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The cost of policy uncertainty in electric sector capacity planning: Implications for instrument choice

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ABSTRACT

A stochastic energy system optimization model is developed to investigate capacity planning under policy uncertainty in the ERCOT area. The optimal hedging strategy under carbon tax uncertainty is to delay decarbonization, but an uncertain carbon cap or renewable portfolio standard precludes this approach. The cost of policy uncertainty is found to be higher under a carbon cap than a tax, and highest under an RPS. Uncertainty considerations appear to favor price-based over quantity-based instruments.

1. Introduction

This study makes two principal contributions. First, it identifies hedging strategies for capacity planning under climate policy uncertainty, with emphasis on robust investments and the timing of decarbonization. Second, it compares the costs of policy uncertainty under three alternative instruments: a carbon tax, a carbon cap, and a renewable portfolio standard (RPS).

The optimal portfolio of generation investments may depend critically on the future policy context. This poses a formidable challenge because it is difficult, if not impossible, to predict how policies will evolve over the life of an asset. One sophisticated methodology that electric sector planners can employ to select investments under uncertainty is stochastic programming. This approach considers multiple states of the world simultaneously to determine an optimal hedging strategy featuring robust investments. In this study, the OSeMOSYS energy system optimization framework is reformulated as a stochastic program. The model is applied to capacity planning in the Electric Reliability Council of Texas (ERCOT) area, and optimal near-term hedging strategies are identified.

There is an extensive literature on instrument choice in which scholars debate the relative merits of alternative climate policy instruments such as a carbon tax, a carbon cap, and an RPS. Despite widespread recognition that uncertainty affects the relative performance of different instruments, previous instrument choice analyses using technologically detailed models have omitted uncertainty. The present study addresses this gap in the literature by considering alternative policy instruments within the stochastic programming version of OSeMOSYS. It compares the costs of policy uncertainty under a carbon tax, a carbon cap, and an RPS.

The remainder of this article is organized as follows. Section (2) reviews relevant literature on instrument choice, stochastic programming, and its application to capacity planning. Section (3) describes the standard OSeMOSYS model and its stochastic reformulation for this study. Section (4) details the OSeMOSYS database developed to represent capacity planning in the ERCOT area. Section 5 delineates the policy scenarios assessed using the model. The results presented in Section 6 elucidate optimal near-term hedging strategies and compare the costs of policy uncertainty under the three instruments. Section 7 concludes by summarizing the most significant findings.

2. Literature review

2.1. Instrument choice

The instrument choice literature can be traced back to Weitzman (1974). His seminal analysis shows that taxes and caps which are equivalent in a deterministic setting may perform quite differently in the presence of uncertainty. Whether a tax or a cap is the preferred instrument depends on the relative slopes of the marginal benefit and marginal cost curves. Based on broad assumptions about the marginal benefit and marginal cost curves that characterize climate change, Weitzman suggests that a carbon cap is likely the more appropriate intervention. Goulder and Schein (2013) conclude that taxes have a

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number of important attractions over caps. Specifically, choosing a tax helps avoid price volatility, problematic interactions with other climate policies, and potential wealth transfers to oil-exporting countries. In addition, a tax helps reduce expected policy errors induced by uncertainty.

An RPS establishes a minimum amount of electricity that must be generated using renewable resources. The RPS is a popular form of regulation in the U.S. power sector, as they have been adopted by more than half of the states (Heeter et al., 2014). An RPS might define its renewables target in terms of absolute capacity or energy units (e.g., MW or MWh), or a share of total retail electricity sales. Individual RPSs feature different rules about which resources count as renewables. Solar, wind, and geothermal are almost universally regarded as renewables, but the eligibility of hydro and biomass varies across particular policies (Wiser et al., 2007).

Theory suggests that an RPS is a more costly means of achieving a desired level of emissions reduction than a tax or a cap. By dictating that emissions must be reduced by deploying renewables in the power sector, an RPS does not incentivize potentially cheaper reductions that could be achieved through energy efficiency, switching from dirtier to cleaner fossil fuels, investing in carbon capture and storage (CCS), or reducing emissions in other end-use sectors. A number of studies have assessed whether an RPS can be a cost-effective policy for reducing emissions. Palmer and Burtraw (2005) compute the additional cost of reducing U.S. electric sector emissions through an RPS instead of a carbon cap. They find that the RPS is roughly 50% more costly than the cap. An adverse consequence of the RPS is that it makes the non-renewable portion of the electricity mix dirtier. Renewables displace natural gas more than coal, and a stringent RPS even displaces nuclear electricity, which produces no carbon emissions. Fischer and Newell (2008) impose various policy instruments in a model of the U.S. electric sector and find that reducing emissions by 4.8% using an RPS is more than twice as costly as achieving the same reduction using a carbon price. Empirical evaluations of RPSs suggest that these policies have had mixed results. Langniss and Wiser (2003) argue that the surge in wind power development in Texas around 2001 was primarily driven by the adoption of an RPS. According to Wiser et al. (2007), the impacts of RPSs on retail electricity rates vary by state, but are generally modest. On the other hand, RPSs in some states do not appear to be effectively spurring growth in renewables. Carley (2009) finds that whether or not a state has an RPS is not a significant predictor of renewable generation.

2.2. Stochastic programming

Stochastic programming is a rigorous methodology for analyzing sequential decision-making under uncertainty. Stochastic programming considers all possible states of the world (and their probabilities of occurring) simultaneously in order to determine the optimal strategy that balances outcomes associated with the different states.[1] The objective function is typically an expected value over states of the world, possibly adjusted to capture attitudes toward risk. Stochastic programming is ideal for evaluating strategies defined over multiple stages where the information available to the decision maker gets updated in each sequential stage. It computes near-term hedging strategies that reflect the tradeoff between immediate action and delay, and preserve flexibility to adapt subsequent decisions to new information as it becomes available. These subsequent decisions are known as *recourse decisions*.

To clarify the benefits of stochastic programming, it is helpful to introduce some formal notation. The following formulation represents a general two-stage stochastic program with a cost minimization objective (Bistline, 2013):

$$\begin{aligned} &min_{x,\{y_\omega\}_{\omega\in\Omega}} z = c^T x + \mathrm{E}_\omega d_\omega^T y_\omega \\ &s.\ t.\ \ Ax = b \\ &B_\omega x + C_\omega y_\omega = f_\omega \ \ \forall\ \omega \in \Omega \\ &x, y_\omega \geq 0\ \ \forall\ \omega \in \Omega \end{aligned} \tag{1}$$

In this formulation, the first-stage objective function coefficients (c vector) and first-stage constraints (A matrix and b vector) are known with certainty. The second-stage objective function coefficients (d_ω) and second-stage constraints (B_ω matrix, C_ω matrix, and f_ω vector) are uncertain when first-stage decisions (x) are made, but are known when recourse decisions (y_ω) are determined. The ω subscripts indicate that these parameters and decisions are specific to the state of the world ($\omega \in \Omega$). First-stage decisions do not depend on ω because they are determined before the state of the world becomes known. The objective is to minimize the expected cost over all states of the world, where the probability of a given state is $p(\omega)$.

This two-stage stochastic program can be evaluated via several solution approaches. The *perfect information solution* assumes that the state of the world is known with certainty at the outset, allowing x to depend on ω. The model is solved as a deterministic problem for each state of the world. In this case the problem can be expressed as follows, where z^{PI} is the expected minimized cost under perfect information:

$$\begin{aligned} &min_{x_\omega, y_\omega} z_\omega = c^T x_\omega + d_\omega^T y_\omega\ \ \forall\ \omega \in \Omega \\ &z^{PI} = \mathrm{E}_\omega z_\omega = \textstyle\sum_{\omega\in\Omega} \mathrm{p}(\omega) z_\omega \end{aligned} \tag{2}$$

The *stochastic solution* assumes that the state of the world is unknown when first-stage decisions are made. It corresponds to the general formulation in Eq. (1) where x is identical in all states of the world and must be feasible for all of them. Denote the minimized expected cost achieved using the stochastic solution by z^{ST}.

In the *expected value solution*, first-stage decisions are made assuming that all stochastic parameters take on their expected values. First, the deterministic problem is solved assuming these expected values occur, yielding optimal first-stage and second-stage decisions $x_{\bar{\omega}}$ and $y_{\bar{\omega}}$. Next, state-dependent recourse decisions y_ω are determined by solving the deterministic problem for each state of the world while holding x fixed at $x_{\bar{\omega}}$. The expected value solution can be formulated as follows, where z^{EV} is the expected minimized cost using the expected value solution approach:

$$\begin{aligned} &min_{y_\omega} z_\omega = c^T x_{\bar{\omega}} + d_\omega^T y_\omega\ \ \forall\ \omega \in \Omega \\ &z^{EV} = \mathrm{E}_\omega z_\omega = \textstyle\sum_{\omega\in\Omega} p(\omega) z_\omega \\ &\mathrm{s.\ t.}\ \ x_{\bar{\omega}}\ \in\ \mathrm{argmin}\ c^T \mathrm{x} + d_{\bar{\omega}}^T y_{\bar{\omega}} \\ &\bar{\omega} = \mathrm{E}_\omega \omega = \textstyle\sum_{\omega\in\Omega} \mathrm{p}(\omega)\omega \end{aligned} \tag{3}$$

The expected costs under the three solution approaches follow the rule $z^{PI} \leq z^{ST} \leq z^{EV}$ (Mandansky, 1960). One useful metric is the *expected value of perfect information*, defined as $EVPI = z^{ST} - z^{PI}$. The EVPI is the upper bound on willingness to pay to know the true state of the world at the outset.[2] In reality, perfect information is typically impossible to obtain, and the best a decision-maker can do is to solve the problem stochastically. Therefore, the EVPI can also be interpreted as the cost of uncertainty, which is how it will be applied in this study.

2.3. Application of stochastic programming to capacity planning

A number of previous studies analyze capacity planning using a stochastic variant of the popular MARKAL family of energy system

[1] In contrast, sensitivity analysis, scenario analysis, and Monte Carlo methods all deterministically map parameter settings to optimal decisions. While these methods are simpler to implement than stochastic programming, they offer limited guidance for decision-makers, who must make choices before uncertainty is resolved.

[2] In decision analysis parlance, the EVPI is known as the value of clairvoyance (Howard, 1968).