NC STATE UNIVERSITY

How to Value Future Uncertainty in Energy System Planning?

International Energy Workshop
Paris, France
20 June 2013

Joe DeCarolis, Kevin Hunter
Dept of Civil, Construction, and Environmental Engineering
NC State University

http://temoaproject.org

Tools for Energy Model Optimization and Analysis (Temoa)

Goals

Repeatable Analysis

- Data and code stored in a publicly accessible web repository (github.com)
- Open source software stack

Rigorous treatment of uncertainty

- Framework designed to operate in a high performance computing environment
- Capability to do stochastic optimization; modeling-to-generate alternatives

Flexibility

- Programming environment with links to linear, mixed integer, and non-linear solvers
- Draws on rich existing open source ecosystem

For more information: http://www.temoaproject.org

What is TEMOA?

TEMOA is a **bottom up, technology explicit model with perfect foresight**, similar to the TIMES model generator.

Features

- Minimizes the present cost of energy supply
- Flexible time slicing by season and time-of-day
- Variable length model time periods
- Technology vintaging
- Separate technology loan periods and lifetimes
- Optional technology-specific discount rates

Stochastic Optimization

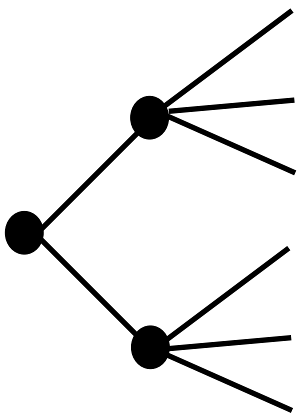
Decision-makers need to make choices before uncertainty is resolved.

Need to make short-term choices that hedge against future risk

→ Sequential decision-making process that allows recourse

Stochastic optimization

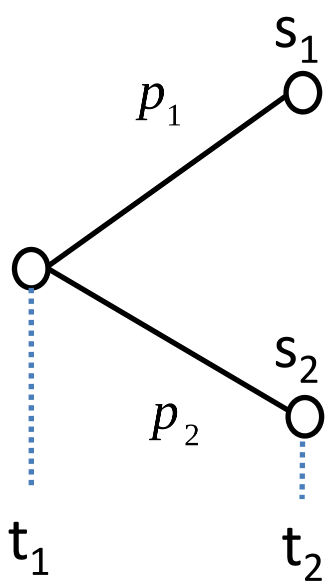
- Build a scenario tree
- Assign probabilities to future outcomes
- Optimize over all possibilities



The resultant solution represents a near-term hedging strategy because it accounts for alternative future outcomes.

Simple Example of Stochastic Optimization

Suppose we have two technologies, *A* and *B*. Let *x* represent the installed capacity.



Stage 1 Decision Variables:

$$x_A, x_B$$

Stage 2 Decision Variables:

$$y_{A,s_1}, y_{B,s_1}, y_{A,s_2}, y_{B,s_2}$$

$$\text{Minimize: } c^T x + \sum_{s=1}^{N} p_s \cdot d_s^T \cdot y_s$$

Subject To:

$$Ax = b$$

$$T_s x + W_s y_s = h_s \quad for \quad s = 1, \ldots, N$$

$$x \geq 0$$

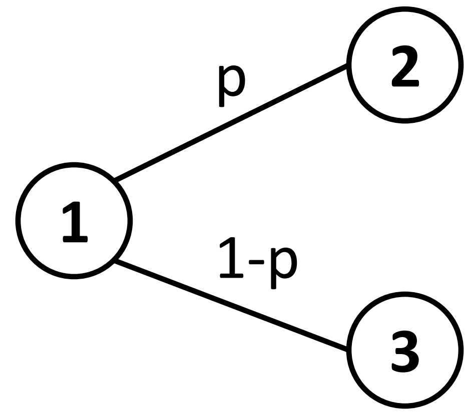
$$y_s \geq 0 \qquad for \quad s = 1, \ldots, N$$

How can we evaluate the effectiveness of the hedging strategy?

Expected Value of Perfect Information (EVPI)

The expected savings if planners knew with certainty the outcome at every stage as opposed to following the hedging strategy:

$$EVPI = C_{hedge} - \sum_{s \in S} p_s \cdot C_s$$

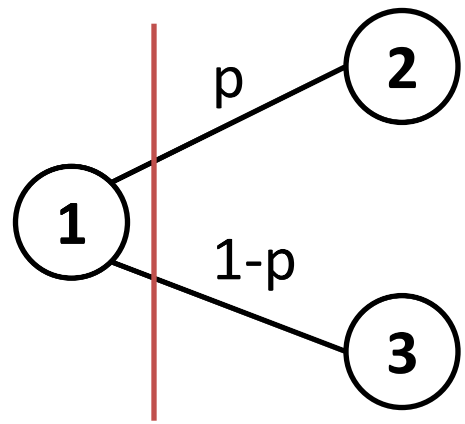


- Quantifies the cost of uncertainty
- Provides a measure of how much planners should be willing to pay to eliminate that uncertainty

But assuming the uncertainty is irreducible, how can we measure the value of our stochastic solution?

Expected Cost of Ignoring Uncertainty (ECIU)

The expected savings by following the hedging strategy rather than naively guessing the outcome:



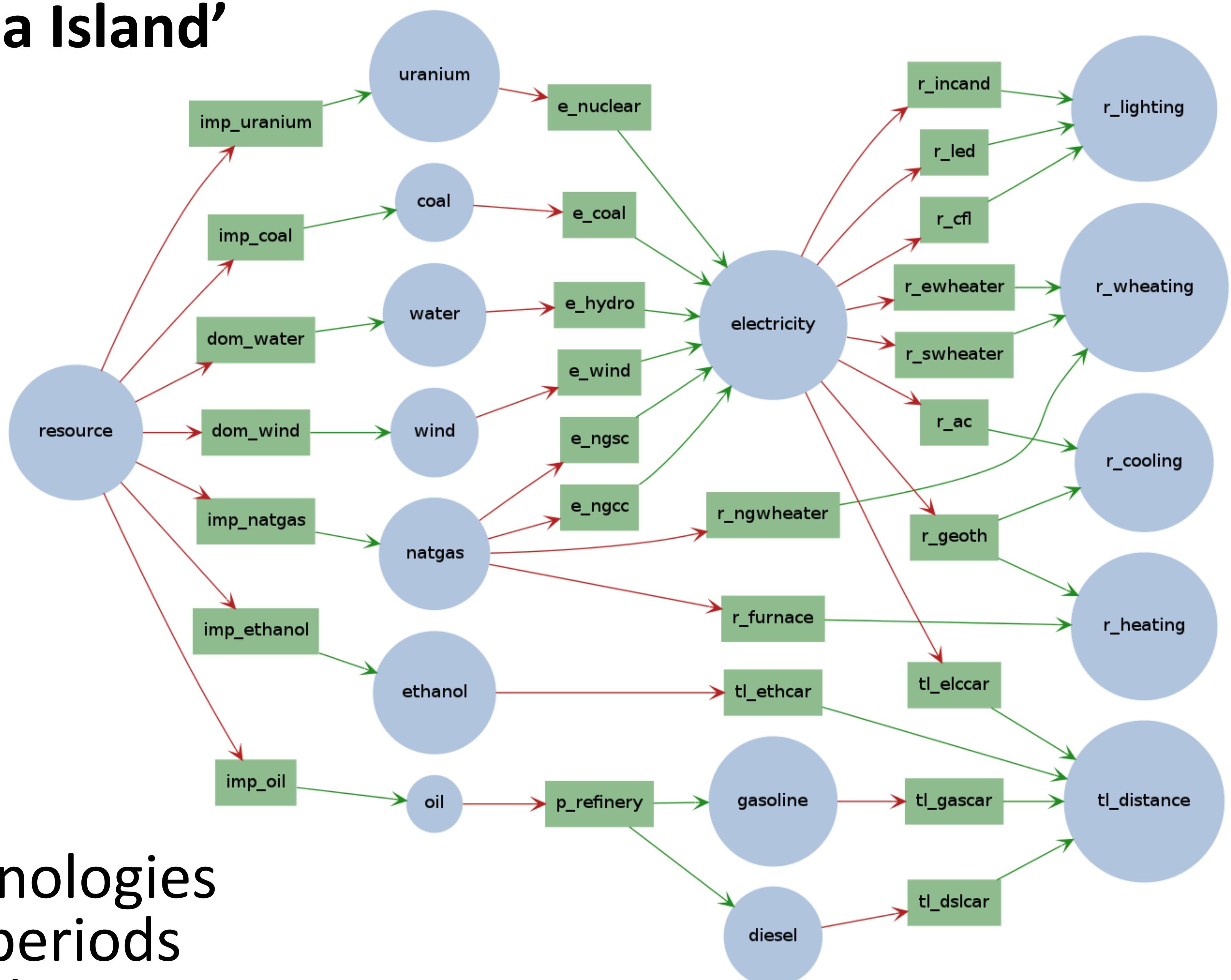
In the 2-stage case:

$$ECIU_2 = \left[C_{1|2} + p \cdot C_{2|2} + (1-p) \cdot C_{3|2}\right] - C_{hedge}$$

- Estimates the value of the stochastic solution
- If the ECIU is close to zero; then we can safely replace the stochastic model with a deterministic one

Case Study

‘Temoa Island’

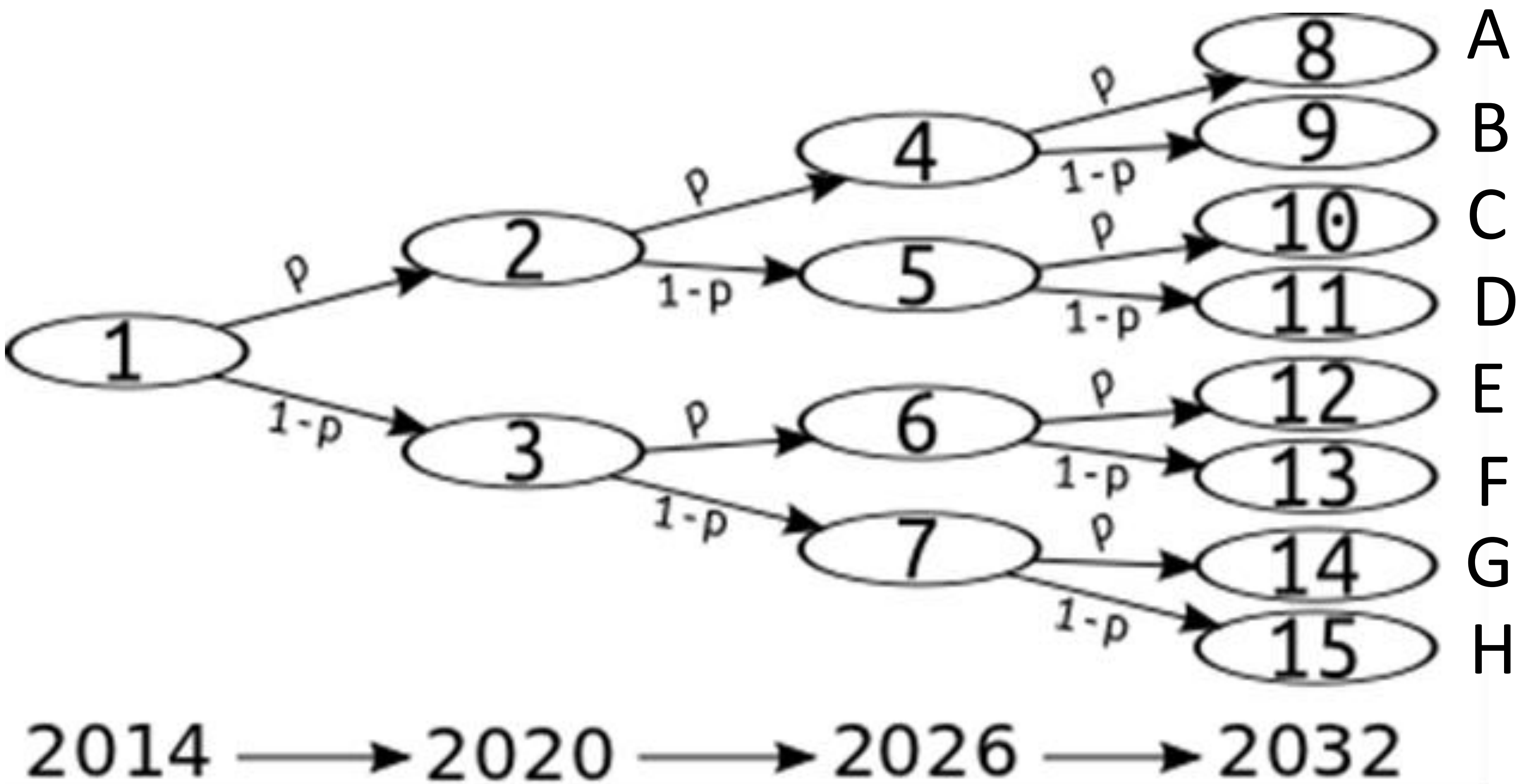


27 technologies
4 time periods
6 time slices

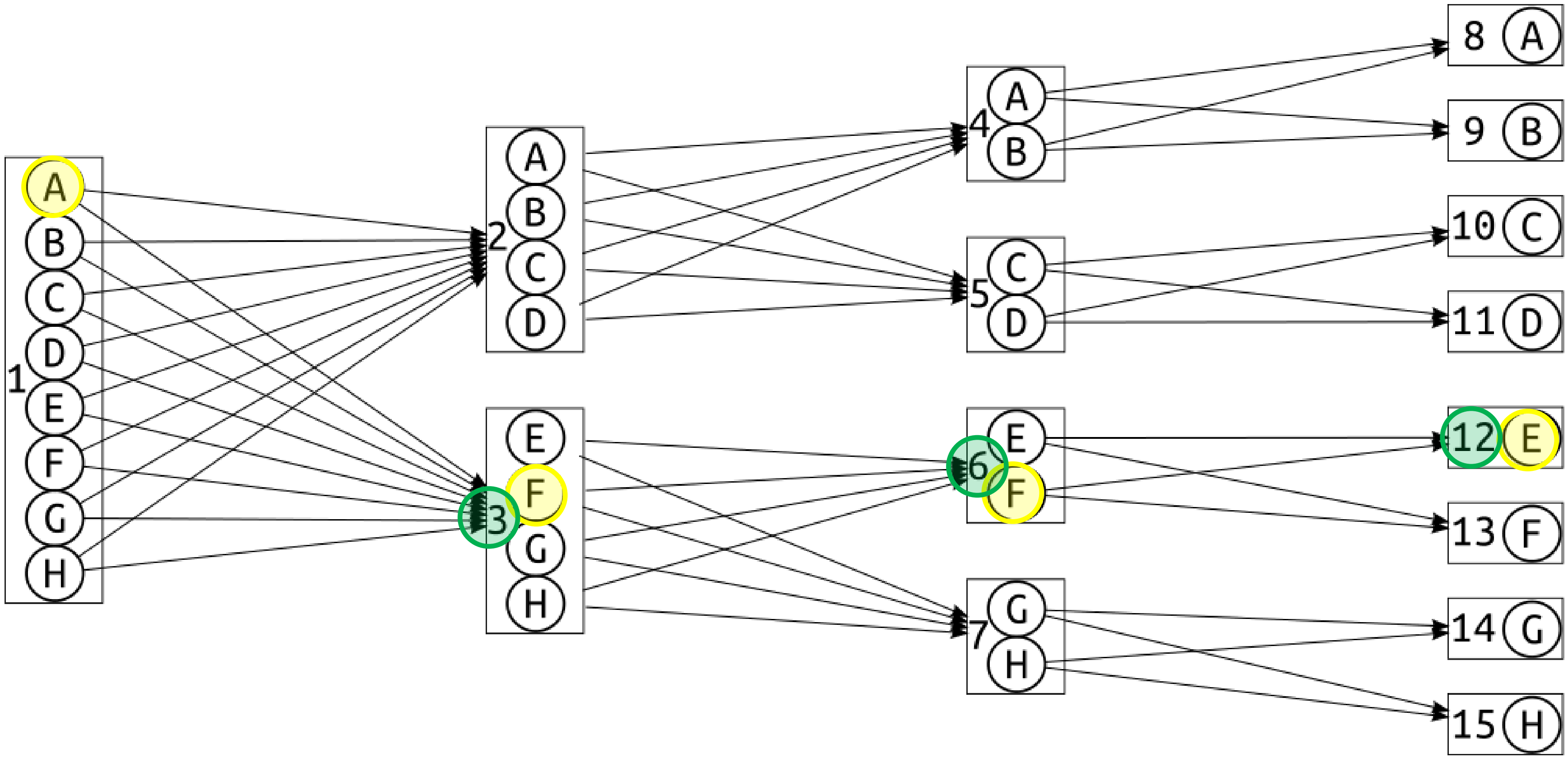
Study Outline

- Suppose there are parliamentary elections every 4 years
  - If the green party wins the majority, they implement a 2.3% annual CO_2 reduction.
  - If the pro-business party wins the majority directly following the green party, they allow CO_2 to grow at 2.3% annually. If they wind a second term in a row, CO_2 is unconstrained.
  - Election outcome probabilities weighted evenly at 50% each
- How do the EVPI and ECIU vary as a function of the discount rate and number of uncertain stages?
- Goal is to begin to explore the limits of stochastic optimization – how far should we go?

Event Tree Used for Stochastic Optimization



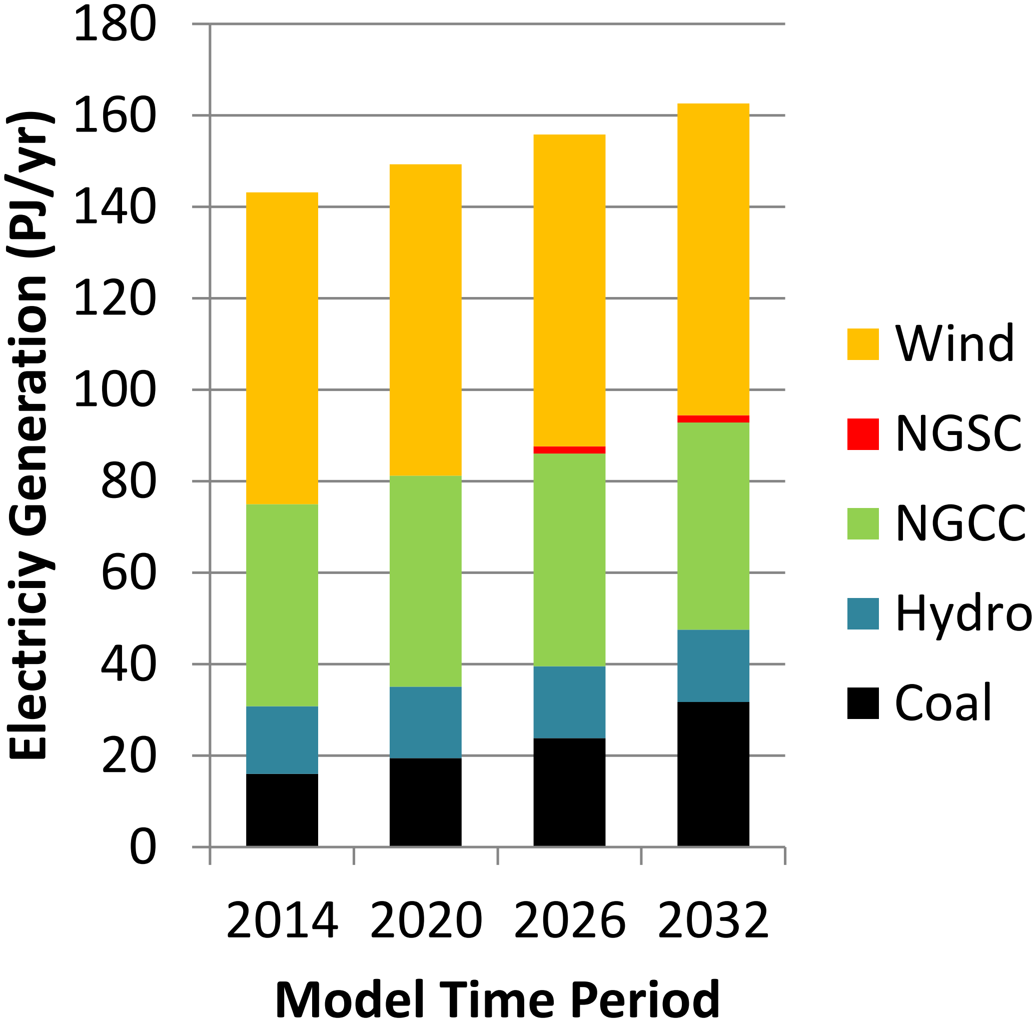
ECIU in the 4-stage case



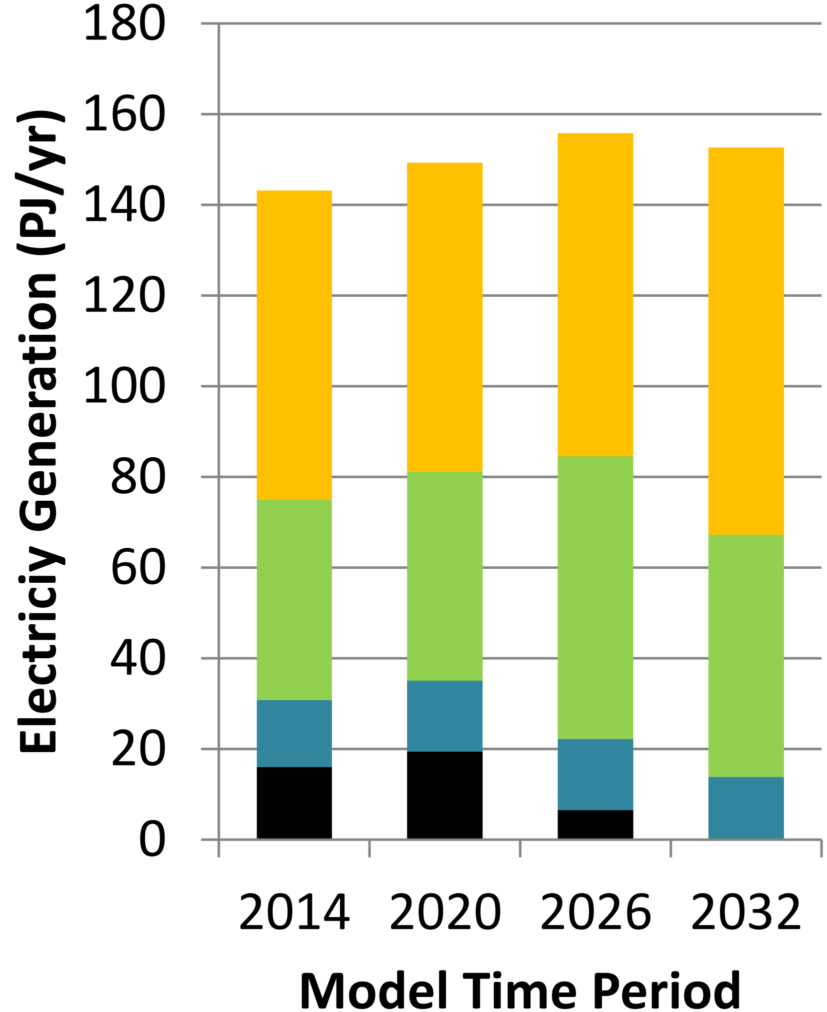
- Each node is designated by a number
- The letters at each node represent the remaining outcomes that are still possible

Electricity Generation

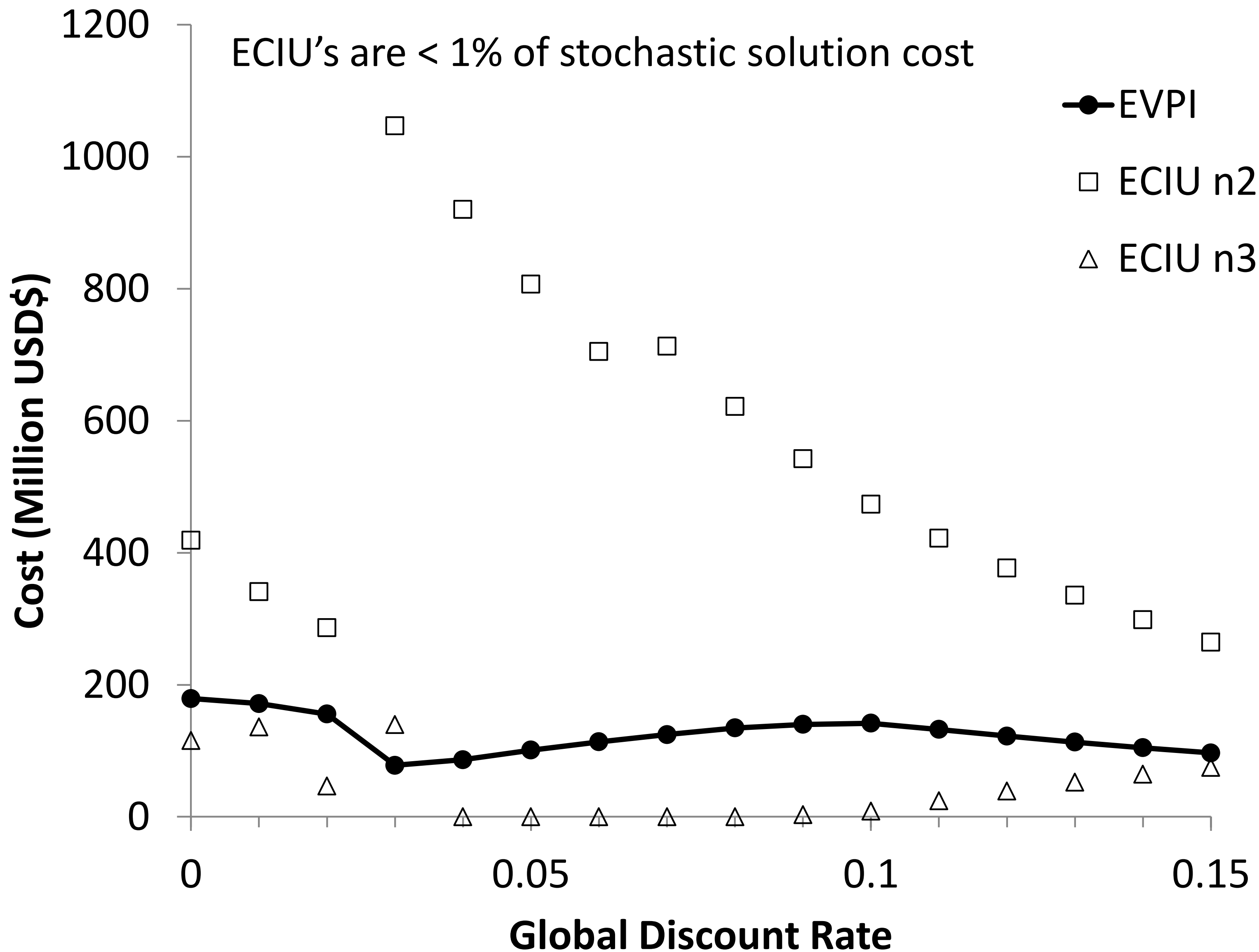
No CO_2 policy throughout



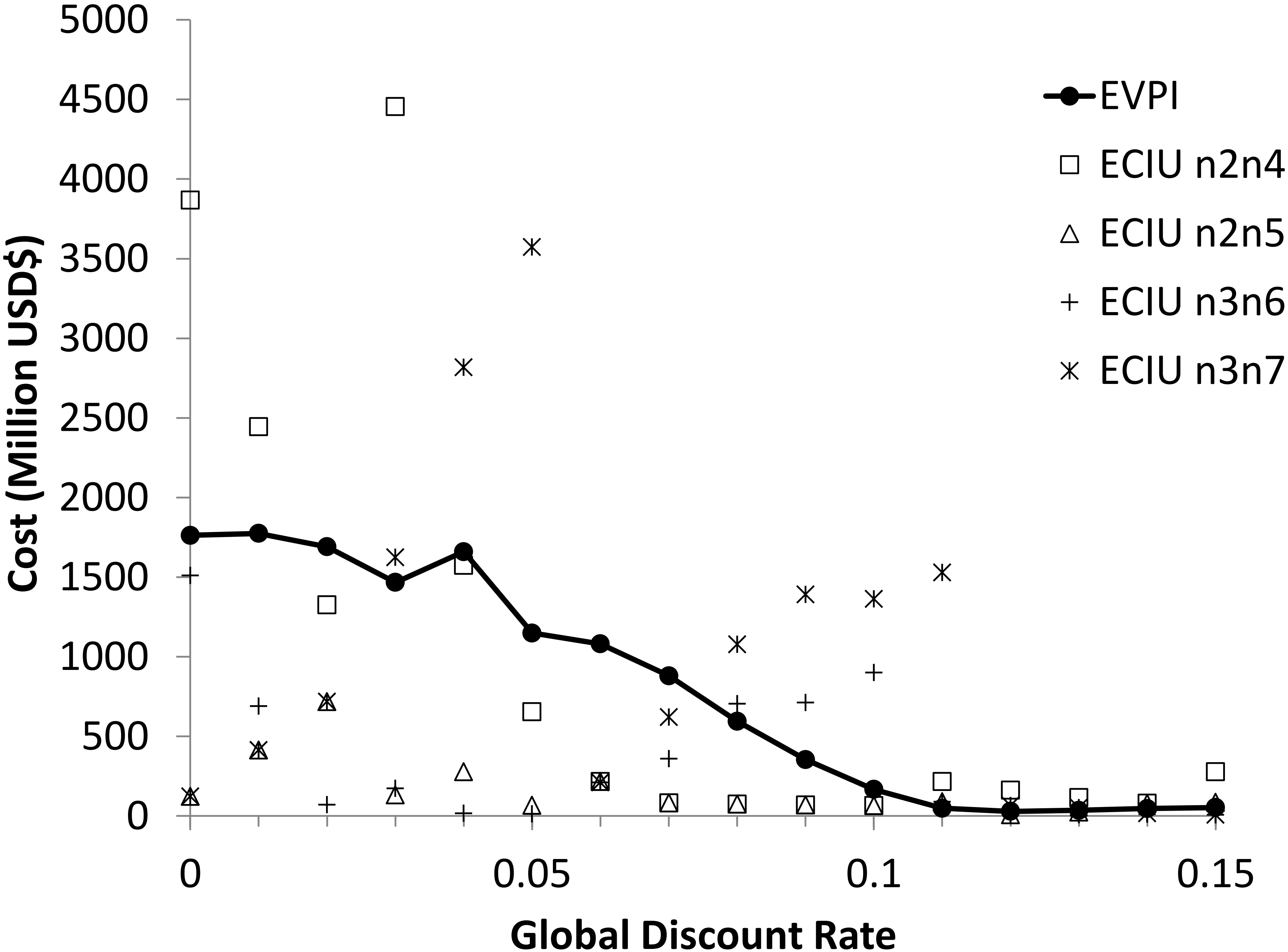
CO_2 policy throughout



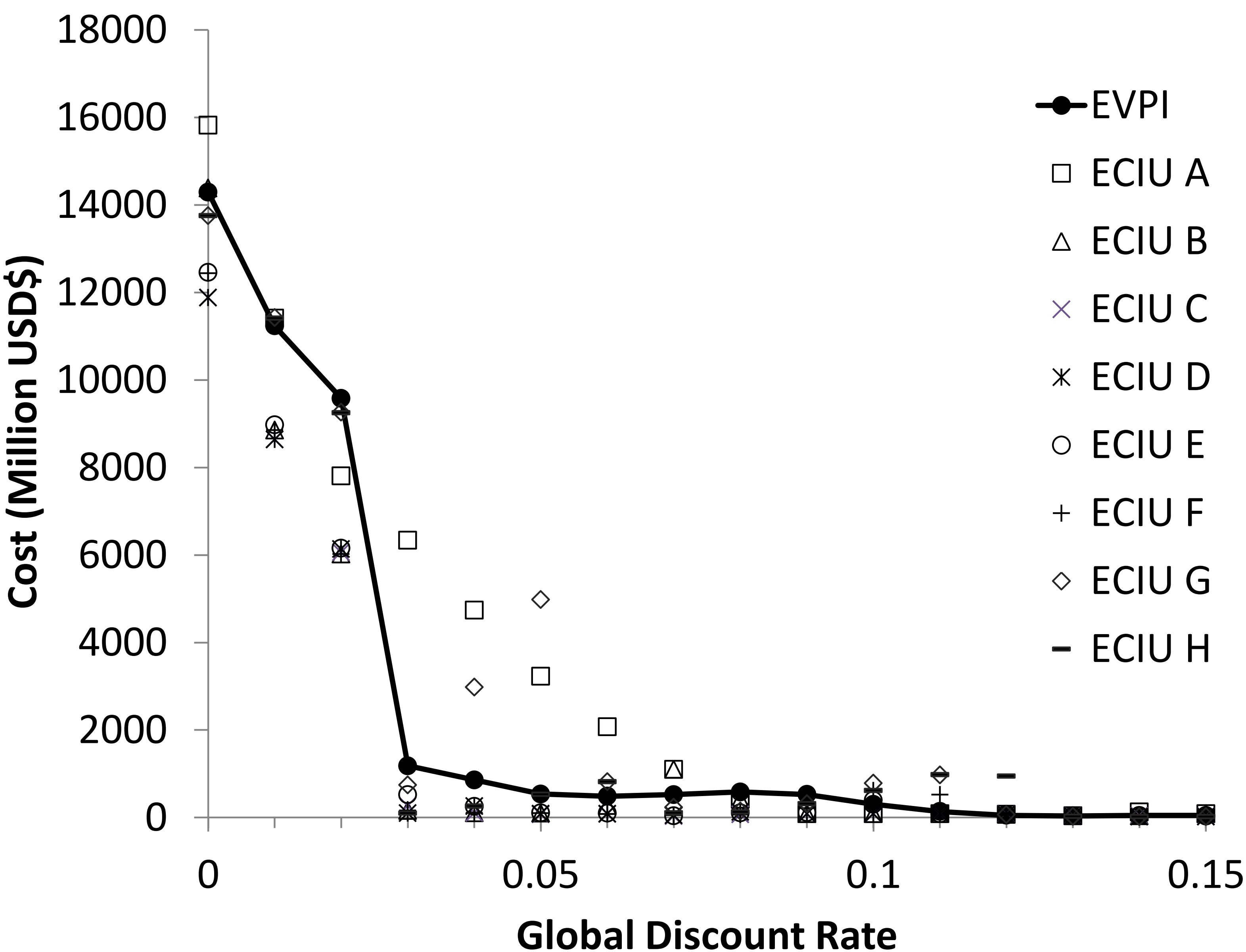
EVPI and ECIU in the 2-stage case



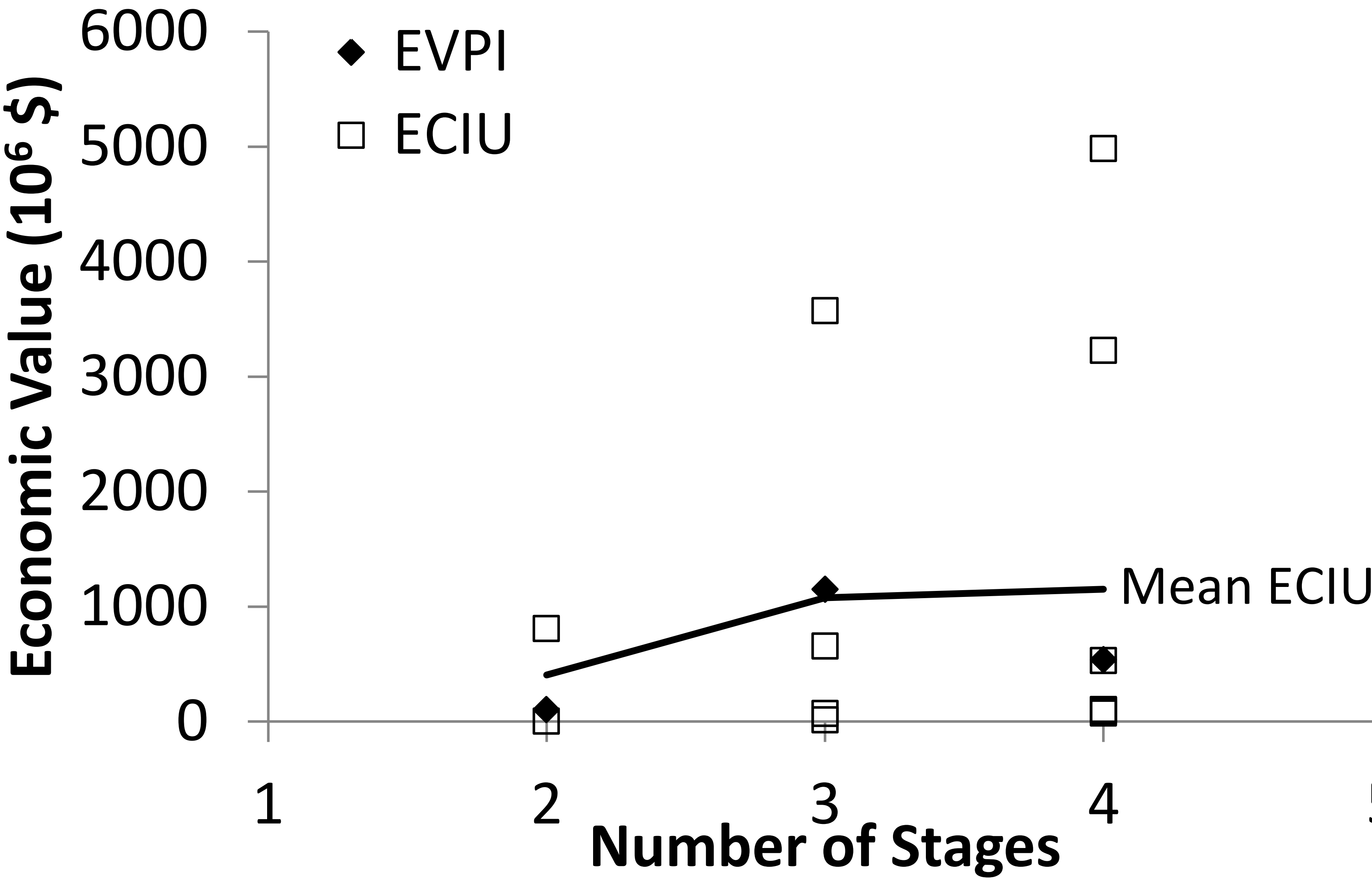
EVPI and ECIU in the 3-stage case



EVPI and ECIU in the 4-stage case



EVPI and ECIU in 2,3,4-stage cases @ 5% DR



Insights

- Discount rate generally decreases the EVPI and ECIU
- Discount rate also affects investment patterns and the distribution of ECIUs
- As number of stages increase, variation in ECIU increases; however, with a discount rate >0, the variation should approach a limit as the number of stages increases.
- Need to have flexible reference scenarios; easy to generate infeasibilities in the ECIU calculation with growth rate constraints
- EVPI and ECIU are a small fraction of the cost from the stochastic solution; need to investigate more

Stochastic Model Performance

2-stage (includes our "Reporting" variables)

5,056 variables (Columns)

6,071 constraints (Rows)

25,701 non-zeros

Time to solution: 6 sec (model gen) + 0.14 sec (CPLEX) = **6.14 sec**

3-stage

17,956 variables (Columns)

22,760 constraints (Rows)

98,213 non-zeros

Time to solution: 17 sec (model gen) + 0.49 sec (CPLEX) = **17.49 sec**

4-stage

53,824 variables (Columns)

71,213 constraints (Rows)

309,185 nonzeros

Time to solution: 56 sec (model gen) + 2.76 sec (CPLEX) = **58.76 sec**

ECIU Performance

2-stage (includes our "Reporting" variables)

Cores Utilized: 2

Total Solve Count: 4

Time: 5 sec

3-stage

Cores Utilized: 8

Total Solve Count: 32

Time: 14 sec

Across 16 discount rates:

Total Solve Number: $548 \times 16 = 8768$

Total Solution Time: 93 min 30 sec

4-stage

Cores Utilized: 8

Total Solve Count: 512

Time Per Solve: 318 sec (5.3 min)

Next Steps

Develop a better understanding of how the EVPI and ECIU vary under various configurations:

- discount rates
- number of stages (add more stages)
- model complexity
- choice of stochastic parameters
- distribution of probabilities

Perform policy-relevant analysis in the US

→ What are the costs and system effects associated with key uncertainties?

Model Access

All model source code and data available for viewing and download through the project website:

http://temoaproject.org

Also, if you'd like a copy of the paper that describes the Temoa formulation, send me an email (jdecarolis@ncsu.edu) :

Hunter K, Sreepathi S, DeCarolis JF, Modeling for Insight Using Tools for Energy Model Optimization and Analysis (Temoa). Energy Economics (under review).

Acknowledgments

This material is based upon work supported by the National Science Foundation under Grant No. 1055622 (CAREER: *Modeling for Insights with an Open Source Energy Economy Optimization Model*). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

National Science Foundation
WHERE DISCOVERIES BEGIN

Stochastic optimization with PySP

Python-based Stochastic Programming (PySP) is part of the Common Optimization Python Repository (Coopr) package, developed at Sandia National Lab.

To perform stochastic optimization, specify a Pyomo reference model and a scenario tree

PySP offers two options:

1. **`runef`**: builds and solves the extensive form of the model.
   "Curse of dimensionality" → memory problems
2. **`runph`**: builds and solves using a scenario-based decomposition solver (i.e., "Progressive Hedging) based on Rockafellar and Wets (1991).
   Can be implemented in a compute cluster environment; more complex scenario trees possible.

R.T. Rockafellar and R. J-B. Wets. Scenarios and policy aggregation in optimization under uncertainty. *Mathematics of Operations Research*, pages 119–147, 1991.

Uncertainty Metrics

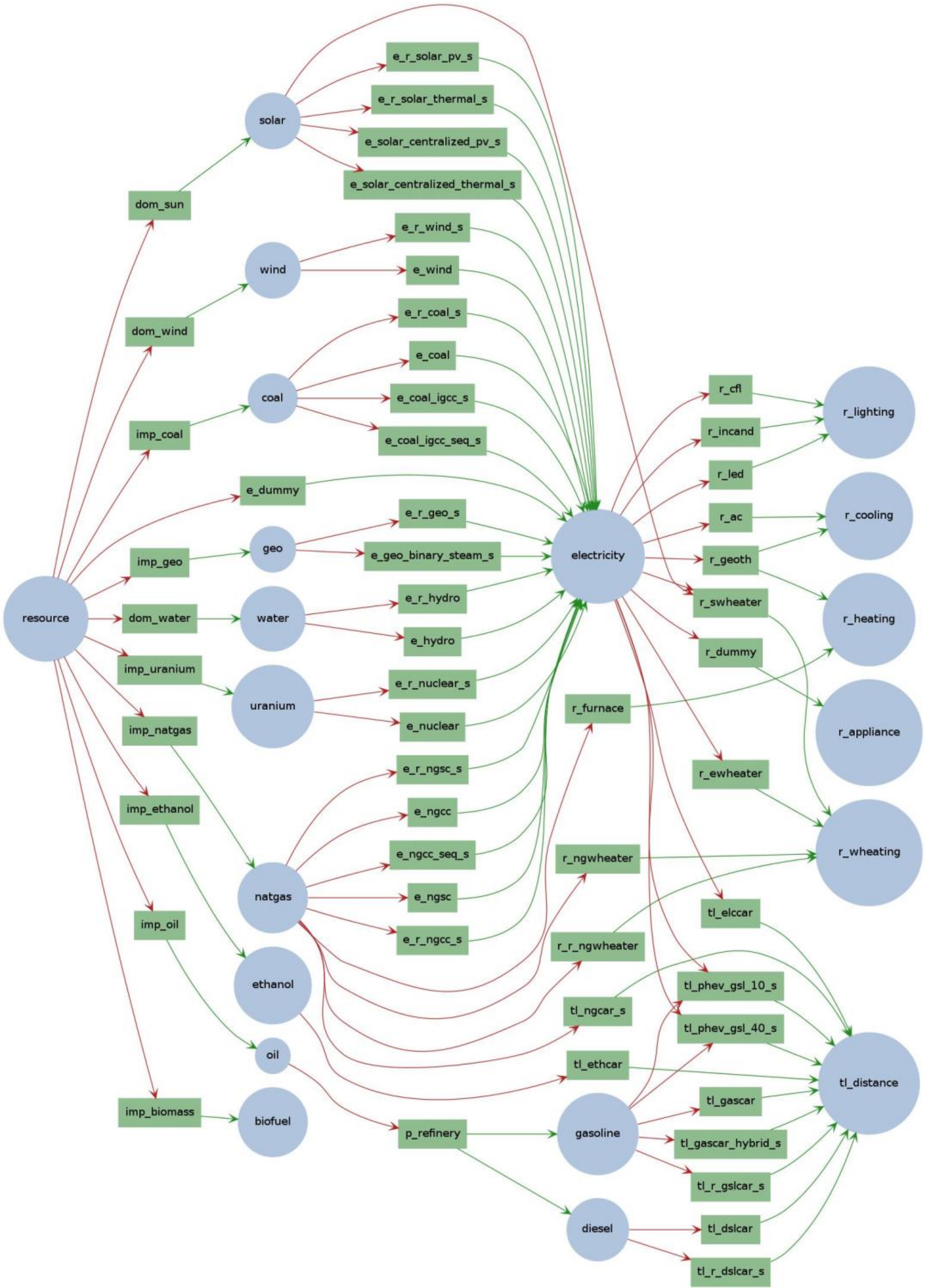
Since we need to make decisions in the face of uncertainty, we need metrics that allow us to value the hedging strategy.

Expected Value of Perfect Information (EVPI): The expected savings if the planners knew with certainty the outcome at every stage as opposed to following the hedging strategy.

Expected Cost of Ignoring Uncertainty (ECIU): The expected savings by following the hedging strategy rather than naively guessing the outcome.

‘Temoa Island’

- 10 import technologies; constant supply prices
- 54 technologies total; each with approximately 9 vintages
- 6 end-use demands: lighting, space heating, space cooling, water heating, and light duty transportation
- 6 time slices: summer/ winter /intermediate day/ night
- 5 time periods, each 5 years long: 2010-2030.



Temoa Island 2013: Stochastic Model Performance

2-stage (includes our "Reporting" variables)

21,000 variables (Columns)

25,600 constraints (Rows)

Time to solution: 30 sec (model gen) + 0.26 sec (CPLEX) = **30.26 sec**

3-stage

58,077 variables (Columns)

74,933 constraints (Rows)

Time to solution: 94 sec (model gen) + 1.44 sec (CPLEX) = **95.44 sec**

4-stage

150,001 variables (Columns)

200,830 constraints (Rows)

Time to solution: 292 sec (model gen) + 4.61 sec (CPLEX) = **296.61 sec**

Temoa Island 2013: ECIU Performance

2-stage (includes our "Reporting" variables)

Cores Utilized: 2

Total Solve Count: 4

Time: 12 sec

3-stage

Cores Utilized: 8

Total Solve Count: 32

Time: 41 sec

4-stage

Cores Utilized: 8 (max)

Total Solve Count: 512

Time Per Solve: 811 sec (13.51 min)

Across 16 discount rates:

Total Solve Number: $548 \times 16 = 8768$

Total Solution Time: 4.2 hours

Related Outputs

DeCarolis JF, K Hunter, S Sreepathi (2012). The case for repeatable analysis with energy economy optimization models. *Energy Economics*, 34(6): 1845-1853.

Hunter K, S Sreepathi, JF DeCarolis. Modeling for Insight with Tools for Energy Model Optimization and Analysis (Temoa). *Energy Economics* (under review).