

2017 Energy Policy  
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# The Cost of Policy Uncertainty in Electric Sector Capacity Planning

## *Implications for Instrument Choice*

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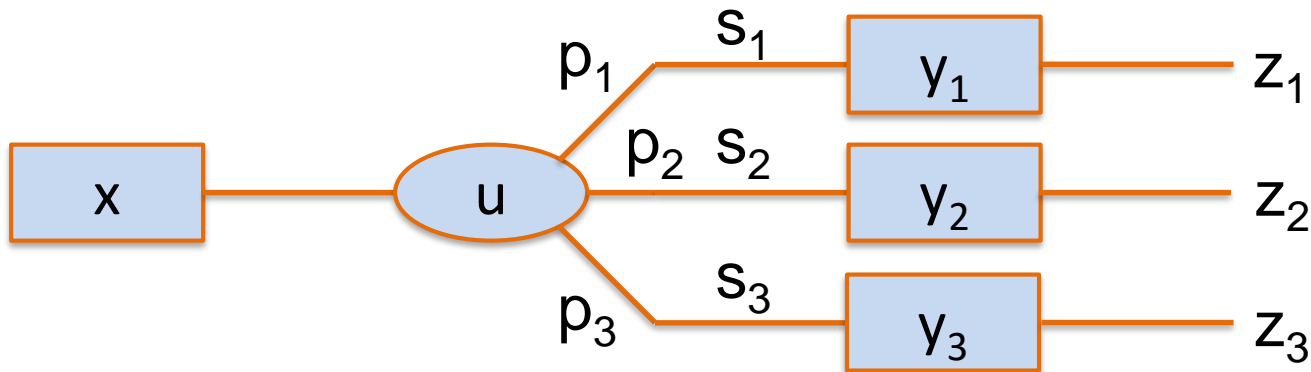
# Dealing with Uncertainty

- Generation assets have long service lives, over which a number of relevant factors are highly uncertain.
  - Energy commodity prices, policies, electricity demand, etc.



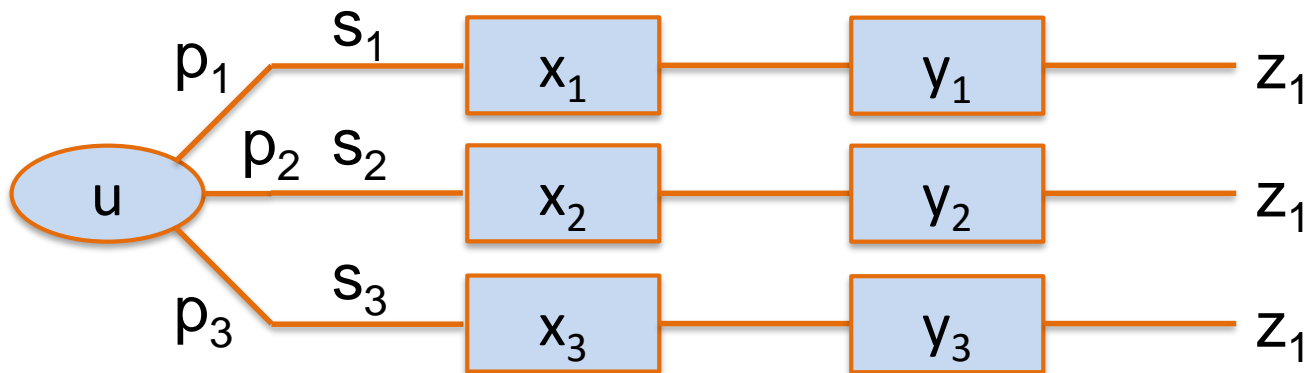
- There are several methodologies for making power sector investment decisions under uncertainty.
  - For example: sensitivity analysis, scenario analysis, Monte Carlo simulation, decision analysis, stochastic programming.

# Stochastic Programming



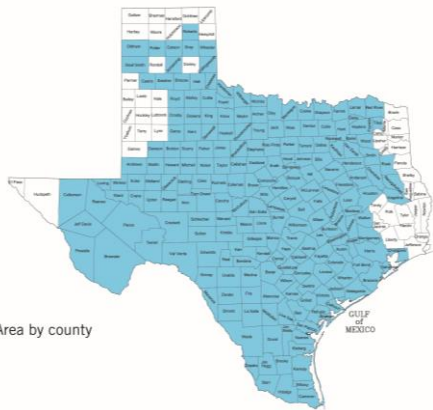
- Determine the optimal **near-term hedging strategy**  $x$  and state-dependent **recourse decisions**  $y$  that maximize (or minimize) the expectation of objective value  $z$  over all states of the world  $s$ .
- Hedging incorporates **generality** and **flexibility**.

# Perfect Information



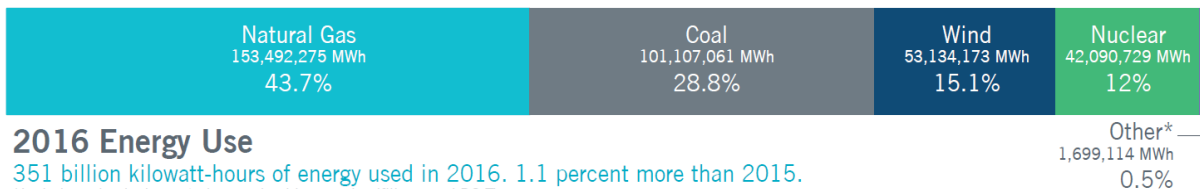
- If we know from the start which state of the world will occur, we can perfectly tailor all decisions to that state.
- Suppose the objective is cost minimization.
- **Expected value of perfect information (EVPI)** tells us how much less costly our perfect information solution is, on average, than our stochastic solution.

# Capacity Planning in ERCOT



ERCOT Area by county

**71,110 MW**  
Record peak demand  
(Aug. 11, 2016)



## 2016 Energy Use

351 billion kilowatt-hours of energy used in 2016. 1.1 percent more than 2015.

\*Includes solar, hydro, petroleum coke, biomass, landfill gas and DC Ties



## 2016 Generation Capacity

\*Includes solar, hydro and biomass



**>17,000 MW** of installed wind capacity, the most of any state in the nation.

Wind Generation record:  
16,022 MW (Dec. 25, 2016)

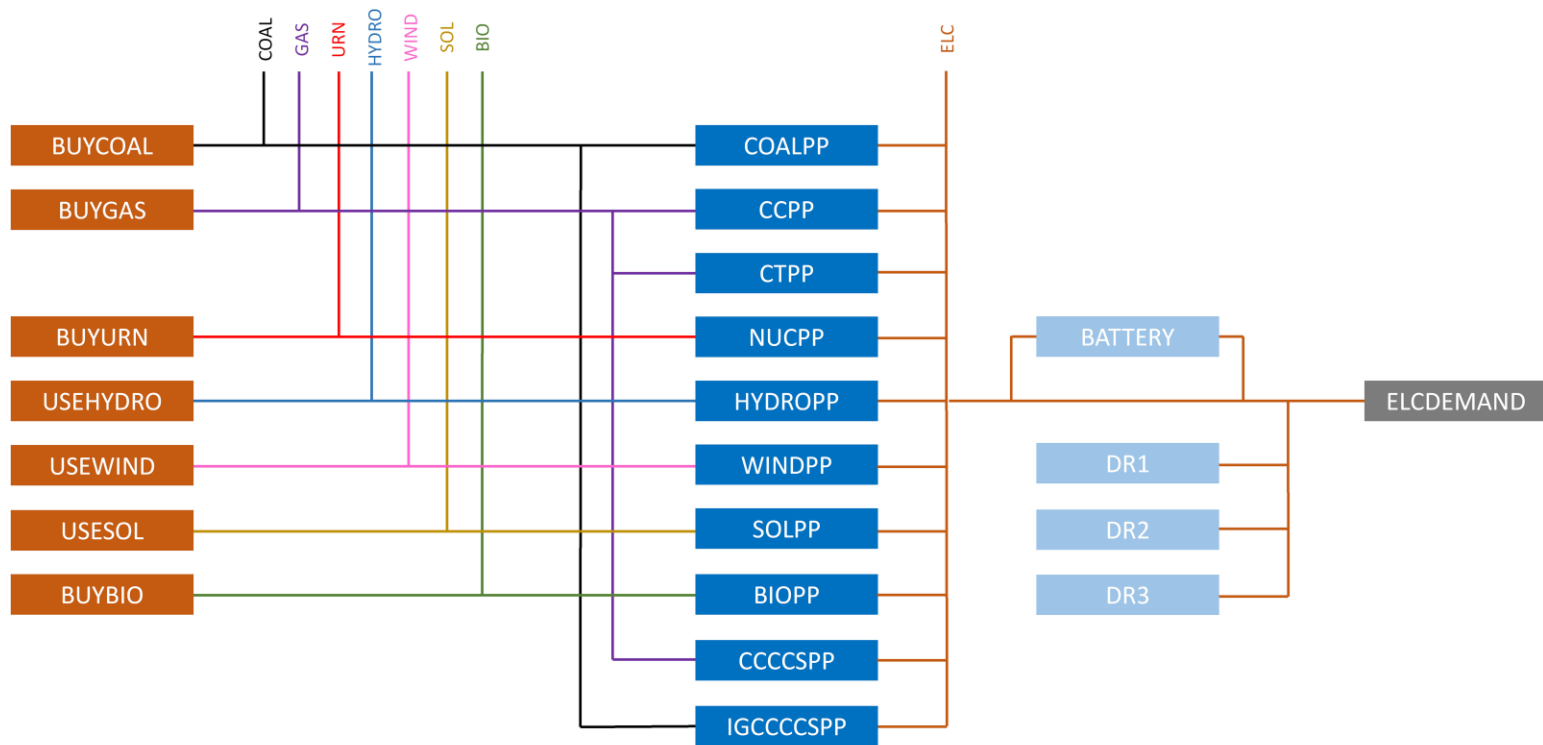
Wind Penetration record:  
48.28 percent (March 23, 2016)



**556 MW** of utility-scale installed solar capacity as of January 2017

Solar capacity in queue:  
2017: 1,211 MW  
2018: 1,511 MW

# OSeMOSYS Model for ERCOT



- Minimize total generation system costs over 2016–2040.
- Dispatch computed for ten representative timeslices parameterized using hourly load, wind, and solar data.

# Climate Policy Uncertainty

- Reformulate OSeMOSYS as a **two-stage stochastic program** to determine the optimal near-term hedging strategy under **climate policy uncertainty**.
- Consider three alternative **instruments**.
  - Carbon tax, carbon cap, renewable portfolio standard.
- Five possible **policy levels** for each instrument.
  - No policy, Weak, Moderate, Strong, Very strong.
- **Calibrate** the instruments so that, in a deterministic setting, they all lead to the same minimized cost objective value at each policy level.

# Most Relevant Literature

- **Energy modeling based on stochastic programming:**
  - Using MARKAL: Kanudia and Loulou (1998), Kanudia and Shukla (1998), Heinrich et al. (2007), Hu and Hobbs (2010), Usher and Strachan (2012), Bistline and Weyant (2013)
  - Using other models: Krukanont and Tezuka (2007), Keppo and van der Zwaan (2012), Bistline (2015)
- **Instrument choice:**
  - Weitzman (1974), Palmer and Burtraw (2005), Fischer and Newell (2008), Goulder and Schein (2013)



# Calibrated Policy Instruments

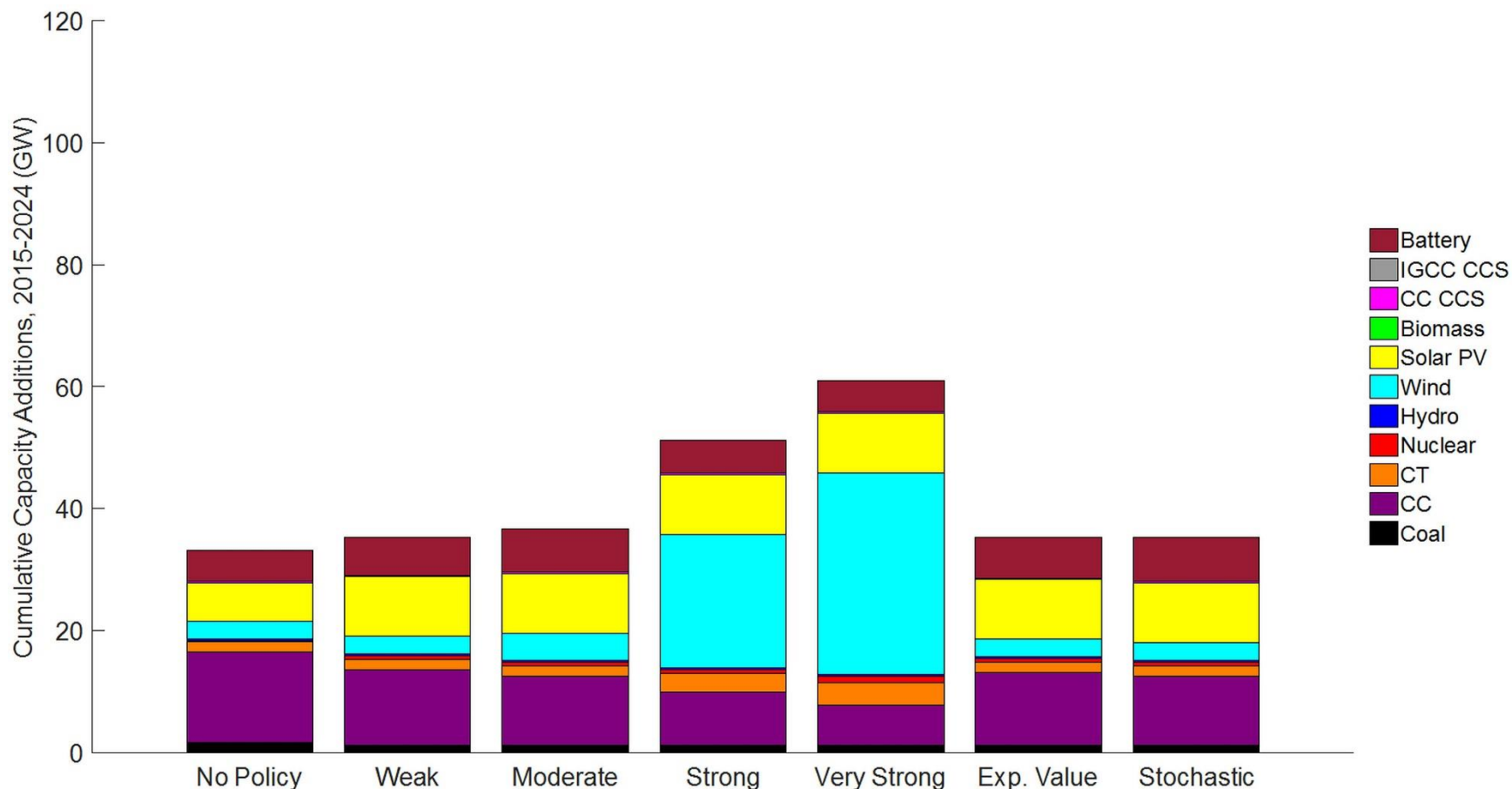
Policy Level	Probability	Tax (\$/tCO <sub>2</sub> )	Cap (MMtCO <sub>2</sub> )	RPS (%)	Cost (\$Billion)
No Policy	0.2	0	159.3	12.5	216.6
Weak	0.4	20	72.1	56.3	235.7
Moderate	0.2	40	33.9	77.2	251.4
Strong	0.1	60	16.9	86.2	260.5
Very Strong	0.1	80	12.9	89.8	265.0

- This carbon tax distribution is based on a survey of 14 utilities in the Western U.S. (Bistline, 2015).
- The other instruments are calibrated to result in the same minimized cost objective values.

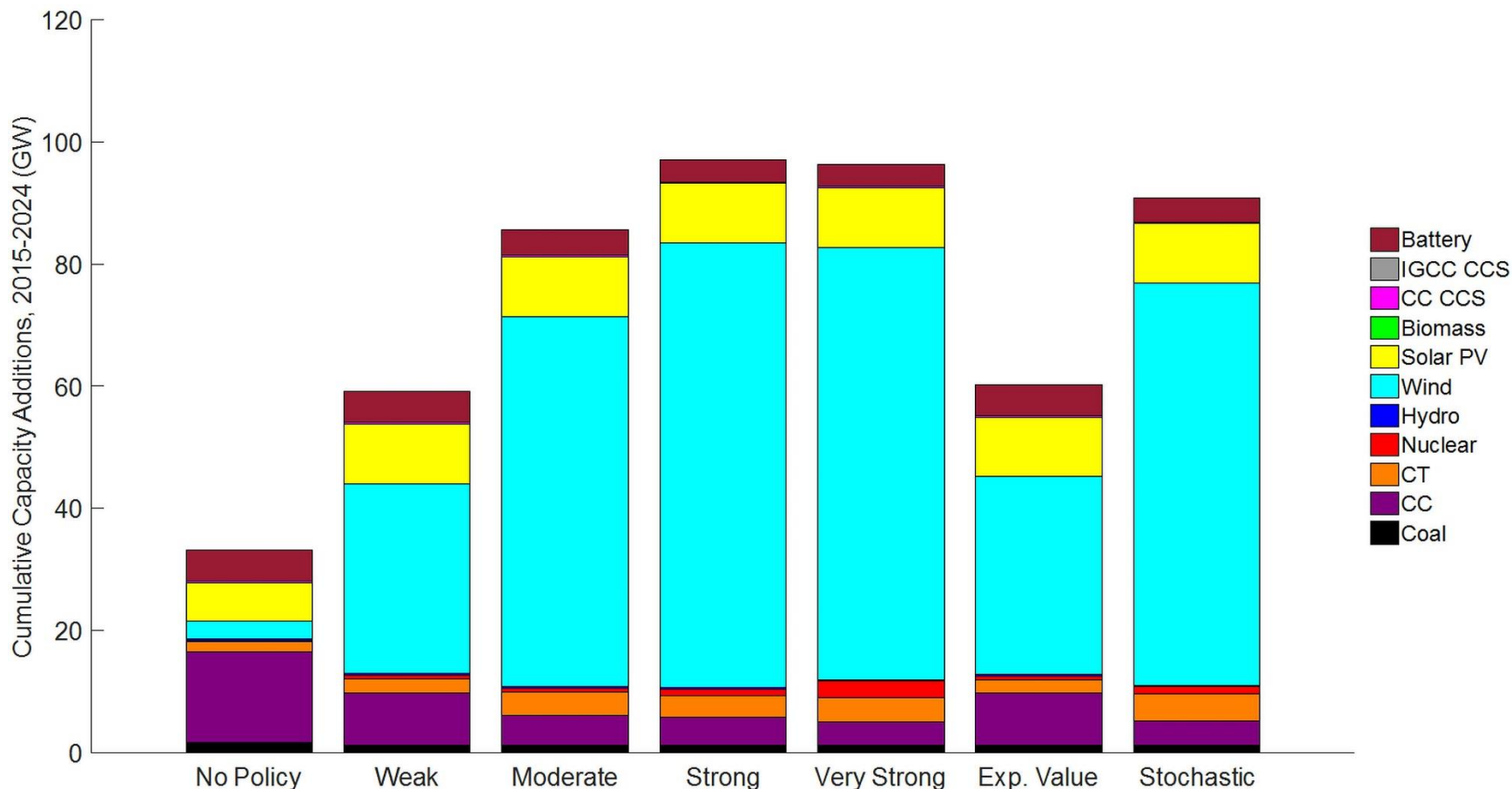
# Summary of Findings

- Facing an uncertain carbon tax, the optimal hedging strategy is a **wait-and-see** approach.
  - Delay action as much as possible, then accelerate decarbonization if the tax turns out to be high.
- Facing an uncertain carbon cap or RPS, the optimal hedging strategy is a **prepare-for-the-strictest** approach.
  - Decarbonize aggressively in the near term, and accept the unnecessary cost this entails if the policy turns out to be weak.
- The **cost of policy uncertainty** is higher under a cap than a tax, and highest under an RPS.

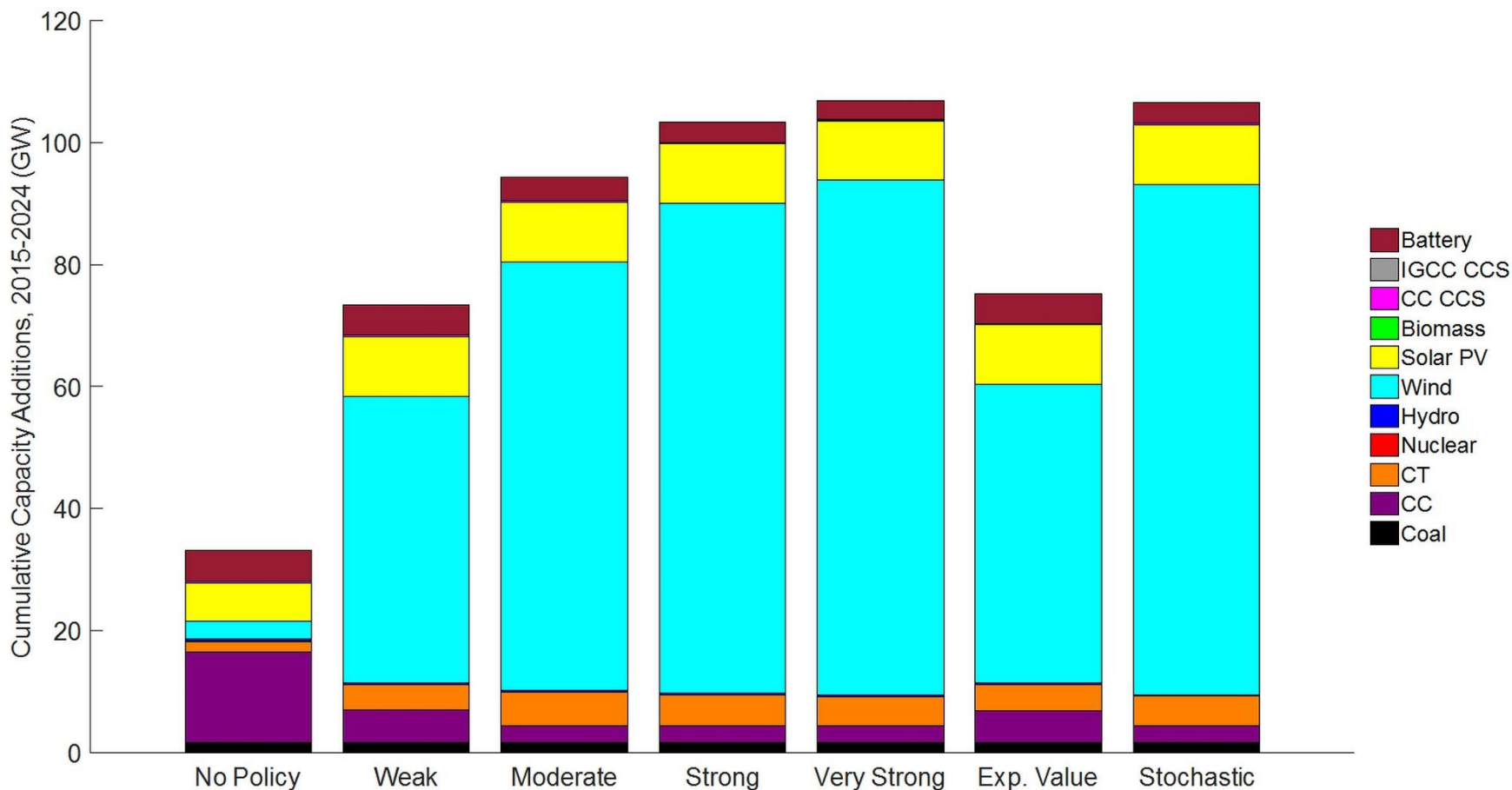
# Hedging Under a Carbon Tax



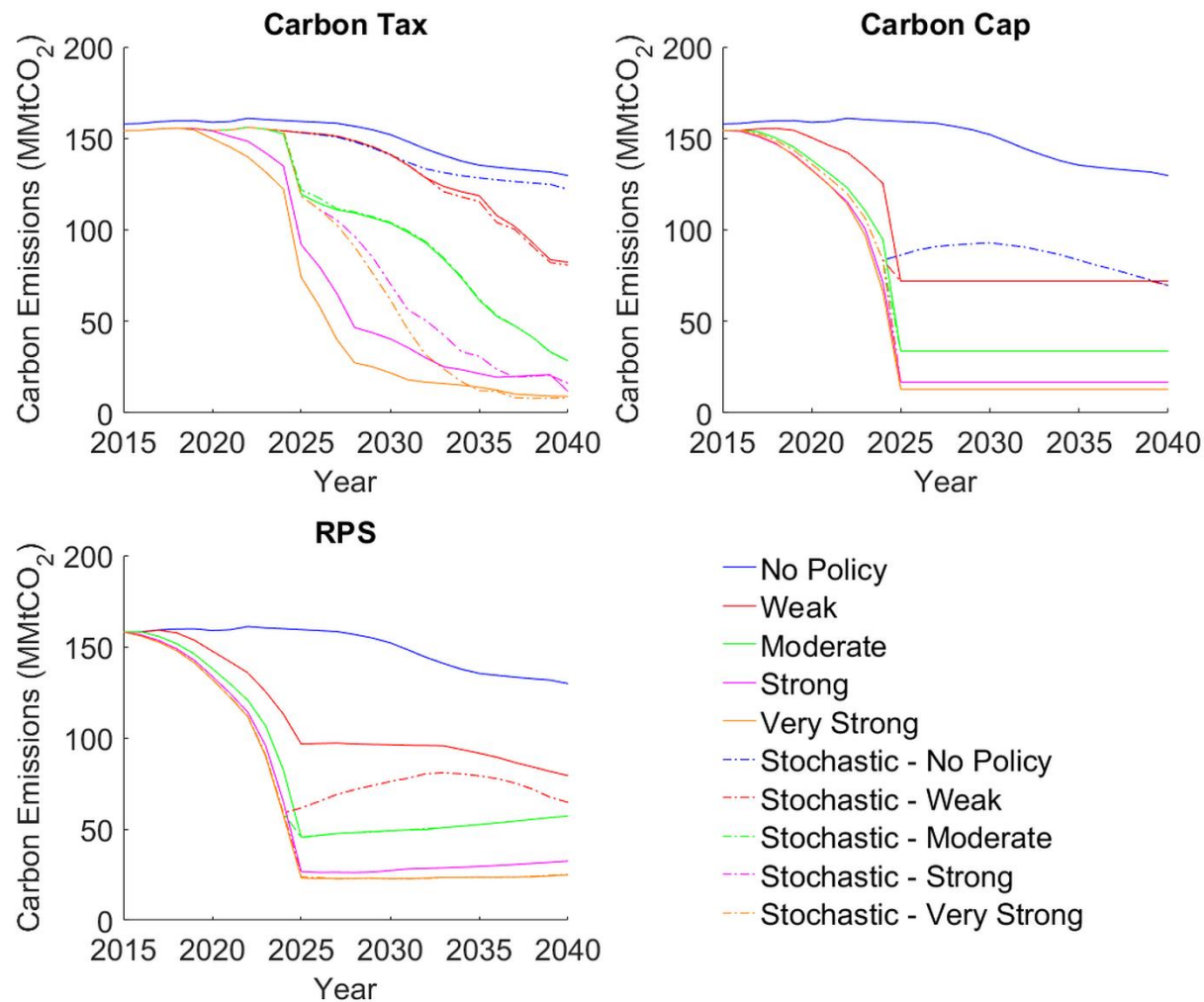
# Hedging Under a Carbon Cap



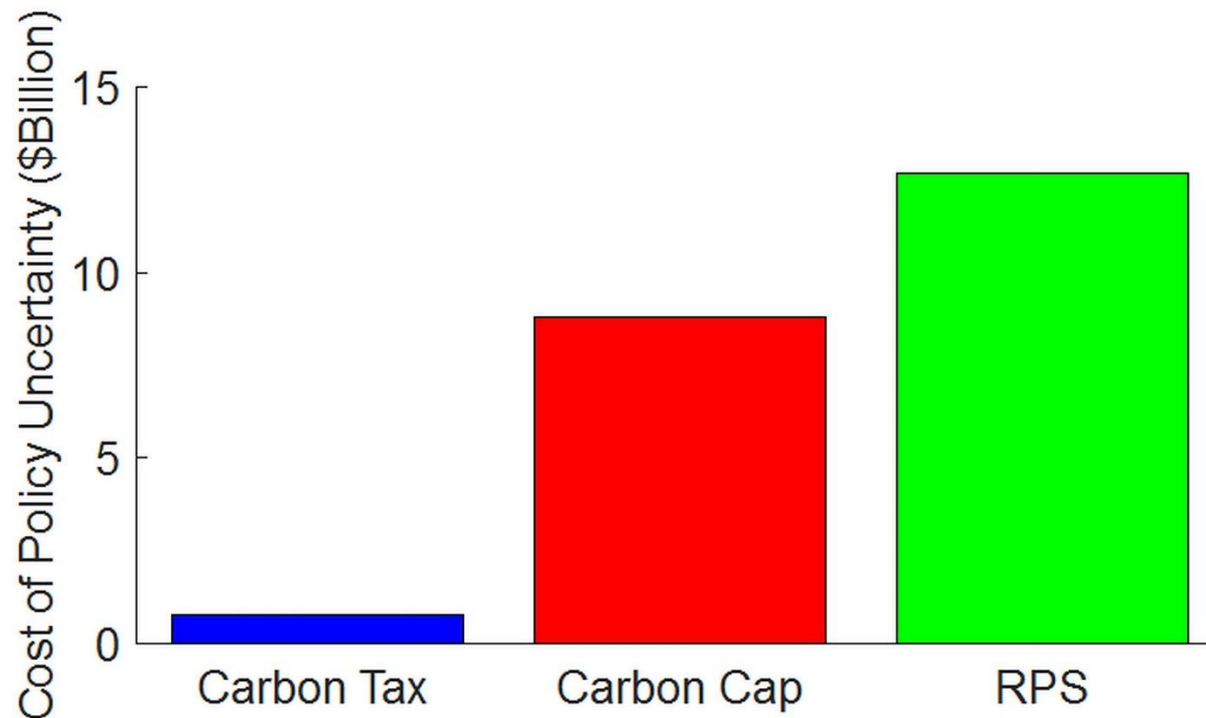
# Hedging Under an RPS



# Carbon Emissions



# Cost of Policy Uncertainty

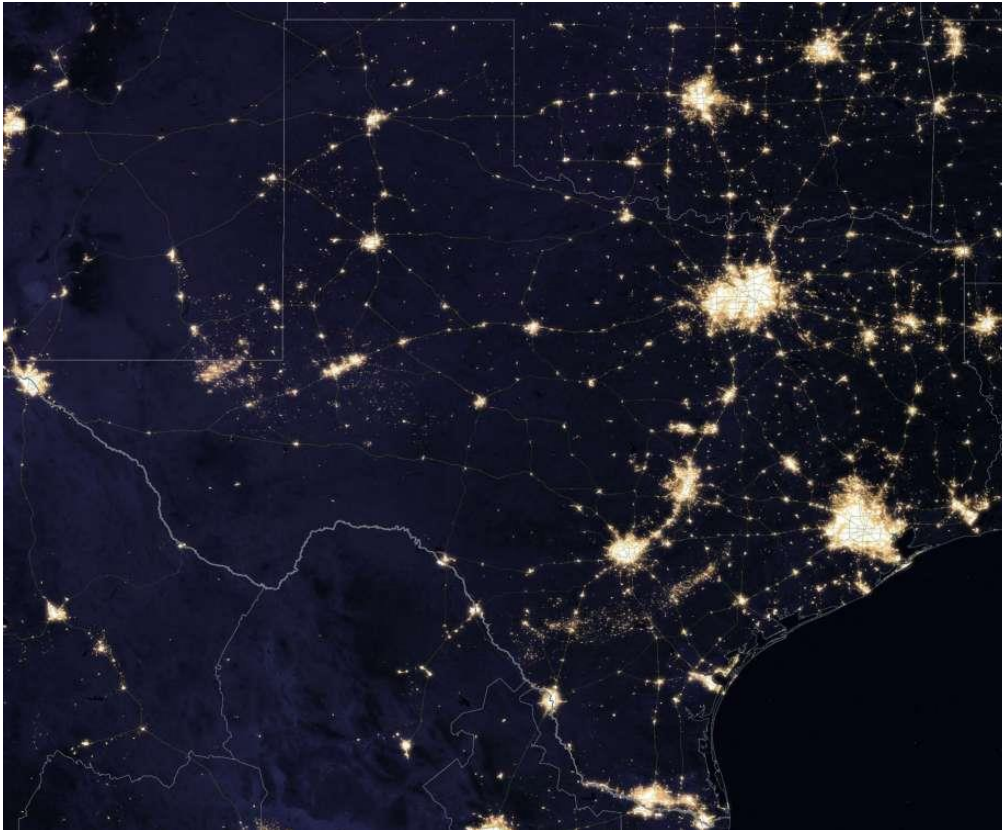


# Takeaways

- Policy uncertainty is costly in the electric sector, so commitments to long-term policies are valuable.
- Some degree of policy uncertainty is inevitable, and from the perspective of electricity decision making, this favors price-based over quantity-based instruments.
- Price-based instruments offer greater flexibility because they affect parameters of the objective function, rather than constraints that restrict the feasible region.



# The End



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 **energy institute**  
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