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Technological change and the role of policy

AMPERE-ADVANCE-PIAMDDI Technology Workshop
Sevilla, España

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Outline

1. Motivation: technology innovation and forecasting
2. Factors contributing to wind power costs in China
3. Evaluation of optimal R&D policies using expert elicitations
4. Concluding remarks

1. Importance of understanding the role of policy technology innovation

- Estimated cost of achieving a given GHG concentration stabilization target is highly sensitive to assumptions about technology costs

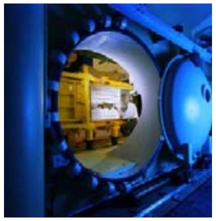
  "assumptions about technological change are critical in the studies"

  "technological change itself relates to R&D programmes and to current technology implementation" IPCC WGIII

- Even if investments in new energy technologies have been sizeable, we still do not know enough about their impact on innovation
  - US: 2005-2009 > $50 billion in renewables
  - Spain: 2005-10 ~ 10 billion $ in renewables
  - China: 2008 ~ $12 billion PPP in energy RD&D (including SOEs)

Many factors can contribute to technological change

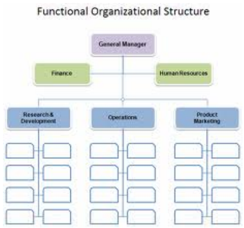
- Learning-by-doing or by using



- Learning-by-searching

- Knowledge spillovers from other sectors

- Economies of scale



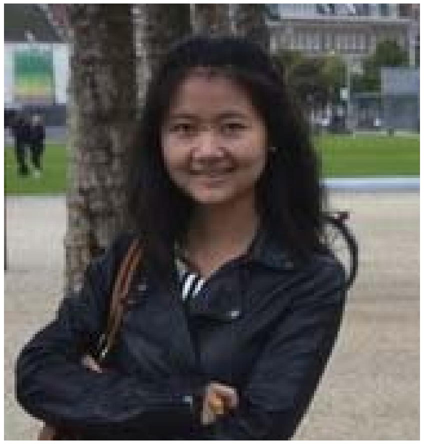
- Economies of scope

- Materials and labor costs

2. Empirical analysis of wind innovation in China

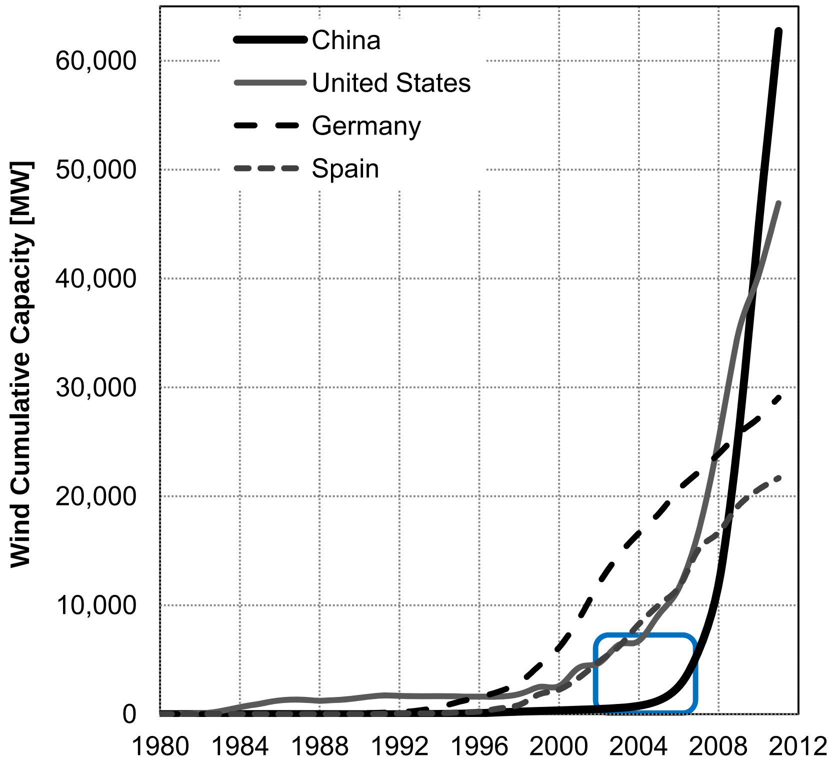
- Largest wind market and manufacturer
- Limited empirical data about technical change outside of OECD
- Investigating alternatives to two-factor learning curves

➔ Possible implications for modeling technological change



Work published in Qiu & Anadon (2012) *Energy Economics*
Yueming Qiu is now at Arizona State University

2003-2007 covers the expansion of wind in China



- Government policies have driven the large growth of wind in China since 2003
  - 2003-2007 wind concession program (bids for guaranteed market demand, local content requirements)
  - Feed-in tariff 2009
- Dataset
  - government wind farm concession program
  - 48% of total installed capacity 2003-2007
  - coincident with rising wind power prices in U.S. and E.U.

Some wind learning curve studies include

- Learning-by-searching using domestic RD&D investments

$$COST_t = COST_{t0}\left(\frac{CC_t}{CC_{t0}}\right)^{\beta}\left(\frac{KS_t}{KS_{t0}}\right)^{\alpha} \qquad LBD = 1 - 2^{\beta} \qquad LBS = 1 - 2^{\alpha}$$

$$KS_t = KS_{t-1} \times (1 - \rho) + RDD_{t-g}$$

- Technical considerations using capacity factor and turbine size

- Economies of scale using wind farm size

- Input prices using GDP deflator or construction price index

But there are areas for improvement

- Possible omitted variable bias
  - regional differences in labor and material costs and wind resource
- Some technical parameters (capacity factor and turbine size) are a function of learning and other factors, so learning estimate is not accurate (underestimated) when they are specified separately
- Endogeneity between costs and installed capacity
  - if wind deployment is a function of wind prices
- **Collinearity** between cumulative capacity and knowledge stock
  - an issue with public R&D and installed wind capacity
- **Public R&D may not be a good learning-by-searching proxy**
  - data on private and non-OECD R&D investments in wind are scarce
  - not all R&D$ are worth the same or take the same time to market
  - knowledge spillovers from other industries not included

Model

- Independent variables
  - *Joint* learning-by-doing and by new technology adoption
  - Fraction of manufacturing in China
  - Wind resource quality
  - Wind farm economies of scale
  - Steel prices
  - Year dummies (changes in other policies, bidding terms, other)
- Random effects model
- The learning coefficient groups learning through the experience of developers, manufacturers, and new technologies
  - also includes manufacturing economies of scale
- Additional tests:
  - learning within and across project developers
    - spillovers from learning by doing across firms?
  - type of developer: SOEs, new firms, or established firms

Technology adoption as a metric for knowledge stock

- Overcomes most of the challenges of R&D investments
  - Spillovers
  - Private R&D
  - International R&D
  - All adoptions likely to add some value
  - 1 year time lag (more accurate, vs. ? years for R&D)

Year	Number of technology adoptions	Average turbine size	% of turbines with fixed speed control system	Number of the technologies from different technology adoption mechanism					
				Foreign subsidiaries	Production license from foreign companies	Joint venture	Joint design with foreign companies	Transfer from domestic research institutes	Technology stemming from firm in-house R&D
1998	2	0.60	100%		2				
2001	1	0.75	100%		1				
2002	2	0.99	50%				1		1
2003	2	1.13	50%		2				
2004	6	1.35	0%		3		1	1	1
2005	7	1.26	29%	1	1	2	1		2
2006	23	1.59	9%	4	2	4	4	2	7

Chinese policies encouraging new technologies

- Concession program itself (2003-07) catalyzed adoption
- 863 R&D program contributed to transfer from domestic research institutes and firms (14/43)
- In 2005 high *localization rates* were favored, including in bidding
- IP laws revised in 2001 and 2004 and joint ventures given preferential tax treatment in 2003 (?)

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Results

	Simple model	Improved model		Firm characteristics test		Inter-firm intra-firm learning test
Model number	1	2	3	4	5	6
ln Cumulative installed capacity	−0.1171 (0.01230)***	−0.0637 (0.0308)**	−0.0604 (0.0315)*	−0.0680 (0.0318)**	−0.0665 (0.0330)**	
ln Cumulative installed capacity of other firms						−0.0748 (0.0310)**
ln Cumulative installed capacity of own firm						0.0006 (0.0006)
LARGESHARE*ln Cumulative installed capacity of other firms						0.0589 (0.0338)**
LARGESHARE						−0.4636 (0.2576)*
ln Localization rate		−0.3285 (0.0925)***	−0.1749 (0.0938)*	−0.3170 (0.0944)***	−0.1659 (0.0956)*	−0.3330 (0.0958)***
ln Wind farm scale		−0.0892 (0.0482)*	−0.1343 (0.0458)***	−0.0889 (0.0488)*	−0.1350 (0.0466)***	−0.1005 (0.0478)**
Wind resource category 1		−0.1451 (0.0310)***	−0.1054 (0.0320)***	−0.1413 (0.0317)***	−0.1013 (0.0328)***	−0.1425 (0.0310)***
Wind resource category 2		−0.0594 (0.0458)	−0.0241 (0.0420)	−0.0580 (0.0465)	−0.0227 (0.0429)	−0.0616 (0.0449)
Wind resource category 3		−0.1080 (0.0592)*	−0.1354 (0.0613)**	−0.1068 (0.0606)*	−0.1352 (0.0622)**	−0.1171 (0.0596)**
SMALL				−0.0192 (0.0257)	−0.0197 (0.0265)	
MEDIAN				0.0058 (0.0264)	−0.0008 (0.0258)	
SOE				−0.0160 (0.0295)	0.0000 (0.0293)	
ln Steel price		0.2370 (0.0885)**		0.2391 (0.0904)***		0.2414 (0.0889)***
Constant	−4.5404 (0.1032)***	−5.1908 (0.5856)***	−3.4868 (0.3571)***	−5.2110 (0.6030)***	−3.4662 (0.3630)***	−5.0619 (0.5981)***
Year dummies	No	No	Yes	No	Yes	No
Chi-square	81.66	172.53	225.58	169.78	221.18	175.95
R-square within	0.3684	0.6087	0.6948	0.609	0.6969	0.6314
R-square between	0.6071	0.6997	0.729	0.7011	0.7246	0.6949
R-square overall	0.4352	0.6331	0.6969	0.6364	0.7001	0.6456
Joint learning rate	***7.80%***	***4.32%***	***4.10%***	***4.60%***	***4.51%***	***4.51%***
Inter-firm learning rate of large share firm						1.10%
Inter-firm learning rate of small share firm						***5.06%***
Intra-firm learning						−0.04%
Effect of localization rate		***20.36%***	***11.42%***	***19.73%***	***10.86%***	***20.61%***
Effect of wind farm scale		***6.00%***	***8.89%***	***5.98%***	***8.93%***	***6.73%***

Results (II)

- Covariates reduced omitted variable bias (and learning rate) from 8% to 4%
- Not possible (at least in this case) to separate LBS and LBD given collinearity
- Wind farm economies of scale, turbine localization, wind resource, and steel prices associated with cost reductions
- Results robust to controlling for years
- Learning-by-doing was not limited to firms building wind farms, but to all firms ➔ learning-by-doing spillovers
- No evidence of SOEs underbidding

Some limitations

- Period only covered 5 years in one emerging economy
- Technology adoption metric still does not differentiate between different impacts of technologies
- Method does not separate the contribution of knowledge spillovers from other sectors

Key insights

- Joint experience and learning-by-searching rates for wind in China between 2003 and 2007 was around 4%

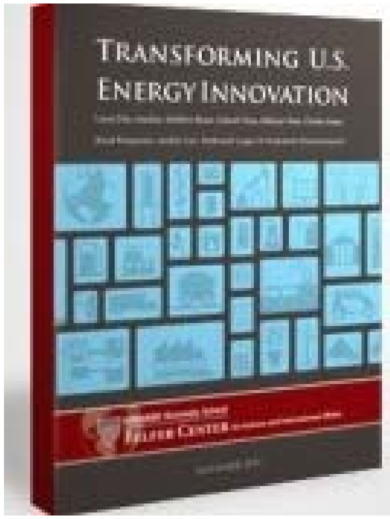
- Policy impacts on cost reduction:
  - Localization requirements
  - Concession program, IP, JV support, and domestic R&D ➔ increased deployment and new technologies, benefits not kept by developers

- Technology adoption as an alternative to R&D knowledge stock

- Not controlling for wind farm economies of scale, manufacturing localization, steel prices, and wind quality can lead to biases

3. Evaluation of optimal energy R&D investment portfolios using expert elicitation data

- Need to consider:
  - tradeoffs between technologies in the market
  - uncertainty
  - transparency and consistency



http://belfercenter.ksg.harvard.edu/publication/21528/

Different parts of this work published in:

- Anadon *et al*. Transforming U.S. Energy Innovation (2011) (link above)
- Anadon, Bunn, Narayanamurti (Eds.). Forthcoming, *Cambridge University Press* book
- Anadon, Bosetti, Bunn, Catenacci, Lee. (2012). *Environmental Science & Technology*
- Chan, Anadon, Chan, Lee (2011). *Energy Procedia*
- Chan & Anadon (2013)

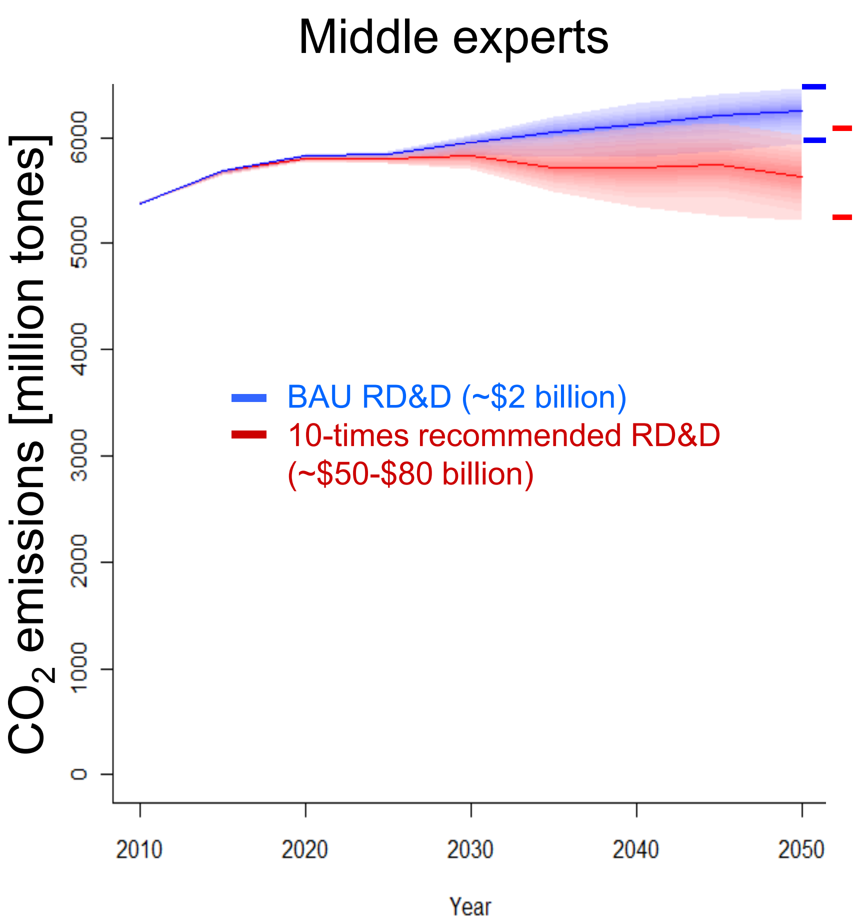
•… and other work in progress with Baker, Bosetti, Nemet, Verdolini

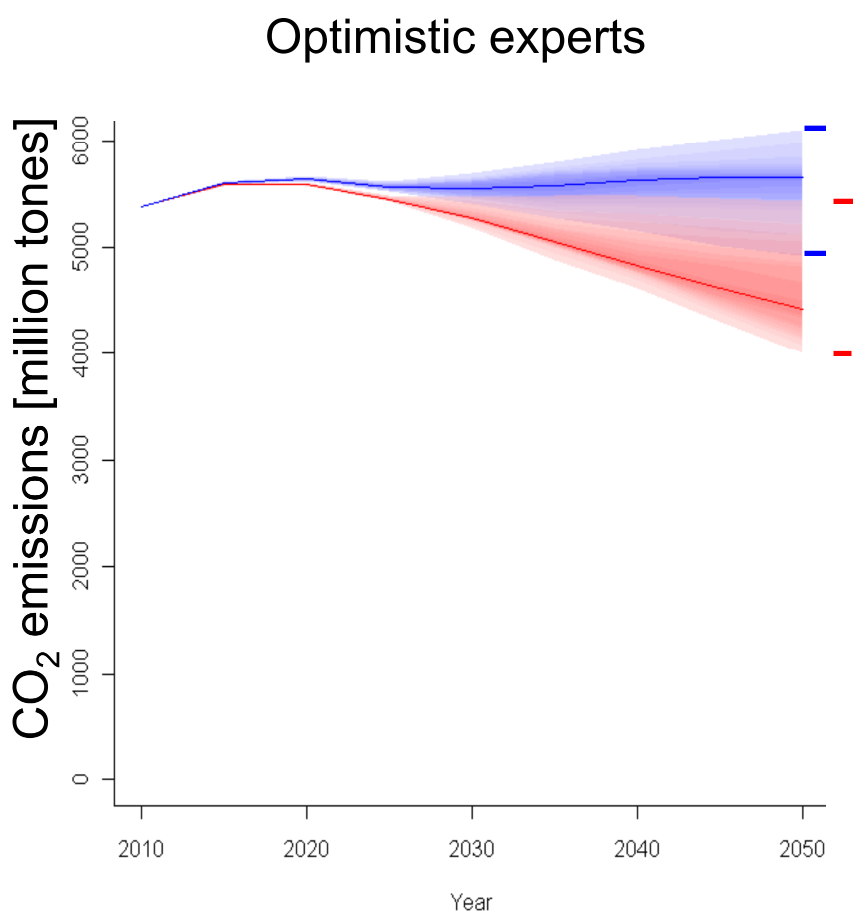
Energy R&D portfolio design with uncertainty

- How much should the U.S. government invest in energy RD&D and on what?

Expert elicitations - 100 experts on the 2030 costs of 25 technologies	→	Generating inputs for MARKAL - 25 technologies, 400 runs per budget and policy scenario	→	Optimizing R&D portfolio - under different policy scenarios and metrics
linking 3 **R&D** budgets and technology **cost**		linking technology **costs** and **outputs** (e.g., system cost)		linking **R&D** and **outputs** (e.g., system cost)

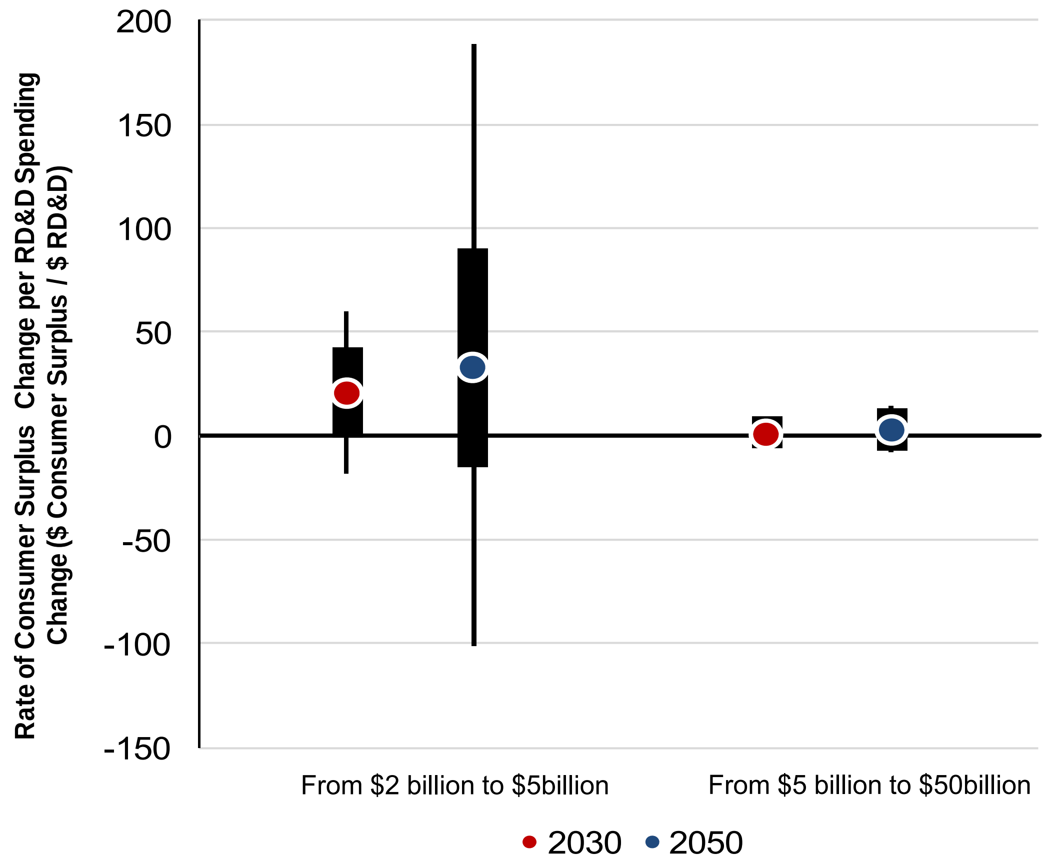
Impact of RD&D on CO_2 emissions under no demand-side policy





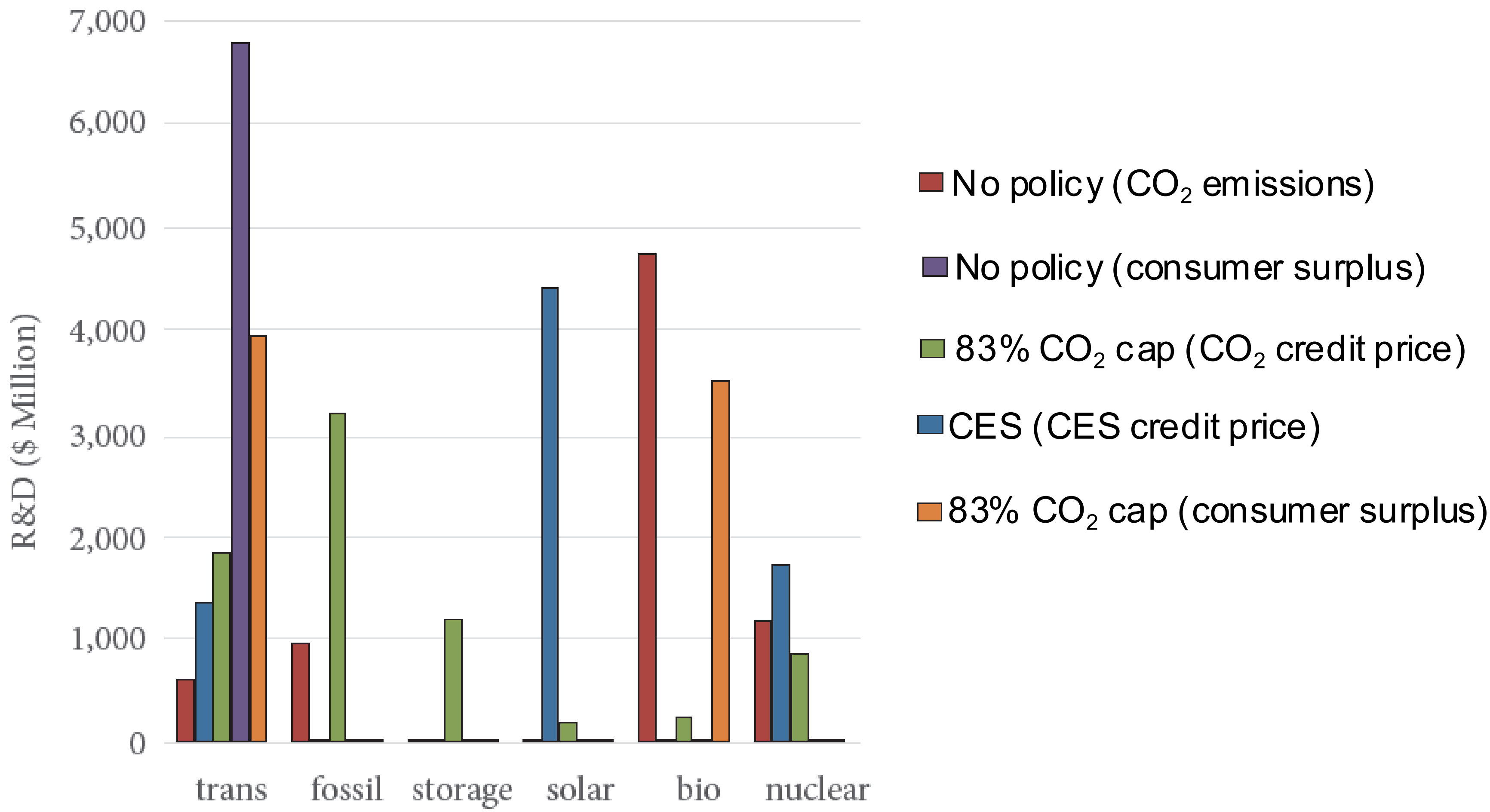
Even if all the optimistic experts are right, and technologies do as well as they possibly can, and the government makes very large RD&D investments, a demand-side policy is needed

Decreasing U.S. marginal returns to RD&D investments



- Large benefit/cost when increasing RD&D$ from $2 to $5 billion (median 25:1)
- Strong decreasing marginal returns on benefits

Optimal energy RD&D allocation by policy and on metric



- $7.5 billion budget constraint

Insights: energy R&D and portfolio design under uncertainty

- *Both* a dramatic increase in energy RD&D investment *and* demand-pull policies to build markets for new energy technologies needed
- Decreasing marginal returns to RD&D after a 2-4 increase in investment depending on policy
- Optimal R&D investment is greater when longer timeframes are taken into account
- Energy storage may be an underfunded technology
- (Results depend on elicitations and model)

Steps for modeling policies and their impact on technological change

Policy
e.g., R&D investments,
CO_2 cap or tax,
deployment subsidies

→ **Technological change mechanisms**

→ **Cost and performance improvements**

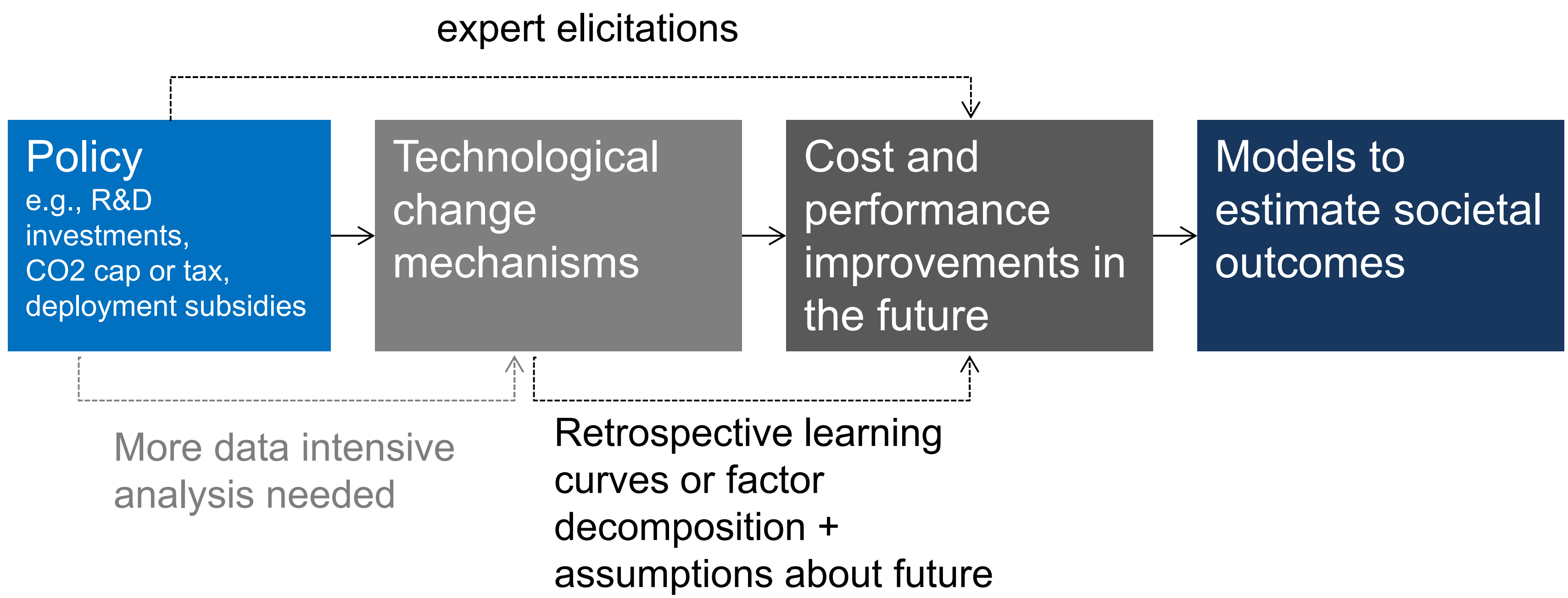
→ **Models to estimate societal outcomes**

Methods for forecasting technological change and the role of policy

Methods	Retrospective (R) or prospective (P)	Role of learning-by-searching	Role of learning-by-doing	Other (e.g., economies of scale, resource quality, input prices)	Example references
Point estimates	P	Involves implicit or explicit assumptions	Involves implicit or explicit assumptions	Involves implicit or explicit assumptions	In some cases questions about transparency and non-consistency.
Expert elicitations	P	Possible to specify R&D$, but difficulty with private $	Possible to specify policy	Could control for some, but burden increases	Curtright et al. 2008; Baker et al. 2010, 2011; Bosetti et al. 2011; Anadon et al. 2011 and 2012; NearZero.org
Learning curves	R	Public R&D a good proxy? Difficulty obtaining private R&D	Need more interpretation	Could control for some	Rubin et al. 2004; Juninger et al. 2005; Coulomb & Neuhoff 2006; Klaassen et al. 2005; Soderholm & Sundqvist 2007; Qiu & Anadon (2012)…
Factor decomposition	R	Through improved efficiency, but no easy link to R&D $	Through capacity factors, faster installation, etc	Some could be included	Nemet (2007); McNerney et al. (2011); Powell et al. (2012)…

- Ongoing work combines insights from elicitations & learning curves

Steps for modeling policies and their impact on technological change



- Approaches have very important tradeoffs
- Data availability is often a defining factor

4. Concluding remarks

- If policies have the goal of making a technology cost-competitive, it is important to know about the factors that may contribute to innovation

- Our understanding of the factors (e.g., different types of learning) contributing to innovation and the impact of policies needs to improve
  - Difficult to separate LBS and LBD in two-factor learning curves
  - Additional systematic bottom-up work on different factors is necessary to determine how good of a proxy simplifications are, or what they assume
  - Possible to use models with a combination of improved retrospective understanding with some version of expert elicitations

- There is a need to improve the characterization and modeling of uncertainty to estimate policy outcomes and design resilient and flexible policies

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Thank you very much for your attention

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