (e.g., new nuclear, direct air capture, bioenergy with carbon capture) are not deployed until the system is closer to net-zero levels (Bistline and Blanford 2021). As a result, lower costs of these options do not accelerate investments to 2035 when net-zero emissions are not targeted until 2050.

**Table A2.** Summary of risk ratios and capacity at risk values across different uncertainties for a reference scenario with current policies.

| Uncertainty       | Risk ratio | Capacity at risk (GW) |
|-------------------|------------|-----------------------|
| Renewable costs   | 1.46       | 30–93                 |
| Natural gas prices| 1.85       | 70–120                |

**Figure A11.** Capacity at risk values across different realizations of the economic growth uncertainty in the Annual Energy Outlook 2021. New capacity investments between 2020 and 2035 are shown.

**Figure A12.** Capacity at risk values across different realizations of the oil/gas supply uncertainty in the Annual Energy Outlook 2021. New capacity investments between 2020 and 2035 are shown.
Figure A13. Capacity at risk values across different realizations of the renewable cost uncertainty in the Annual Energy Outlook 2021. New capacity investments between 2020 and 2035 are shown.

Figure A14. Capacity at risk values across different realizations of the natural gas price uncertainty. Capacity investments between 2020 and 2035 are shown. Scenarios assume Reference case by 2035 climate policy.
Figure A15. Capacity at risk values across different realizations of the renewable cost uncertainty. Capacity investments between 2020 and 2035 are shown. Scenarios assume Net-Zero by 2035 climate policy.

Figure A16. Capacity at risk values across different realizations of the natural gas price uncertainty. Capacity investments between 2020 and 2035 are shown. Scenarios assume Net-Zero by 2050 climate policy.

Table A3. Summary of risk ratios and capacity at risk values across different uncertainties for Net-Zero by 2050 scenario.

| Uncertainty           | Risk ratio | Capacity at risk (GW) |
|-----------------------|------------|-----------------------|
| Technology costs      | 1.18       | 40–80                 |
| Natural gas prices    | 1.18       | 4–120                 |
**Figure A17.** Capacity at risk values across different realizations of the technology cost uncertainty. Capacity investments between 2020 and 2035 are shown. Scenarios assume Net-Zero by 2050 climate policy.

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