Uncertainty in Experience Curves for Climate Policy Analysis:

Some insights from case studies

Edward S. Rubin
Department of Engineering and Public Policy
Department of Mechanical Engineering
Carnegie Mellon University
Pittsburgh, Pennsylvania

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Focus on Environmental Technologies

- "Environmental technologies" are those employed solely for the purpose of reducing or eliminating emissions to an environmental medium (air, water, land)
- Common examples include:
  - Sulfur dioxide scrubbers and other emission control systems used at coal-fired power plants
  - Catalytic converters installed on automobiles
- No "natural" markets for these technologies; rather, major markets are established via government policies or regulations that restrict environmental emissions, requiring new technology for compliance

Carbon Capture and Storage (or Sequestration) Technology

- CCS is an environmental technology that could be used to eliminate most of the atmospheric CO_2 emissions from a power plant or other large industrial process (including "clean fuels" production)
- CCS is widely viewed as a critical technology for achieving climate change policy goals at the lowest cost, in conjunction with other mitigation measures
- However, CCS has not yet been demonstrated at a full-scale power plant; commercial applications have been mainly in industrial settings at scales smaller than typical electric utility situations.

Questions

- How best to represent in climate policy models the future cost trajectory of energy systems with new environmental technologies, esp. power plants with carbon capture and storage (CCS)?
- What are the uncertainties associated with use of a traditional one-factor log-linear model?
- How big of an impact do these uncertainties have on projected energy costs of plants w/CCS?

Results from prior case studies

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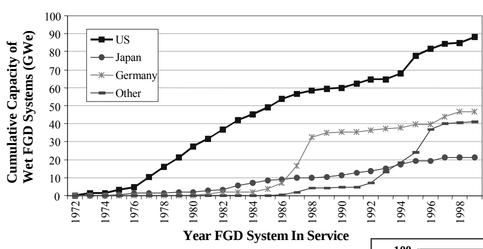
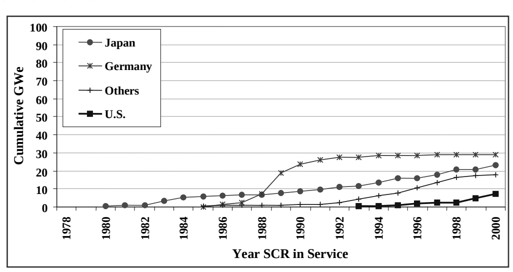
Trends in Use of Post-Combustion SO_2 and NO_x Capture at Coal-Fired Plants



FGD = Flue Gas Desulfurization system (typical SO_2 removal ~90%)

SCR = Selective Catalytic Reduction system (typical NO_X removal ~80%)



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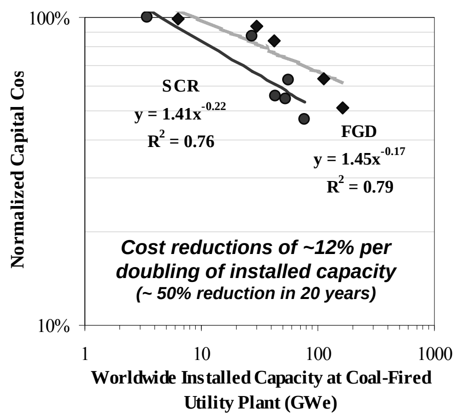
Best-Fit Experience Curves for FGD and SCR Capital Costs

These values reflect real changes in the cost of doing the <u>same job</u> at different points in time for the same power plant and fuel specifications



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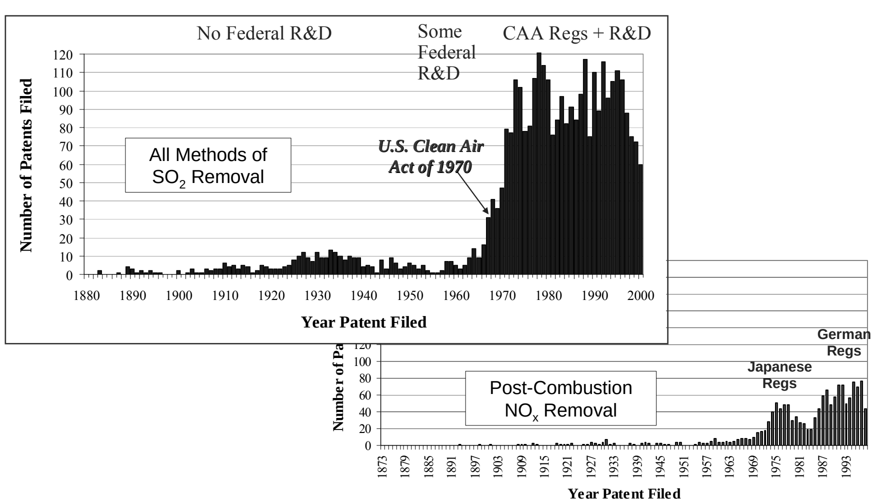
U.S. Patenting Activity in SO_2 and NO_x Control Technology



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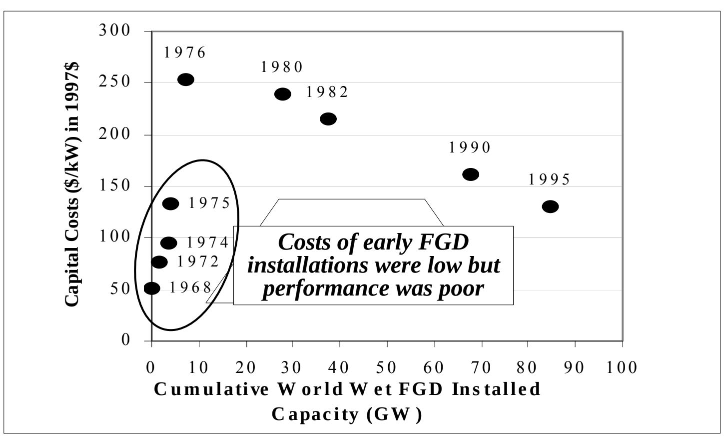
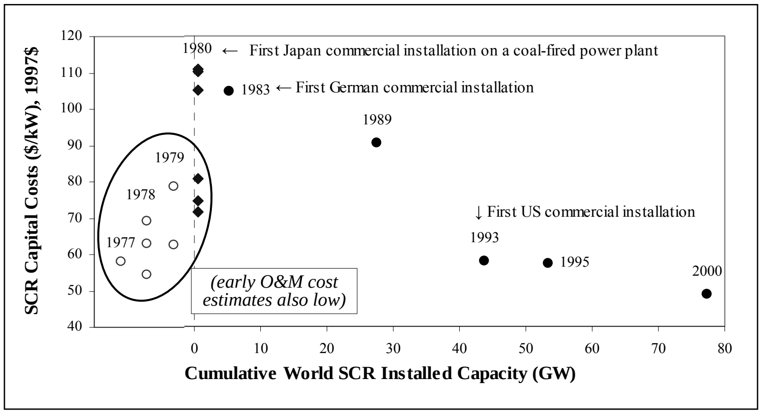
Common Uncertainties in the One-Factor Model

- Starting point for experience curve
- End point for experience curve
- Measure of cumulative experience
- Basis for cumulative experience data
- Basis for associated cost data
- Shape of the experience curve

Early Trend of FGD Capital Cost



Early Trend of SCR Cost Estimates



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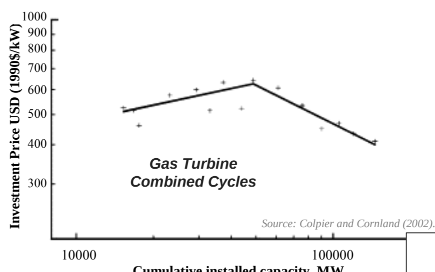
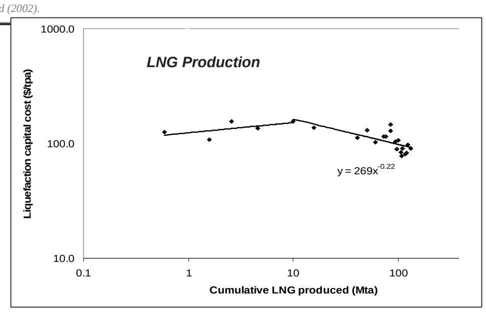
Other Examples of Early Increases in Capital Cost





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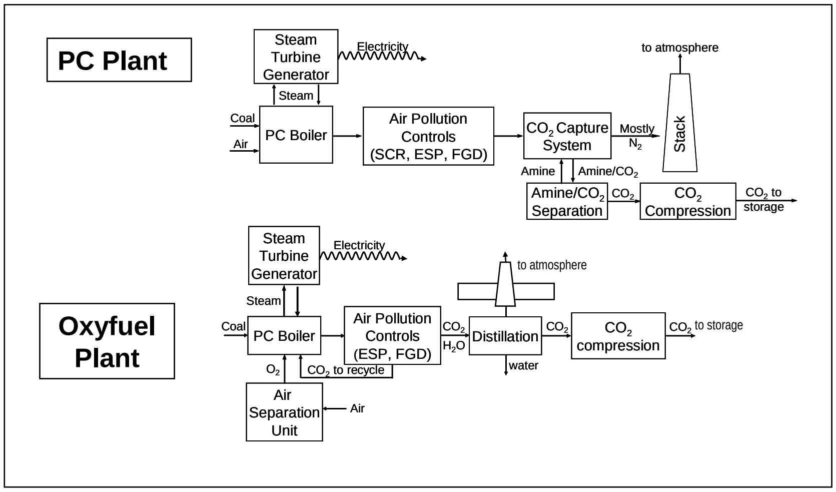
Case Study Learning Rates

Technology	"Best Estimate" Learning Rates Capital Cost	O&M Cost
Flue gas desulfurization (FGD)	0.11	0.22
Selective catalytic reduction (SCR)	0.12	0.13
Gas turbine combined cycle (GTCC)	0.10	0.06
Pulverized coal (PC) boilers	0.05	0.18
LNG production	0.14	0.12
Oxygen production (ASU)	0.10	0.05

Application to power plants with CO_2 capture

Power Plants with CO_2 Capture



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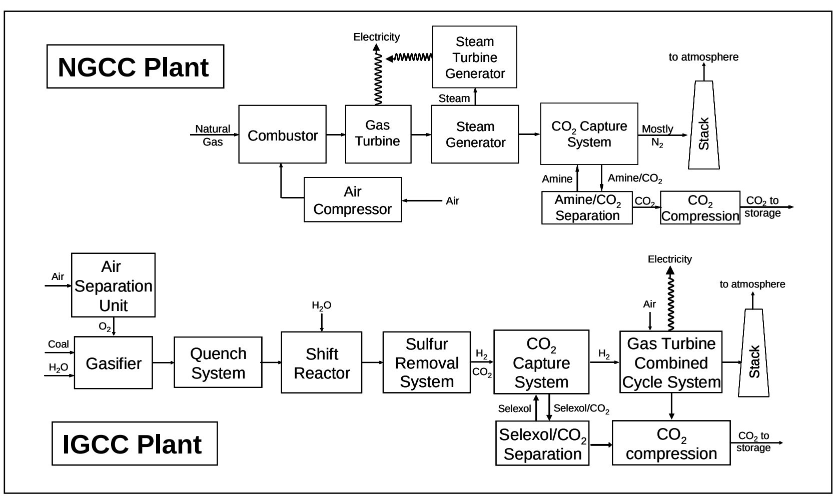
Power Plants with CO_2 Capture



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Approach

- Apply best-estimate learning rates to major plant components, then aggregate to estimate learning curves for the overall power plant with CO_2 capture

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Step 1: Specify baseline plant characteristics and costs

- 500 MW net output (approximate)
- Supercritical PC and Quench gasifier IGCC
- Pittsburgh #8 bituminous coal
- Annual average capacity factor
- All costs from IECM in constant dollars

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Step 2: Disaggregate each plant into major sub-sections

For example:

- IGCC Plant Components
  - Air separation unit
  - Gasifier area
  - Sulfur removal/recovery system
  - CO_2 capture system
  - CO_2 compression
  - Gas turbine comb. cycle power block
  - Fuel cost

Step 3: Select learning rate analogues for each plant component

Plant Type & Technology	FGD	SCR	GTCC	LNG prod	O_2 prod
IGCC Plant					
Air separation unit					X
Gasifier area				X	
Sulfur removal/recovery	X	X			
CO_2 capture system	X	X			
CO_2 compression					
GTCC (power block)			X		

Step 4: Estimate contribution of each sub-section to current plant costs

Plant Type & Technology	Capital Cost	Annual O&M Cost*	Levelized Cost of Electricity*
IGCC Plant w/ Capture	$/kW	$/MWh	$/MWh
Air separation unit	18 %	8 %	14 %
Gasifier area	27 %	17 %	24 %
Sulfur removal/recovery	6 %	3 %	5 %
CO_2 capture system	13 %	7 %	11 %
CO_2 compression	2%	2 %	2 %
GTCC (power block)	34 %	9 %	25 %
Fuel cost	--	54%	19 %

*Excluding T&S cost

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Step 5: Estimate current capacity of major plant components

Plant Type &Technology	Current MW_{net} Equiv.
IGCC Plant Components	
Air separation units	50,000
Gasifier area	10,000
Sulfur removal/recovery	50,000
CO_2 capture system	10,000
CO_2 compression	10,000
GTCC (power block)	240,000

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Steps 6&7: Specify start and stop of the learning curve

Plant Type	Cumulative CCS Capacity (MW) Learning Begins at: 1st Plant	N Plants	Learning Projected to:
NGCC Plant	432	3,000	100,000
PC Plant	500	5,000	100,000
IGCC Plant	490	7,000	100,000
Oxyfuel Plant	500	10,000	100,000

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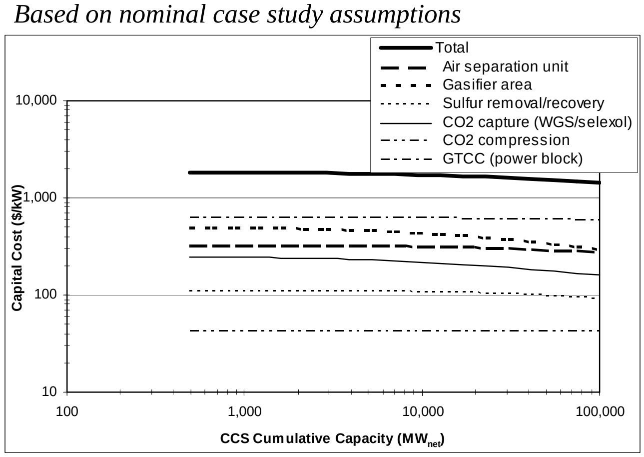
Results for IGCC Capital Cost
(Assuming learning begins at first capture plant)

Based on nominal case study assumptions



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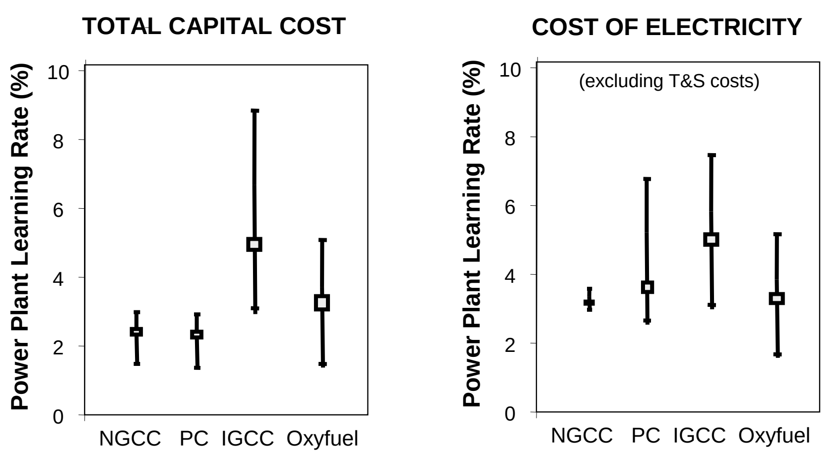
Step 8: Sensitivity Analysis

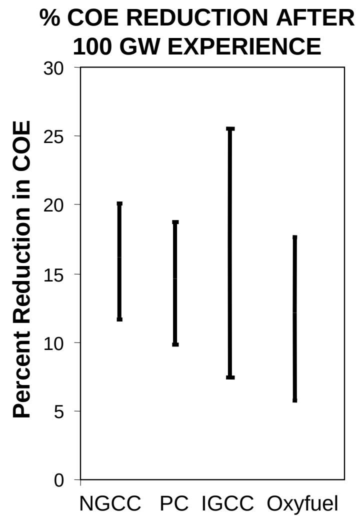
- Learning starts at either first or *N*[th] plant
- Range of component learning rates
- Projection to 50 GW of worldwide capacity
- Lower estimates of current component capacity
- Effect of additional non-CCS experience
- Higher fuel prices for coal and natural gas
- Lower financing costs + higher plant utilization

Range of Learning Rate Results



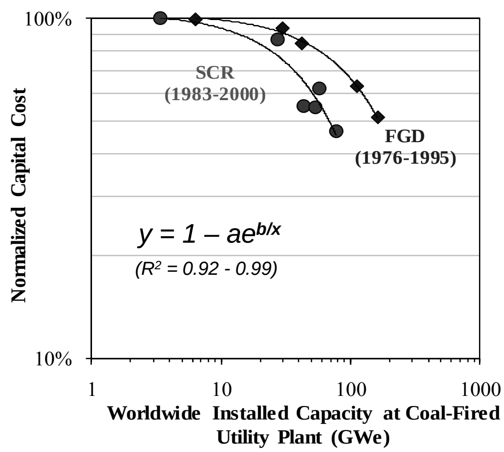
Summary of Results

- Learning rates for a given plant type vary by about a factor of 3
- Projected reductions in total cost of electricity (COE) production vary by factors of ~2 to 4
- Cost estimates from "bottom-up" models are generally at the high end of this range



Is the experience curve really log-linear?

Best-Fit Curves for Initial Deployment of Two Environmental Technologies



Hypothesis:

The regulatory-driven deployment of these technologies leads to large initial increments of capacity before the subsequent benefits of LBD, R&D, etc begin to lower future costs

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Other Empirical Studies Also Find "S-Shaped" Experience Curves

- Carr (1946)
- Stanford Research Institute (1949)
- Asher (1956)
- Conway and Schultz (1959)
- Klepper and Graddy (1990)
- Claeson (1999)
- Goldemberg (2004)
- Hettinga et al. (2009)

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Many factors not explicitly modeled by traditional experience curves

- Influence of R&D expenditures on product cost
- Knowledge "spillover" effects
- Discontinuities and organizational forgetting
- Societal influences on technology use or design, e.g.,
  - New safety regulations that increase technology cost
  - New emission regs that influence technology deployment
- Influence of competition on market dynamics
- Contribution of exogenous change vs. learning

How can we do better ?

Two-Factor Learning Curves

- Model form: $C_i = a\,(x_i^{-b,LBD})\,(RD_i^{-b,LBR})$

where: C = unit cost of technology i
x = cumulative adoption of technology i
RD = cumulative R&D investment or knowledge stock for i
b_{LBD} = learning-by-doing parameter
b_{LBR} = learning-by-researching (R&D) parameter
a = unit cost at unit cumulative capacity and unit knowledge stock

- Example Applications:
  - Bahn and Kypreos (2003)
  - Barreto and Klassen (2004)
  - Klassen, Miketa et al. (2005)
  - Jamasb (2007)
  - Söderholm and Klassen (2007)
  - Fischer and Newell (2008)

Multi-Factor Models and Formulations

- Linear regression models that fit unit cost reductions to changes in explanatory parameters (e.g., efficiency, material costs, labor costs, scale); e.g.,
  - Joskow and Rose (1985) [US coal plants]
  - Nemet et al (2006) [world PV]
  - Söderholm and Sundqvist (2007) [European wind turbines]
- Endogenous learning-diffusion models; endogenous plus exogenous learning through time; e.g.,
  - Jamasb (2007)
  - Ferioli et al. (2009)
  - Nordhaus (2009, 2010)

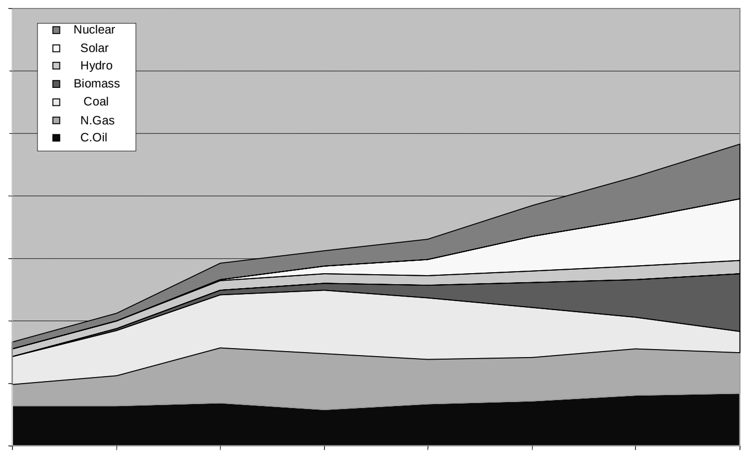
Some Issues and Limitations

- Availability of data
- Credibility of data
- Co-linearity between R&D and adoption
- Distinguishing between private and public R&D
- Extrapolating to other technologies

So What's a Modeler to Do ?

- *In the near term:* Much stronger efforts to improve the transparency of complex models, e.g.,
  - Quantify, incorporate and display the impacts on key results of uncertainties in model formulations, assumptions, and underlying data
  - Admit (where applicable) that we just can't answer (yet) many questions that are of policy interest
- *Over the longer term:* Develop a coherent research strategy to define and acquire the data needed to develop and validate improved modeling methods

Typical Display of a Model Run



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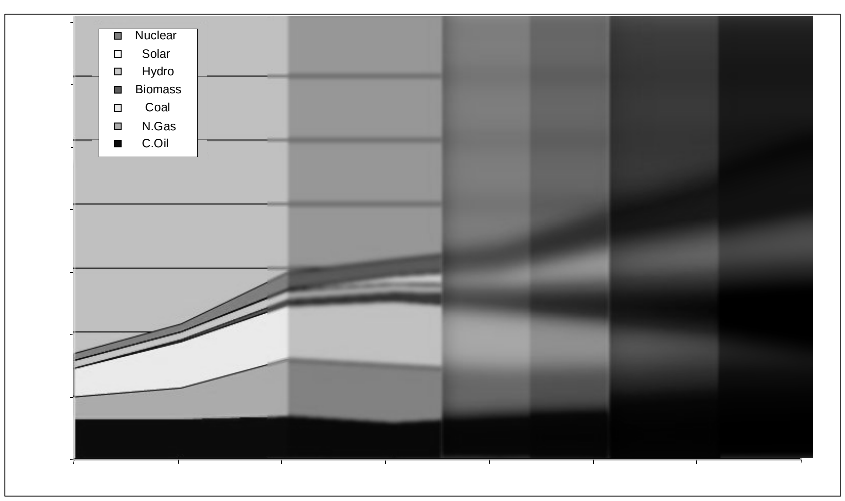
What I'd Like to See



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Thank You

rubin@cmu.edu