

Patterns of technological evolution

SFI complex systems summer school
June 25, 2009

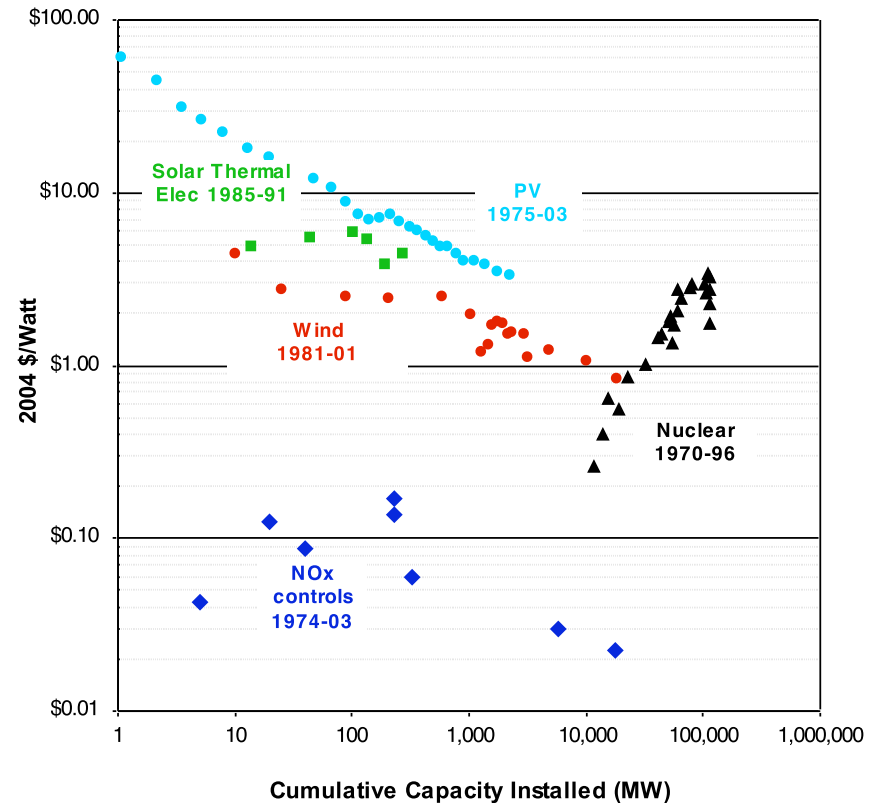
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Outline

- Are there patterns in technological evolution and improvement?
- Can they be used to forecast technological trajectories?
- What might cause these patterns?

Performance curves

- Worker output in airplane manufacturing (Wright, 1936)
- Cost of a technology across entire industry (BCG, 1968)
- Observed for aggregates of technologies and diverse metrics
- Functional form assumed:
 $y = ax^{-b}$ and *Progress ratio* = 2^{-b}
- Used to predict future costs
- How reliable are projections?
- How to design portfolios?



(Nemet, *Energy Policy*, 2007)

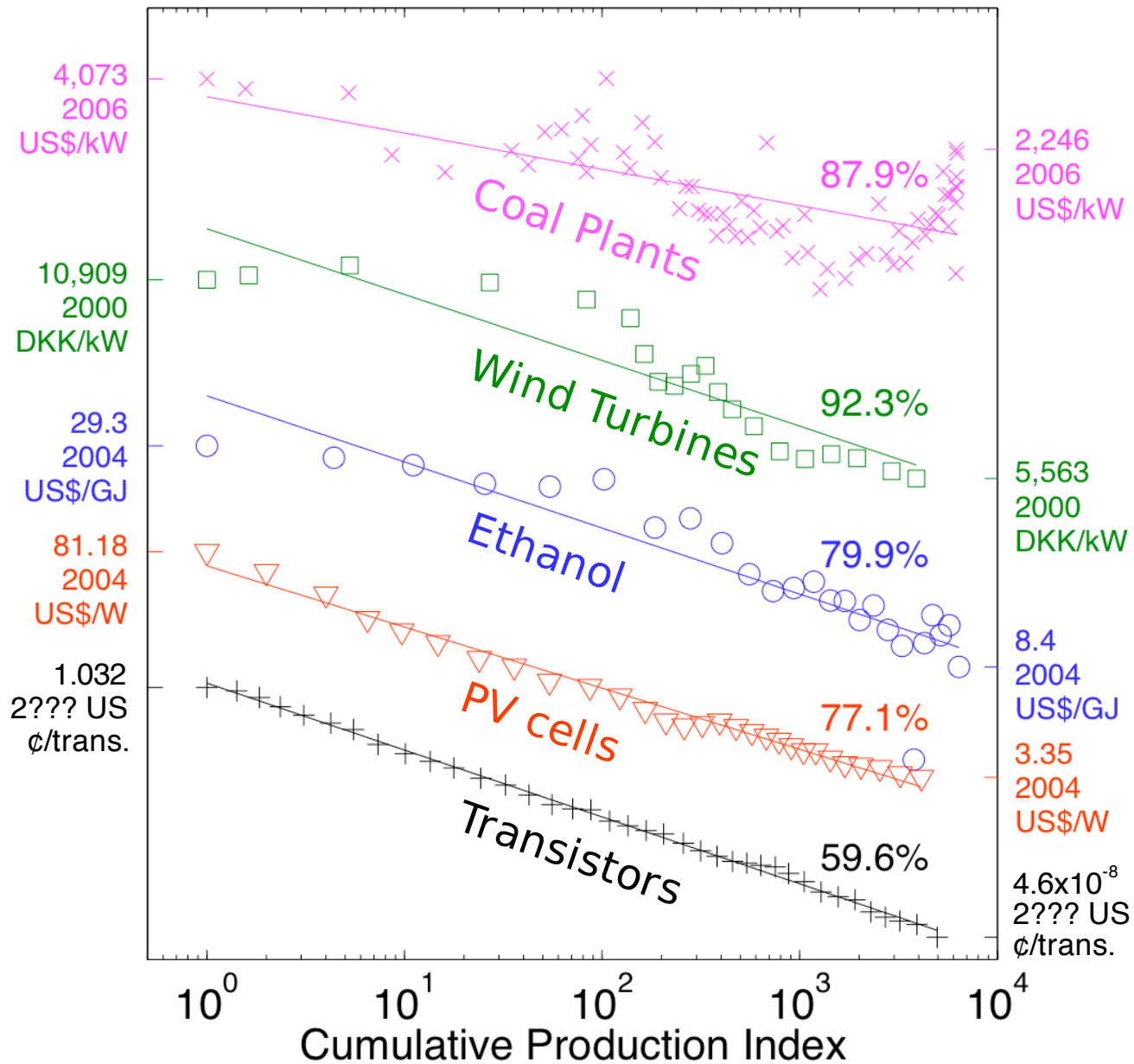
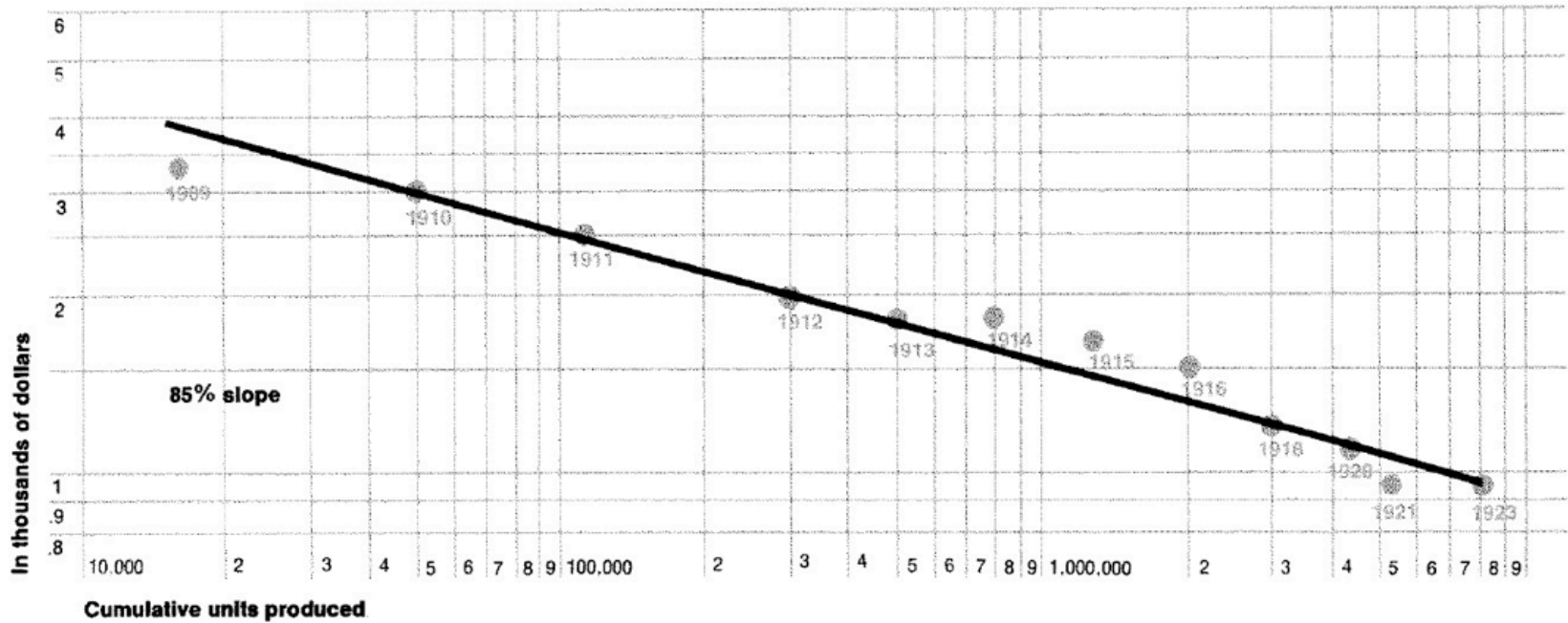
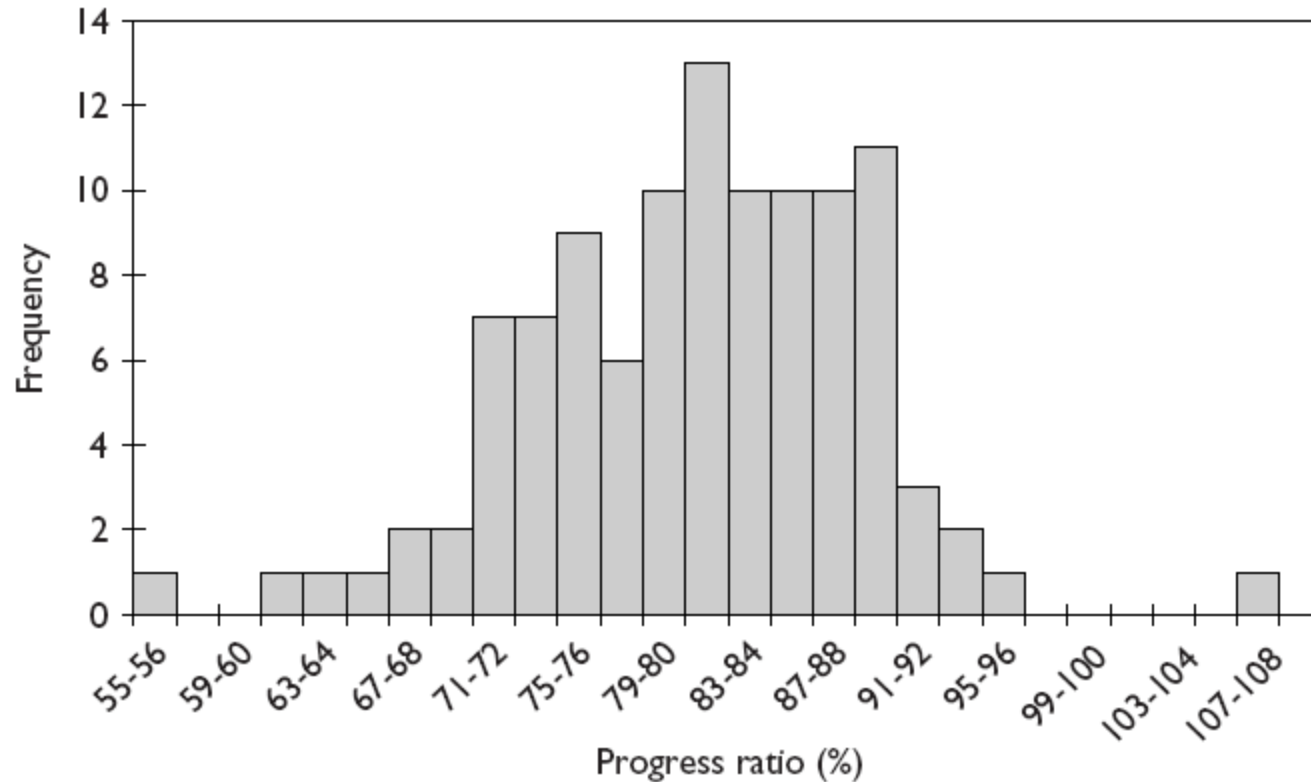


Exhibit I

Price of Model T, 1909-1923 (Average list price in 1958 dollars)



Diversity of performance ratios



Progress ratios 108 cases, 22 field studies, electronics, machine tools, system components for electronic data processing, papermaking, aircraft, steel, apparel, and automobiles (Dutton and Thomas, 1984)

Cross-over sensitively depends on progress ratio

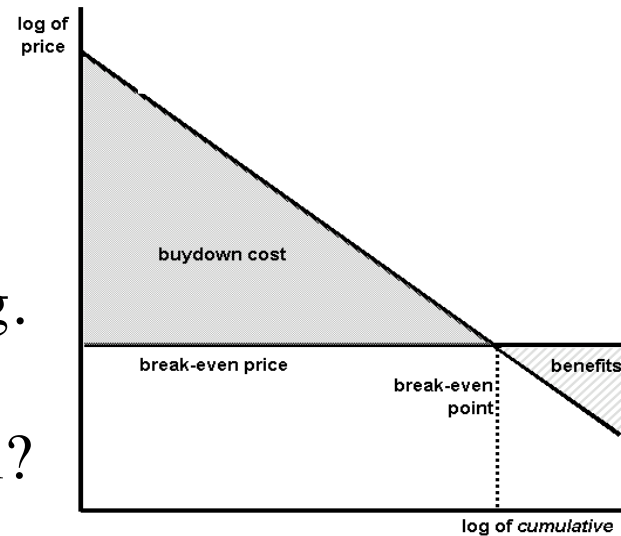
- Under assumptions about progress ratios, can estimate cost of achieving parity between two technologies. E.g. what is capacity increase needed to break even with coal?

- Very sensitive to PR:

- 0.75 $\Rightarrow$ 30B

- 0.8 $\Rightarrow$ \$60B

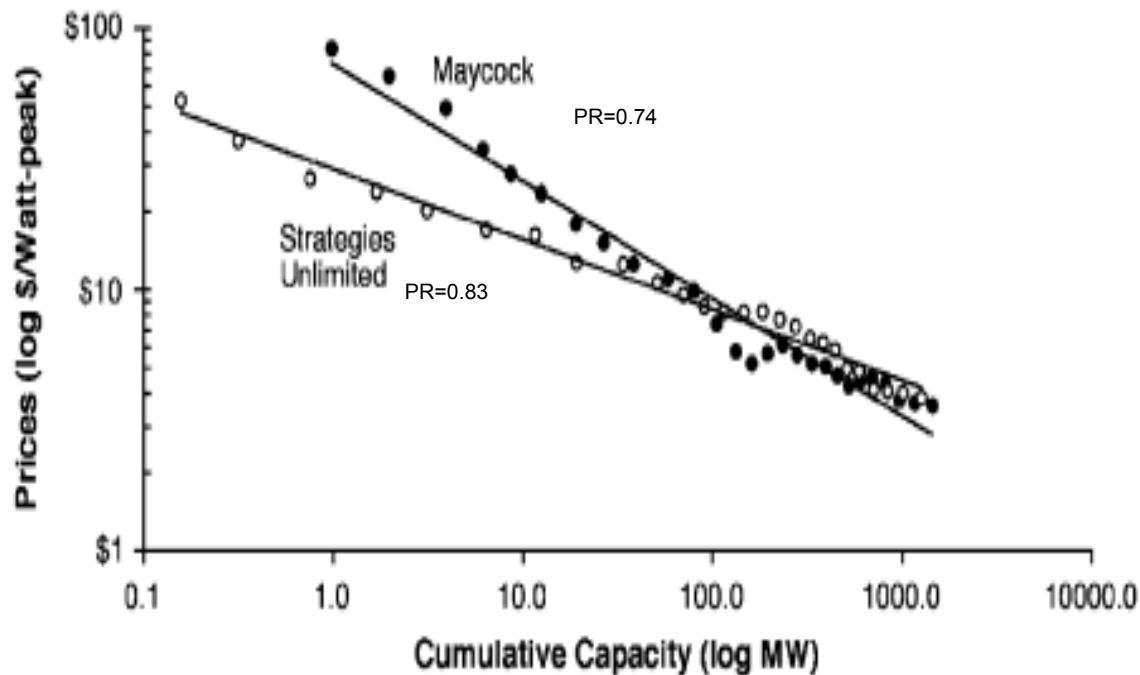
- 0.85 $\Rightarrow$ \$300B



(Duke, RFF presentation, 2003)

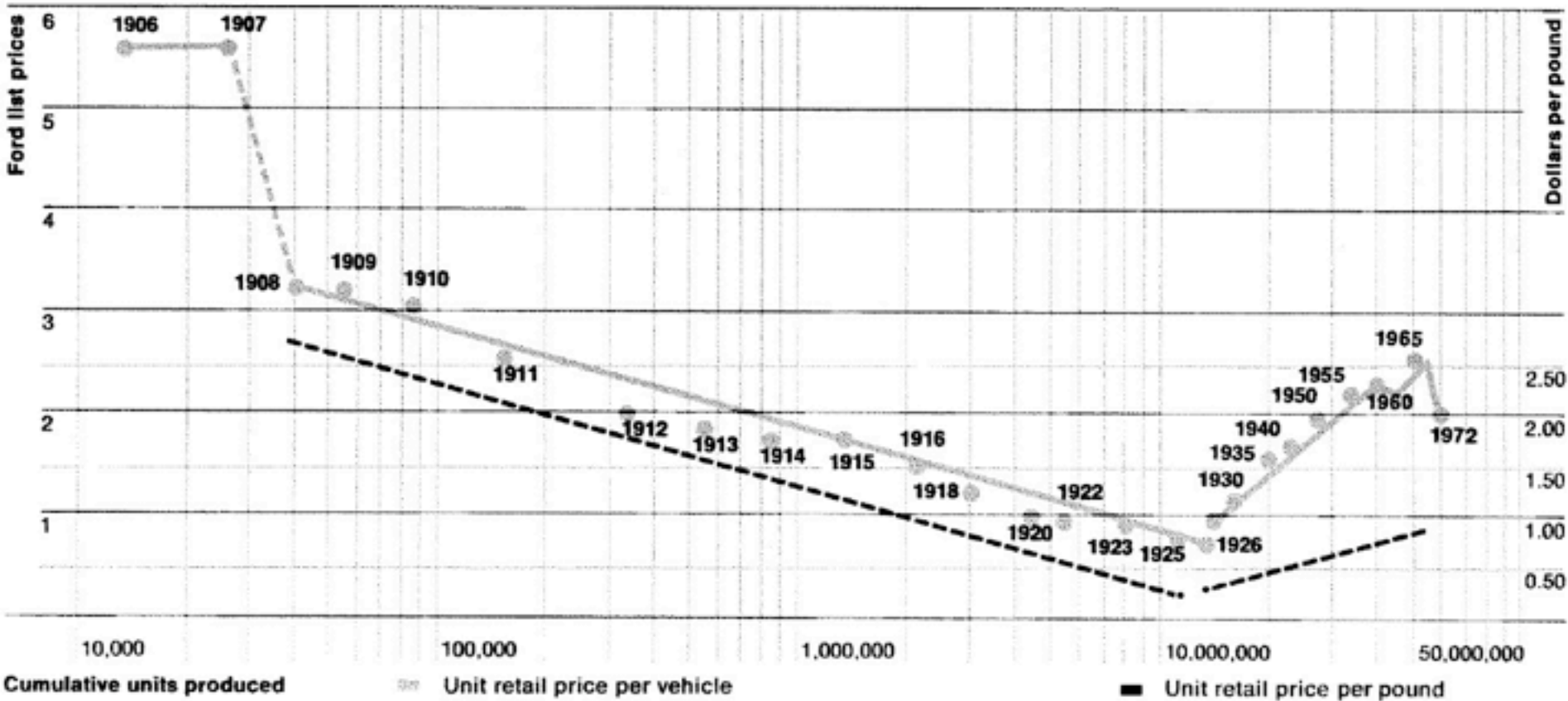
Performance curves -data problems

- Data discrepancies / curve fitting
(lack of out-of-sample testing)
- Price data vs. cost data



Photovoltaics performance curves (Nemet, *Energy Policy*, 2006)

Models	ABCNRSK	T	A	Annual model changes
Engines (H.P.)	2 (15 & 50)	1 (20)	1 (24)	2 or more (50 & more)
Wheel bases	2	1	1	2 or more
Weights	Up to 1800	1100-1820	2312 (average)	2335 and up (average)



IS TECHNOLOGICAL PROGRESS PREDICTABLE?

- Joint work with Bela Nagy and Jessika Trancik

**IS TECHNOLOGICAL
PROGRESS
PREDICTABLE?**

y_t = price in year t

q_t = number of units produced in year t

e_t = number of units produced prior to year t

Moore: $\log y_t$ = intercept + slope t + random error

Goddard: $\log y_t$ = intercept + slope $\log q_t$ + random error

Wright: $\log y_t$ = intercept + slope $\log(e_t + q_t)$ + random error

Sinclair: $\log y_t$ = intercept + slope₁ $\log e_t$ + slope₂ $\log q_t$ + random error

Nordhaus: $\log y_t$ = intercept + slope₁ t + slope₂ $\log(e_t + q_t)$ + random error

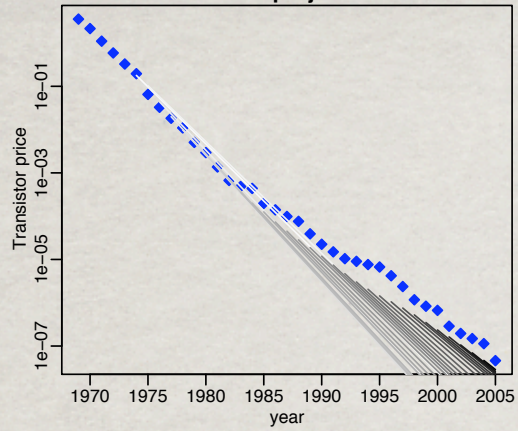
- Double exponentials

$$x(t) = \exp(at)$$

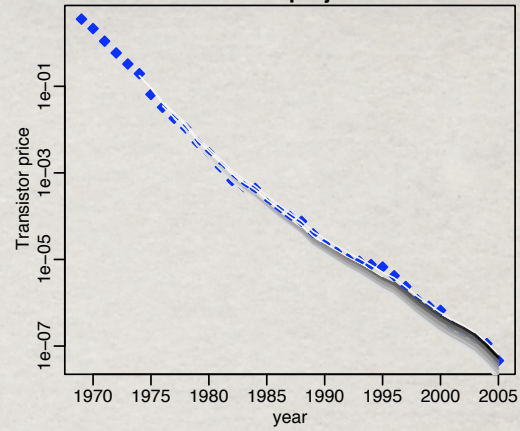
$$y(t) = \exp(-bt)$$

$$y(x) = x^{-b/a}$$

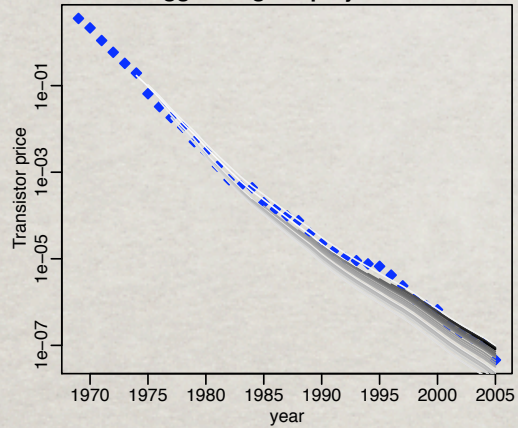
Moore's projections



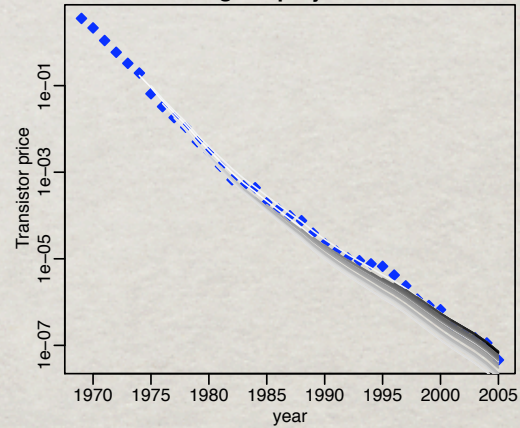
Goddard's projections



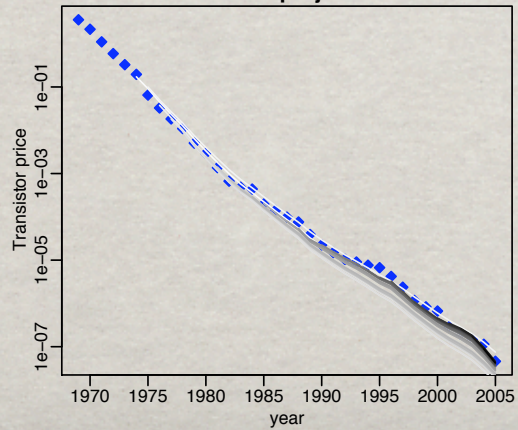
laggedWright's projections



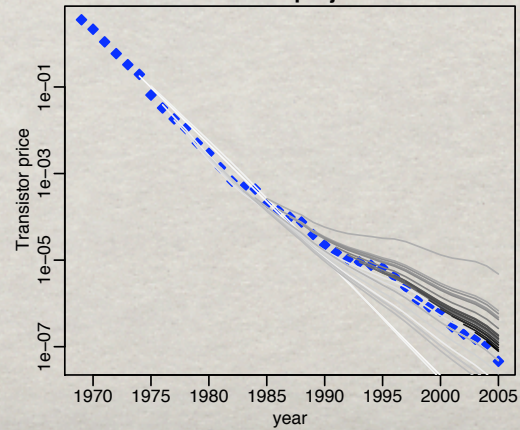
Wright's projections



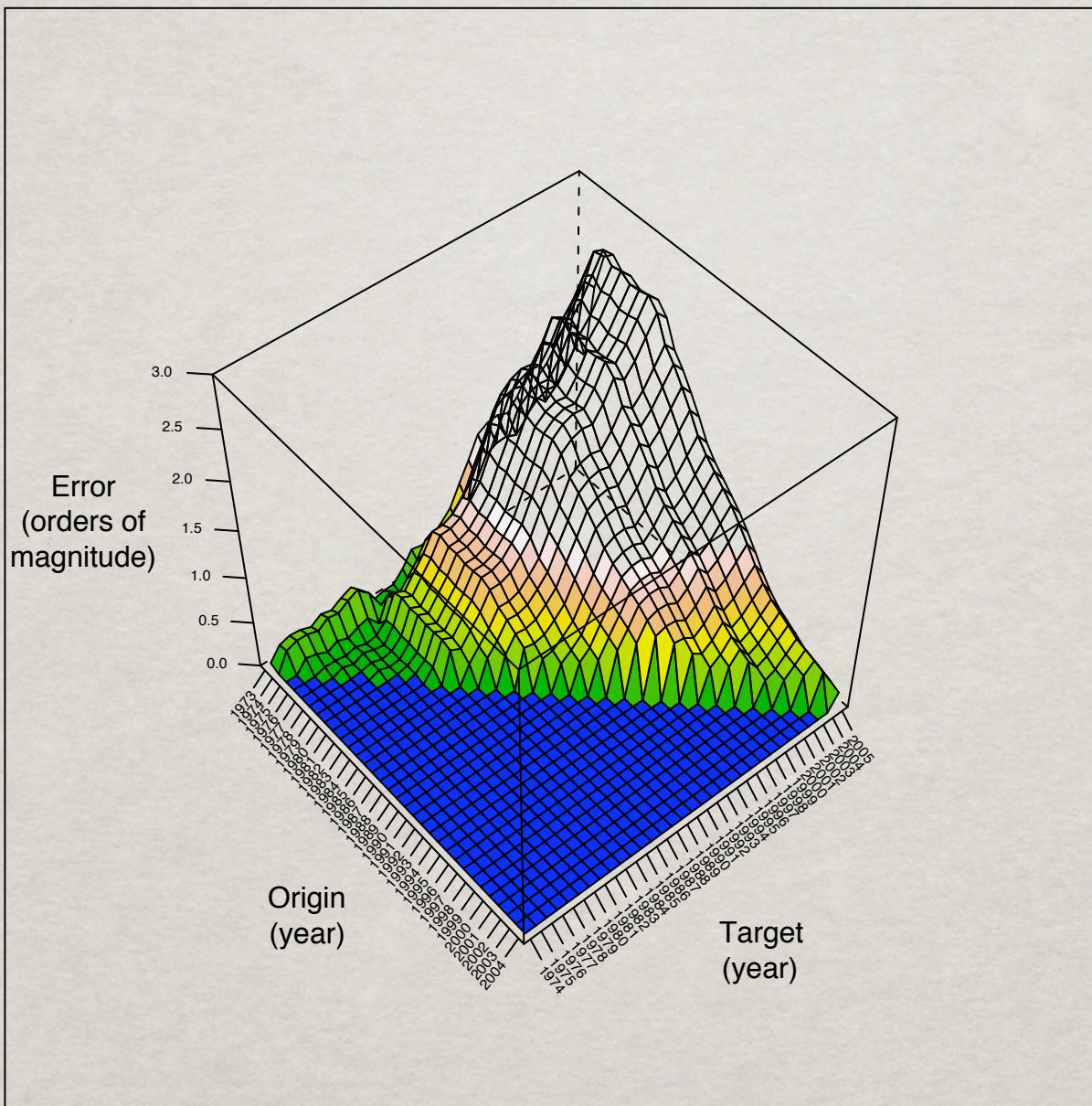
Sinclair's projections

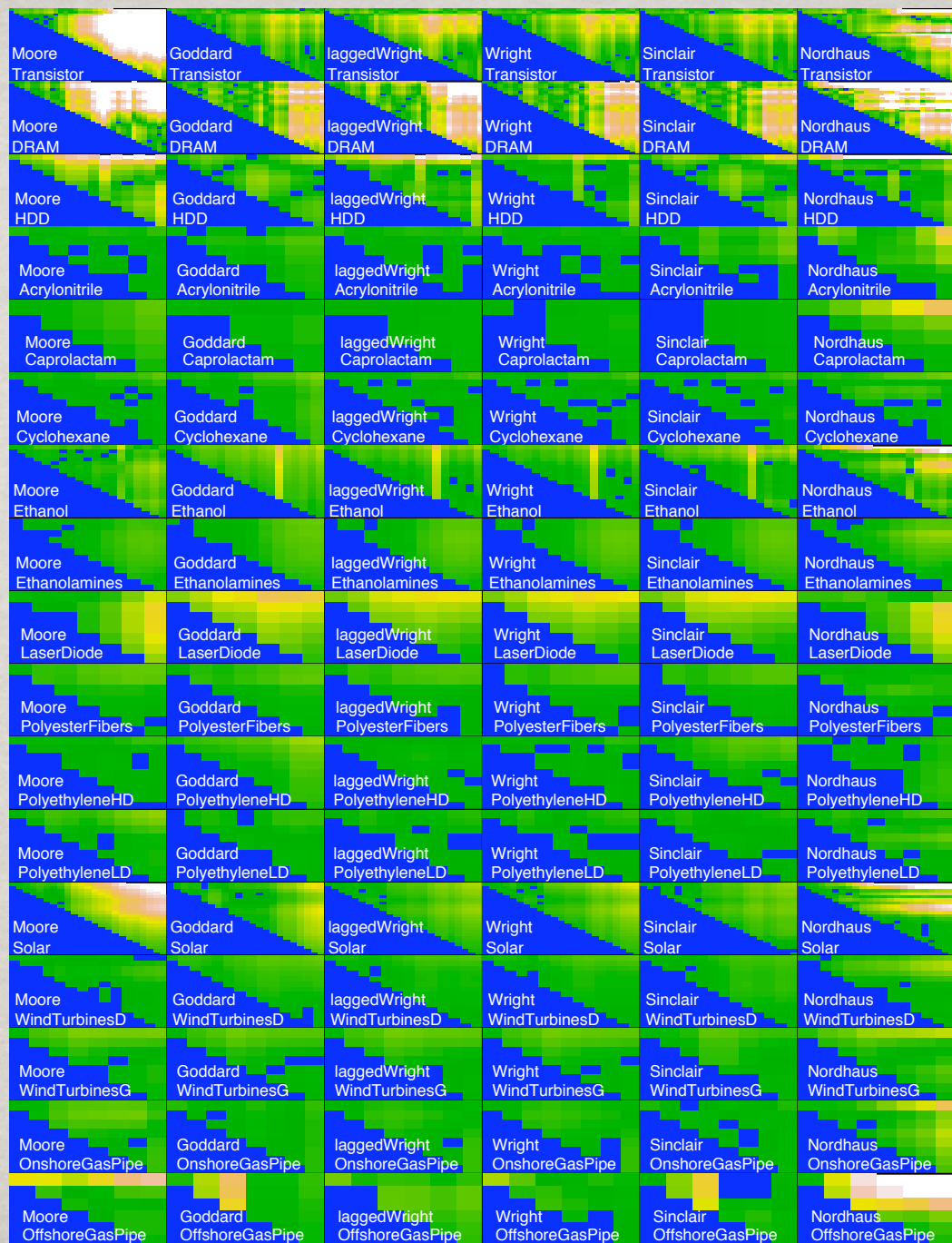


Nordhaus's projections



Moore's error mountain





ERROR ANALYSIS

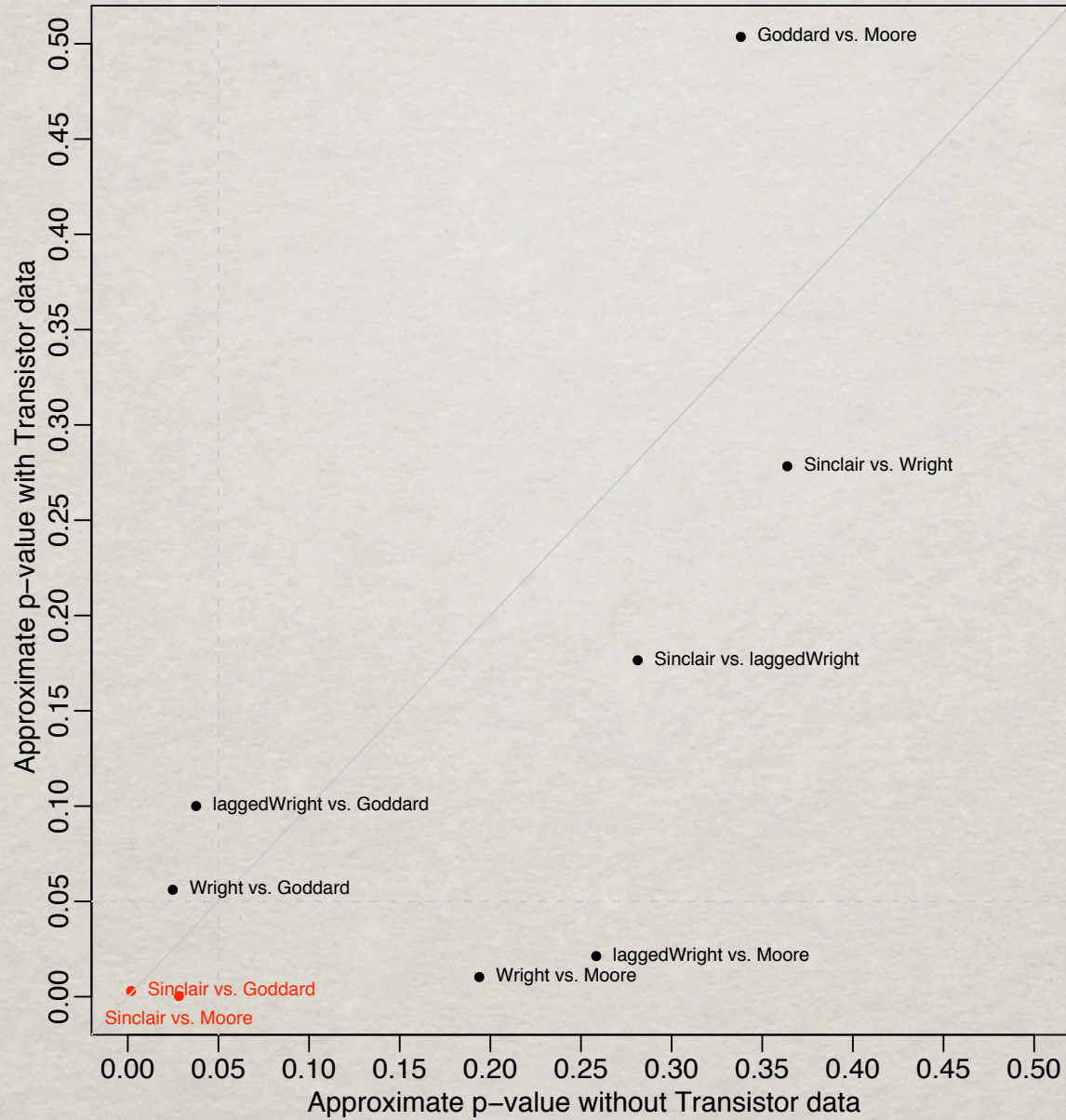
$$r_{fdij} = \left| \log y_j^{(d)} - \log \hat{y}_j^{(f,d,i)} \right|^{0.5},$$

$$r_{fdij} = \alpha_f + \beta(j - i) + a_d + b_d(j - i) + \varepsilon_{fdij}$$

<i>Fixed effect parameters</i>	<i>Estimates with Transistor data</i>	<i>Estimates without Transistor</i>
α_{Moore}	0.241	0.219
α_{Goddard}	0.230	0.234
$\alpha_{\text{laggedWright}}$	0.205	0.202
α_{Wright}	0.202	0.199
α_{Sinclair}	0.188	0.187
β	0.025	0.026

Table 1: Parameter estimates for the fixed effects with and without the Transistor data set (rounded to three digits).

Testing the differences between the functional form effects



RESULTS

- Sinclair consistently beats Moore and Goddard
- Sinclair is slightly better than Wright, but this is not statistically significant.
- Economic interpretation:
 - Learning: More production implies more demand, implies more effort to improve.
 - Economy of scale may also be important.

MODEL OF LEARNING

- Joint work with James McNerney, Sid Redner, and Jessika Trancik

AUERSWALD ET AL.

$$\omega = (\omega_1, \dots, \omega_n)$$

- Production recipe

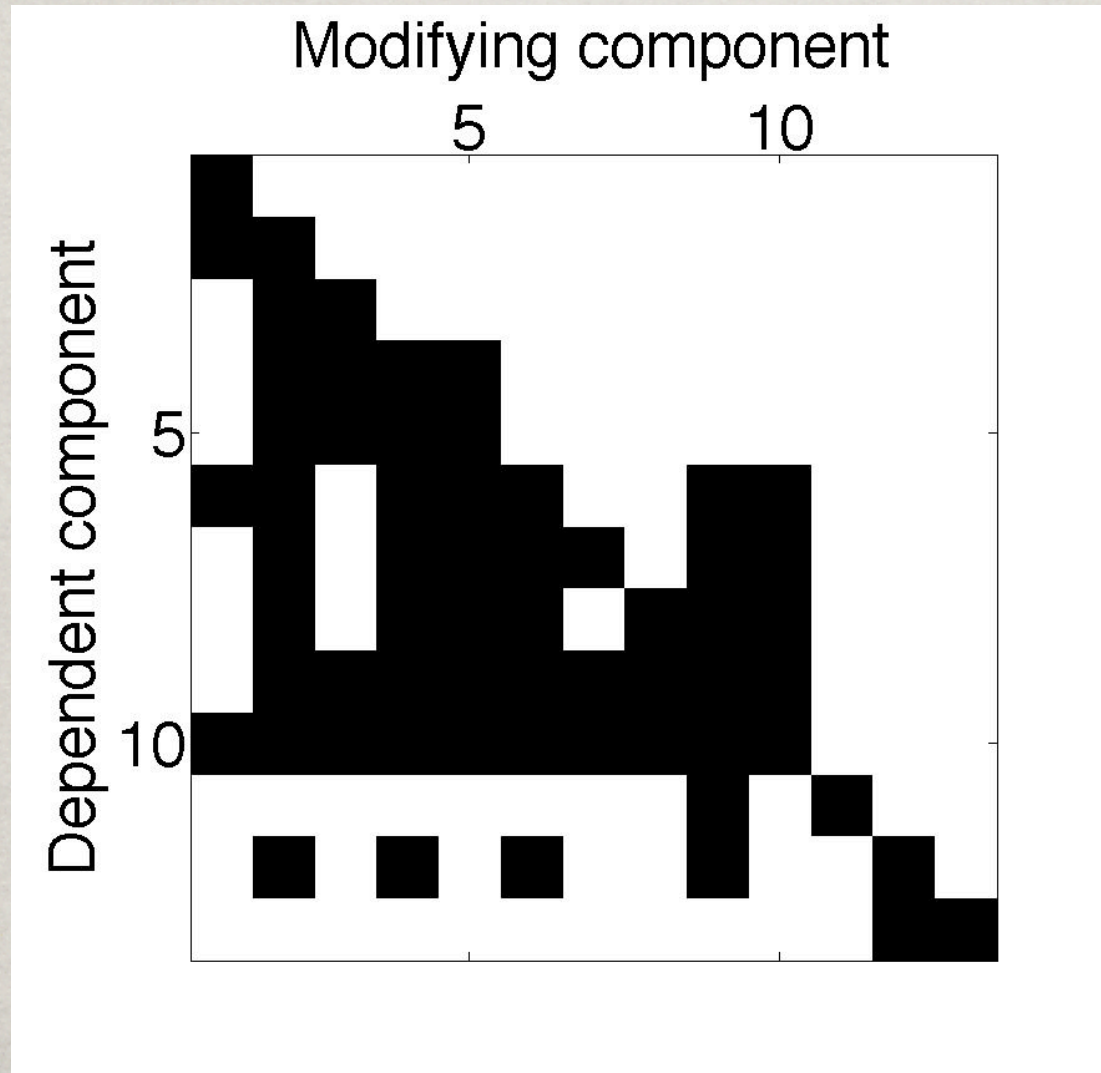
$$\phi(\omega) = \sum_{i=1}^n \phi^i(\omega)$$

- Production costs are additive

- Each operation is affected by d operations.

- Innovation proceeds through a series of trials in which d operations ω_i are altered.

DESIGN STRUCTURE MATRIX FOR AUTOMOBILE BRAKE SYSTEM



- Pick a component i
- Randomly change its cost and all the costs of the d components that it affects.
- If the total cost decreases, accept the change.

Analysis

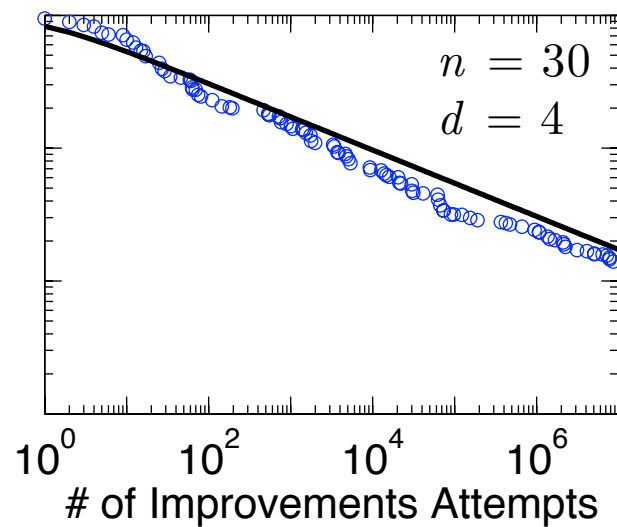
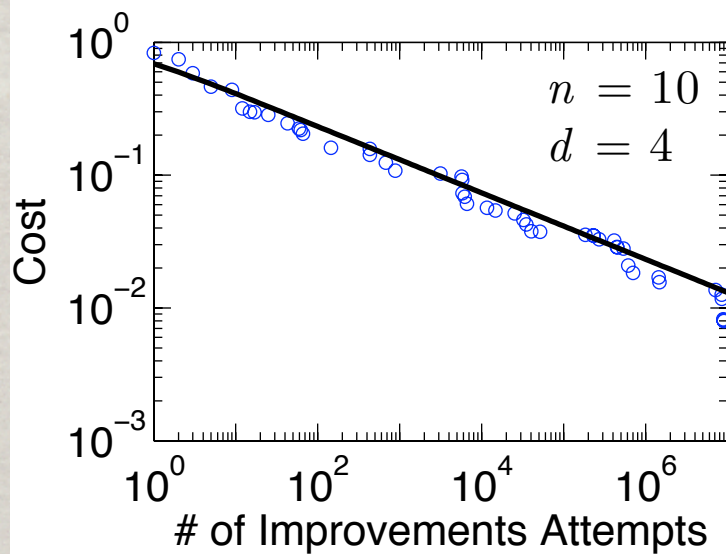
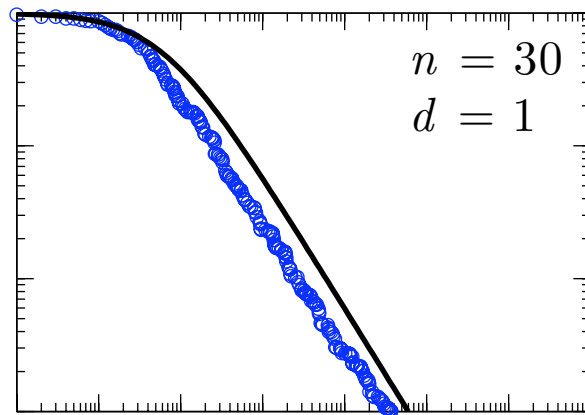
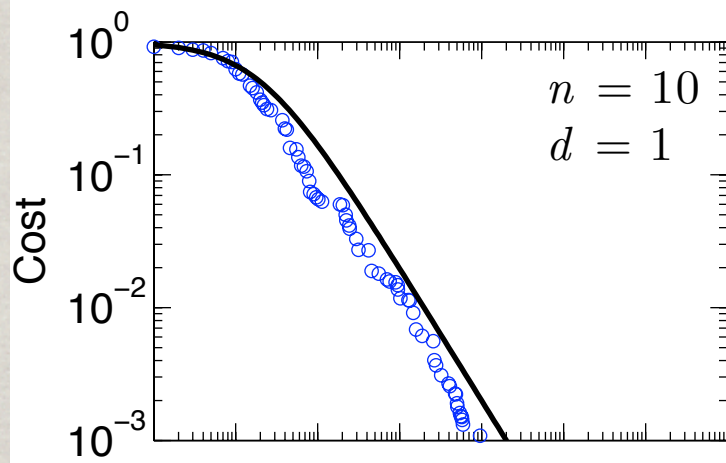
1 dependency:

$$\frac{d\phi}{dy} \propto -\phi \left(\frac{\phi}{2} \right) \quad \longrightarrow \quad \phi(y) \sim y^{-1}$$

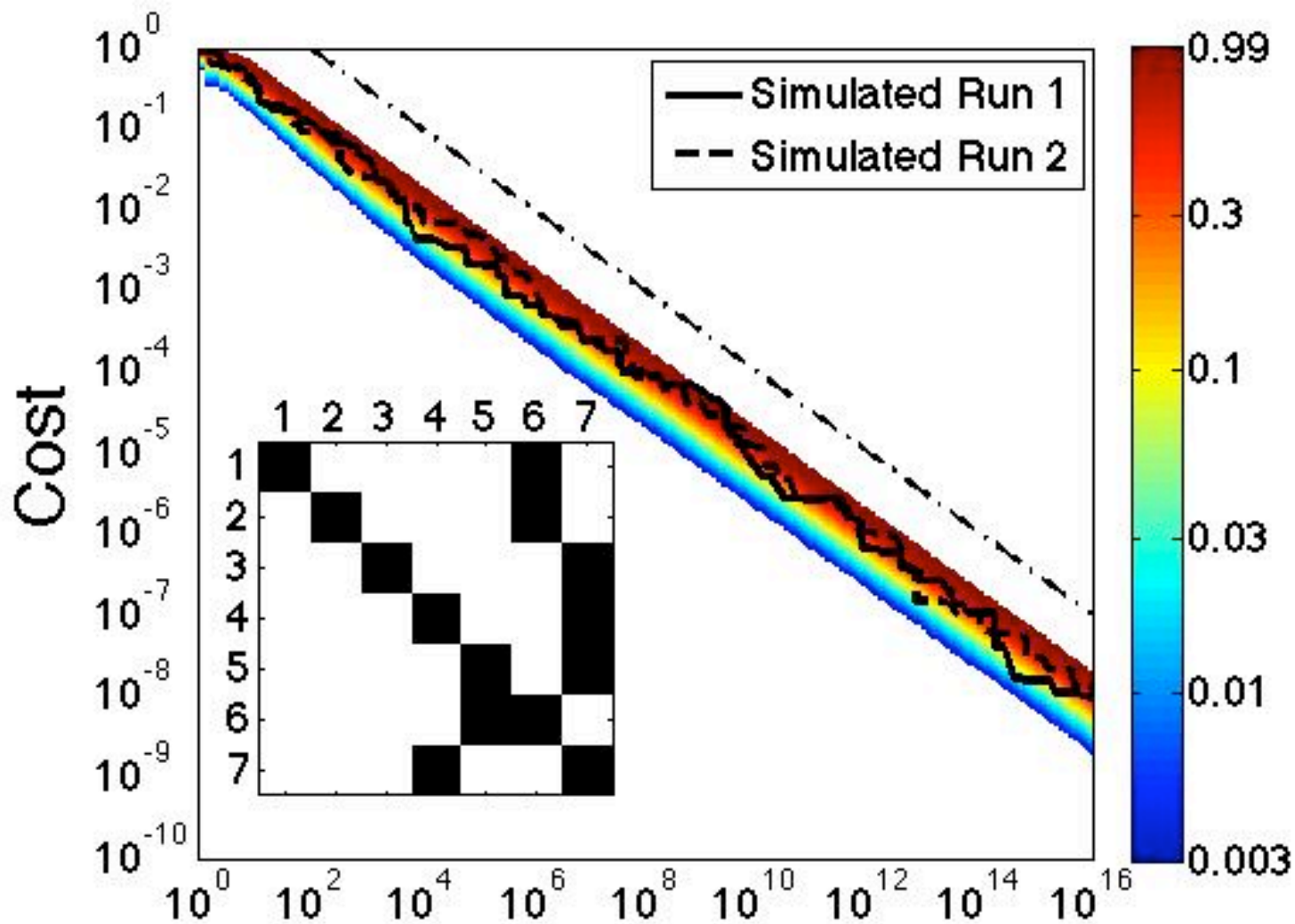
- Size of reductions decreases exponentially, and it takes exponentially more time to reach reductions

d dependencies:

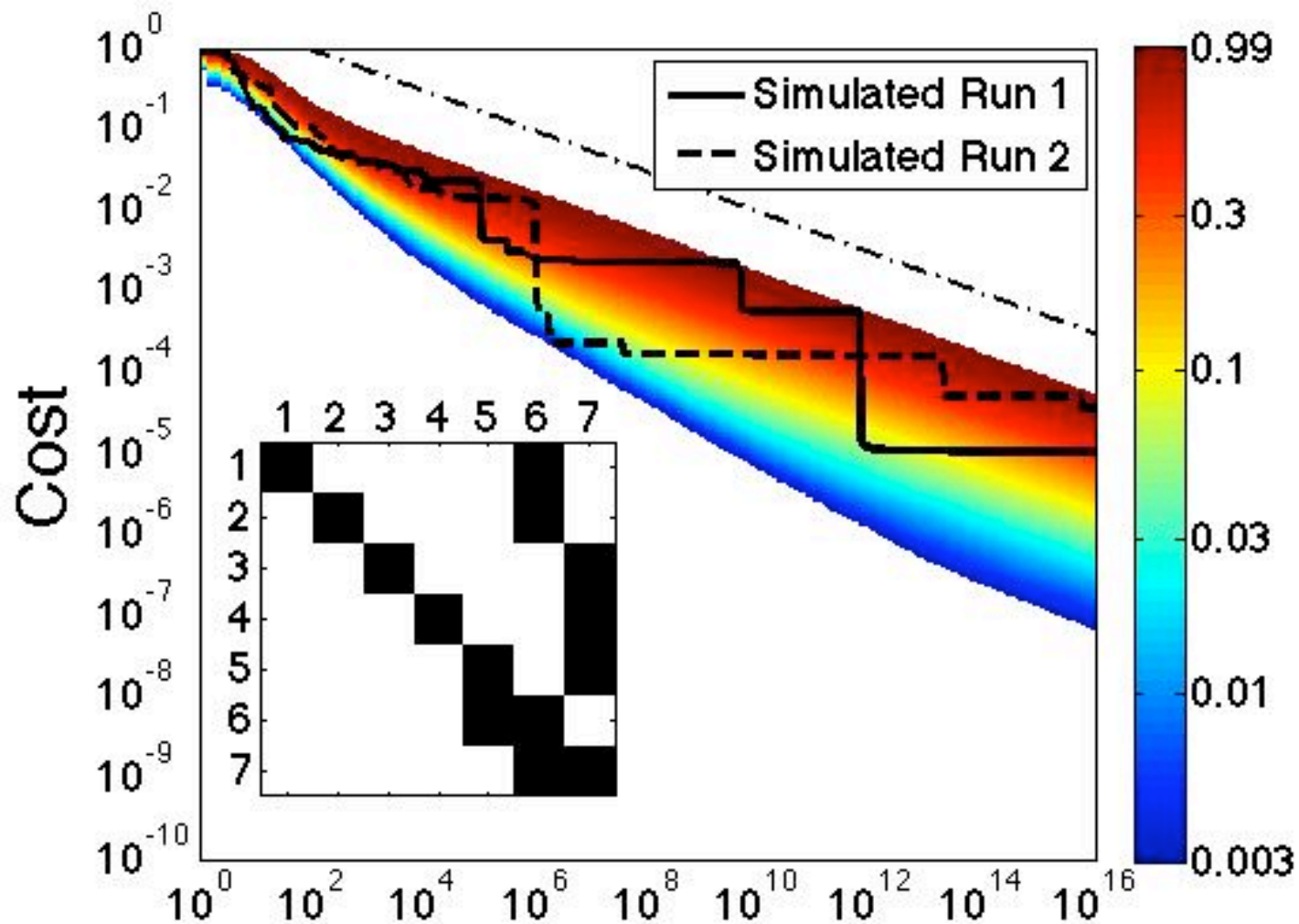
$$\frac{d\phi}{dy} \propto -p(\phi' < \phi) \left(\frac{\phi}{2} \right) \quad \longrightarrow \quad \phi(y) \sim y^{-\frac{1}{d}}$$
$$p(\phi' < \phi) \sim \phi^d$$



CONSTANT OUT-DEGREE



VARIABLE OUT-DEGREE



PREDICTIONS OF MODEL

- Rate of improvement depends on interconnectness of components, not on total number.
- Variable interconnectness can cause punctuated equilibria in performance curve.

OVERALL CONCLUSIONS

- Improvement of existing technologies is predictable.
- How to deal with new technologies?
- Need better learning models.
- Better economy of scale models.