An evolutionary view of technological progress

Complex systems summer school
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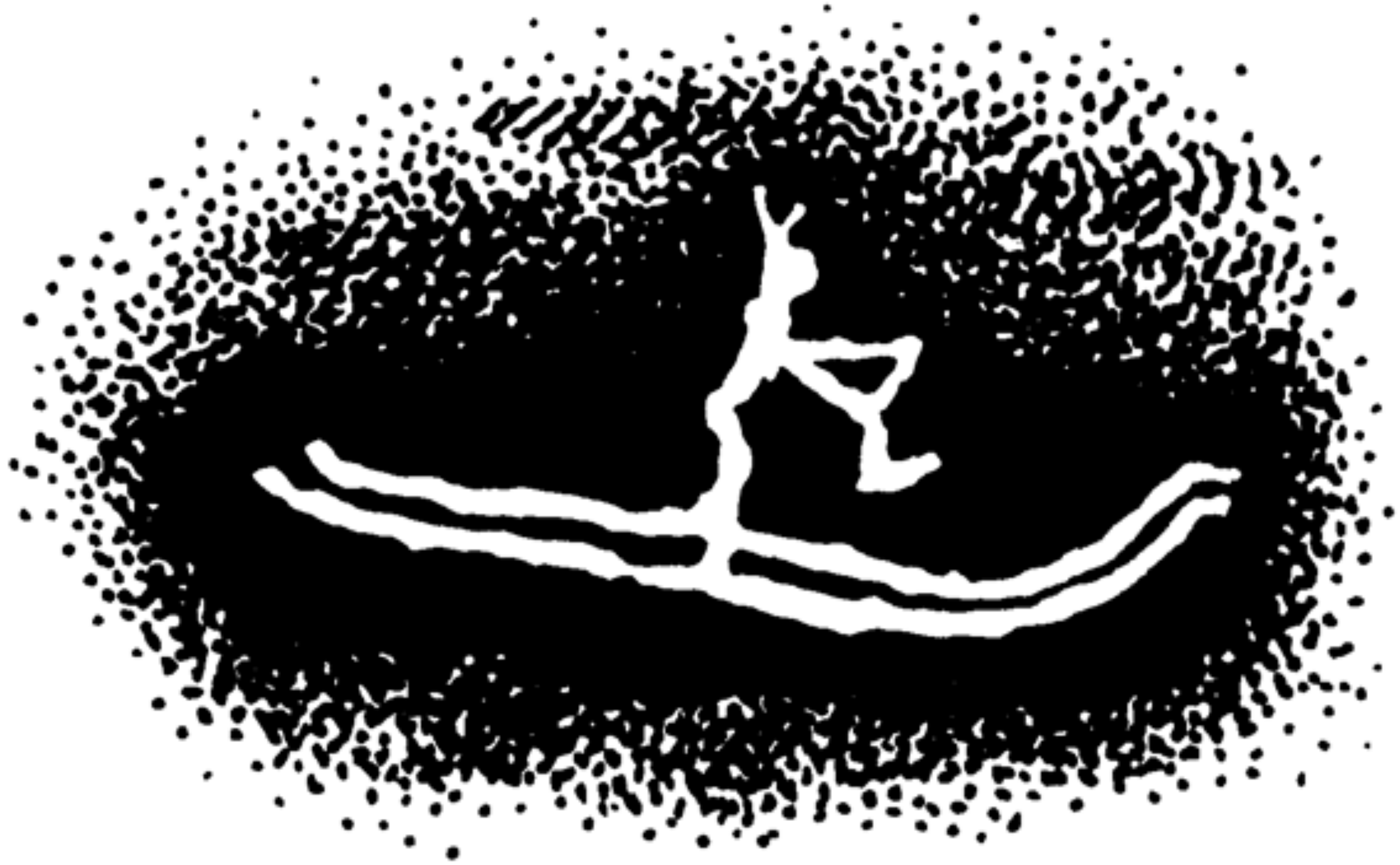
Outline of talk

- Motivation
  - technology as evolutionary process
  - understanding economic growth
  - economic mitigation of global warming
- Empirical study of rates of technological change
- Empirical laws for technological improvement
  - Wright's law
  - Moore's law
- Recipe model for Wright's law
- Analogy to autocatalytic networks
- Evolutionary extension of Leontief model
- Patent history as fossil record

Technology is an evolutionary process

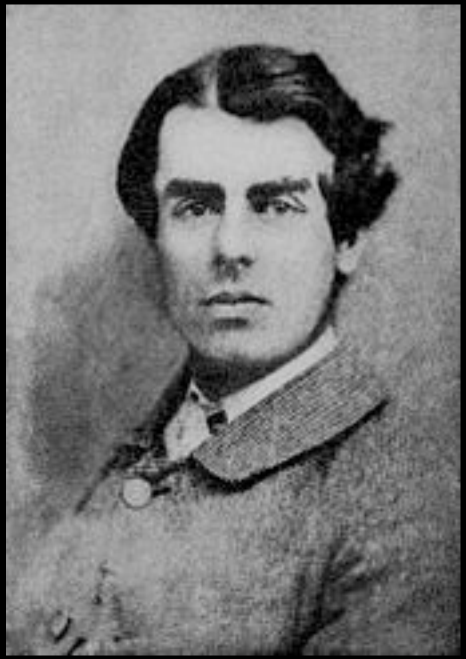


Man on skis. Stone Age rock carv-
ing, north Norway

Technology co-evolved with genus homo

First tool use, homo habilus, 2.3M yrs ago.

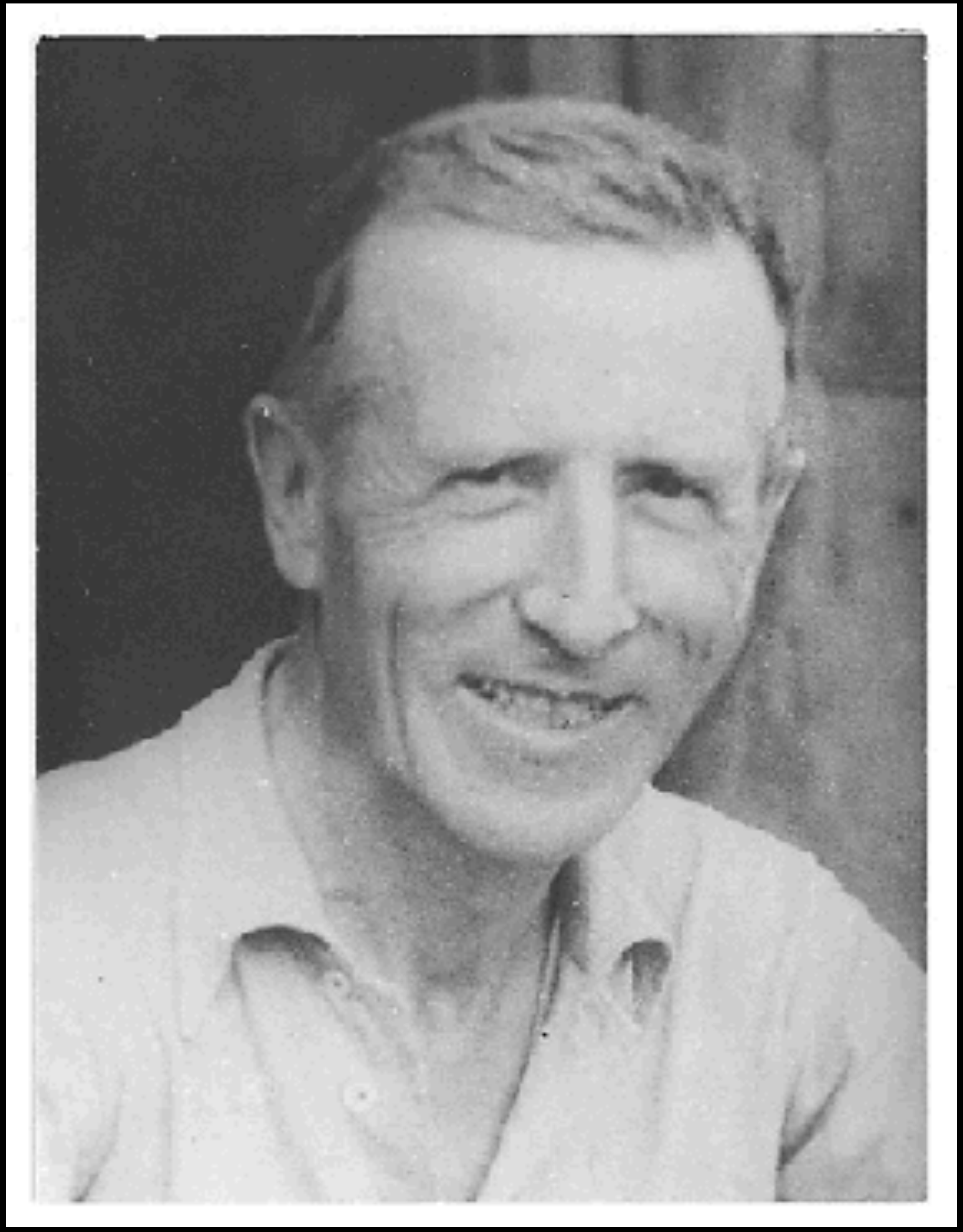
Darwin among the machines
(Samuel Butler, 1863)



- Evolution in the Darwinian sense:
  - descent with modification and selection
  - Erewhon (1872)

Butler imagined technology competing with humanity:
"In the course of the ages we shall find ourselves the inferior race"

The noosphere



Pierre Teilhard de Chardin

- de Chardin envisioned biology, technology and culture co-evolving to form a greater whole, the “noosphere”.

Biological vs. technological evolution

(see Sole et al., Complexity, 2012)

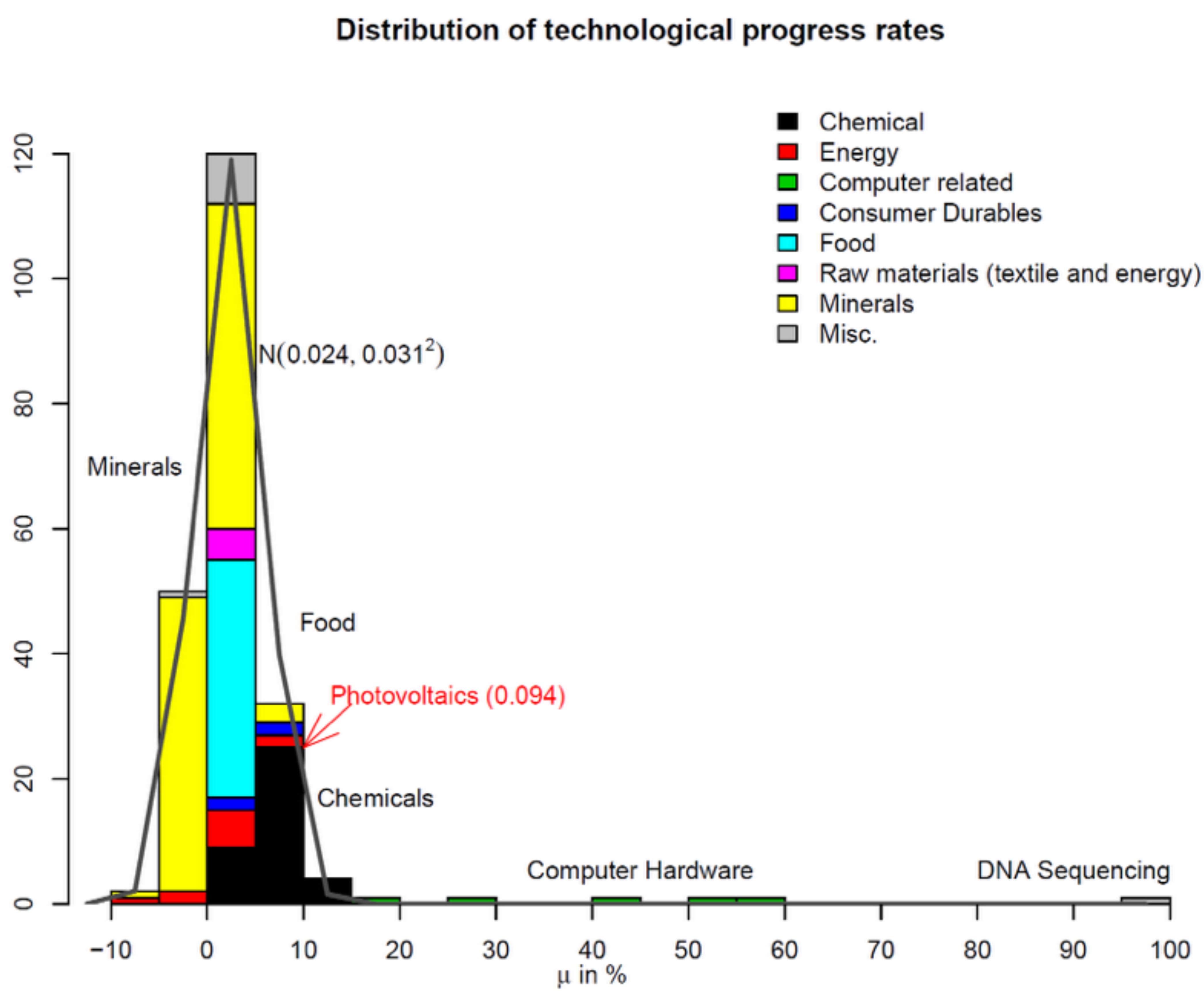
- Similarities
  - Both driven by selection
  - Both result in diversity
  - Incremental variation
  - Temporal progression
  - Purposeful function of units
- Differences
  - Self-reproduction vs. artificial manufacture
  - Random variation vs. conscious design
  - Microscopic vs. macroscopic scale of organization
  - Innovation in technology analogous to horizontal gene transfer (like bacteria)
  - Developmental process of technology is highly distributed

What drives economic growth?

- Solow (1956): Investment can’t explain it — technological progress is dominant cause
  - technology is just a scalar “A(t)”.
- Rosenberg: Must get inside the black box.
- Arthur: Emphasizes role of combination

Need a predictive theory

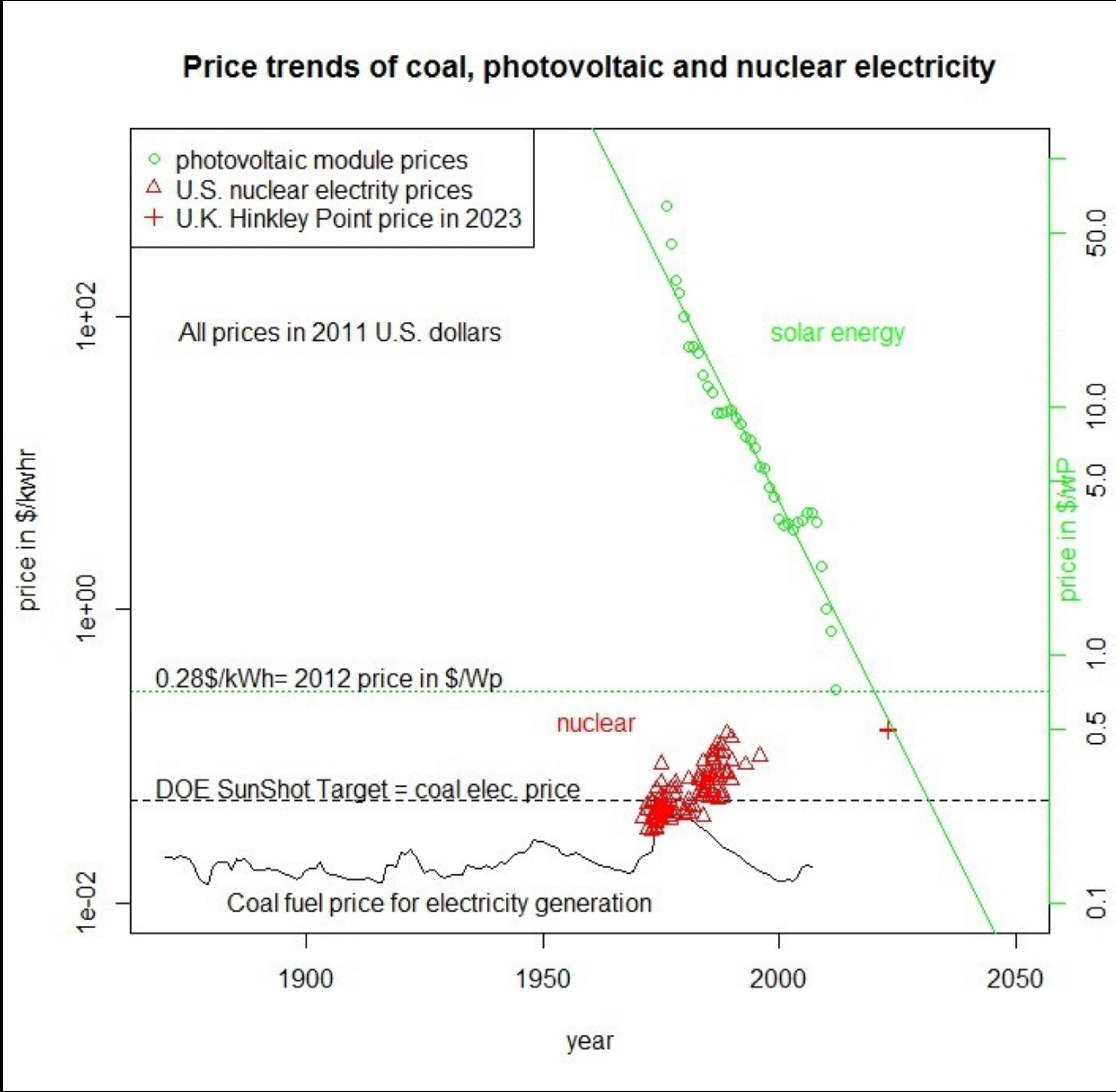
Technologies improve at very different rates



Distribution of technological progress rates
Chemical
Energy
Computer related
Consumer Durables
Food
Raw materials (textile and energy)
Minerals
Misc.
N(0.024, 0.031²)
Minerals
Food
Photovoltaics (0.094)
Chemicals
Computer Hardware
DNA Sequencing
0
20
40
60
80
100
120
−10
0
10
20
30
40
50
60
70
80
90
100
μ in %

Consequences for public investment

It is essential that we take the dramatic differences in rates of technological evolution into account when we consider public investment in technology R&D.



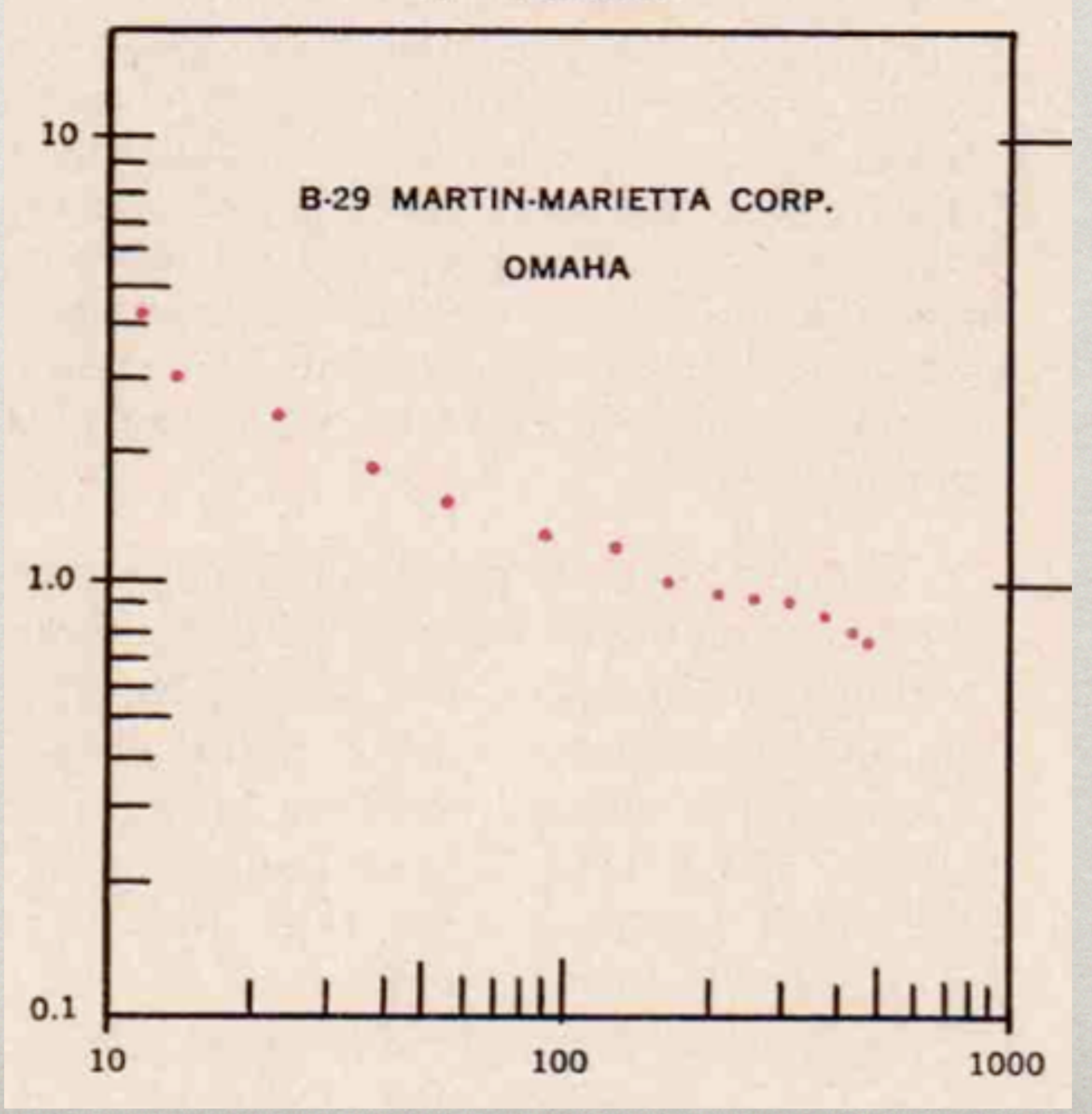
Price trends of coal, photovoltaic and nuclear electricity
photovoltaic module prices
U.S. nuclear electrity prices
U.K. Hinkley Point price in 2023
All prices in 2011 U.S. dollars
solar energy
0.28$/kWh= 2012 price in $/Wp
nuclear
DOE SunShot Target = coal elec. price
Coal fuel price for electricity generation
price in $/kwhr
1e+02
1e+00
1e-02
price in $/WP
50.0
10.0
5.0
1.0
0.5
0.1
1900
1950
2000
2050
year

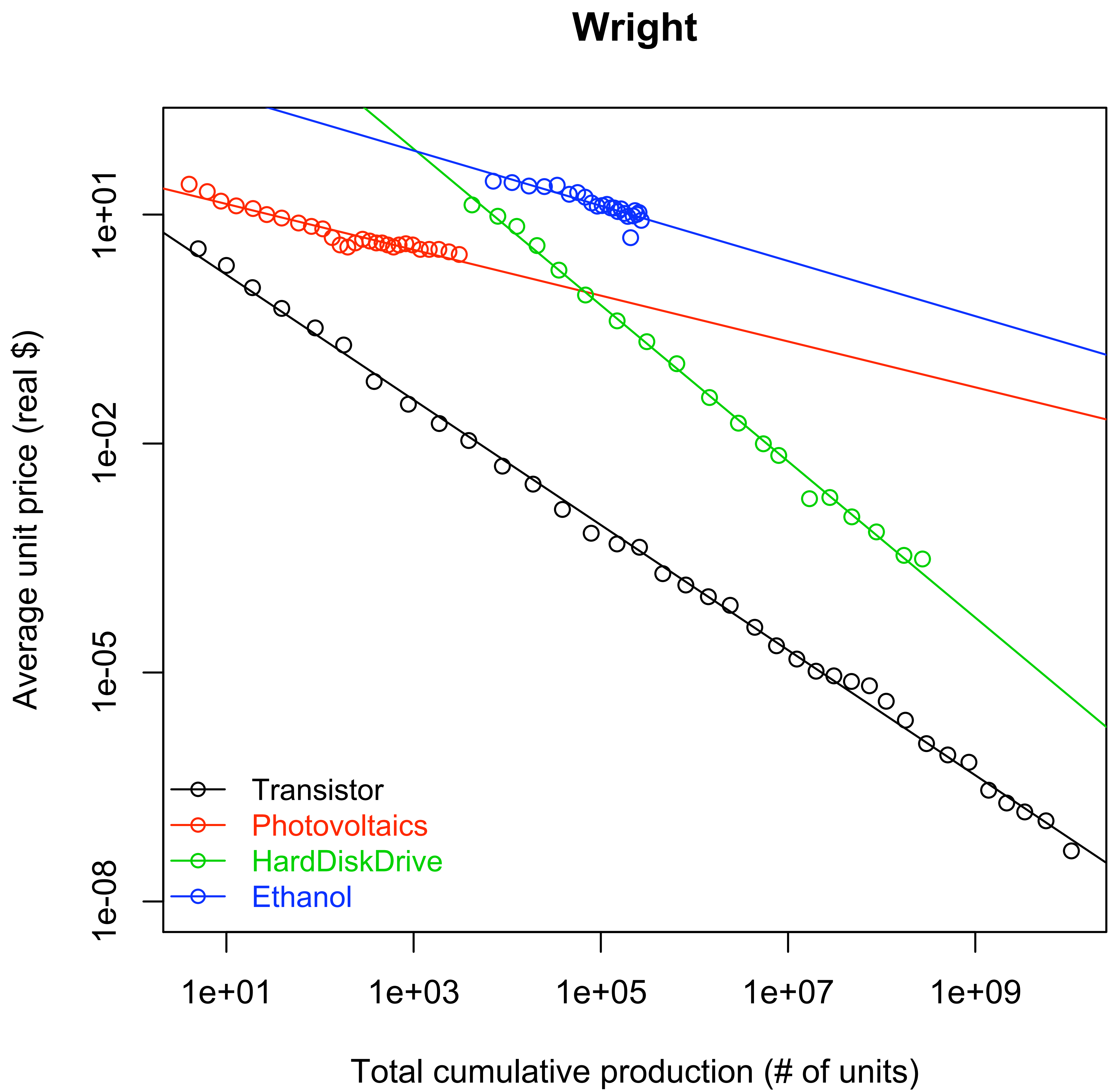
Empirical laws for technological improvement

Wright's law
(1936)

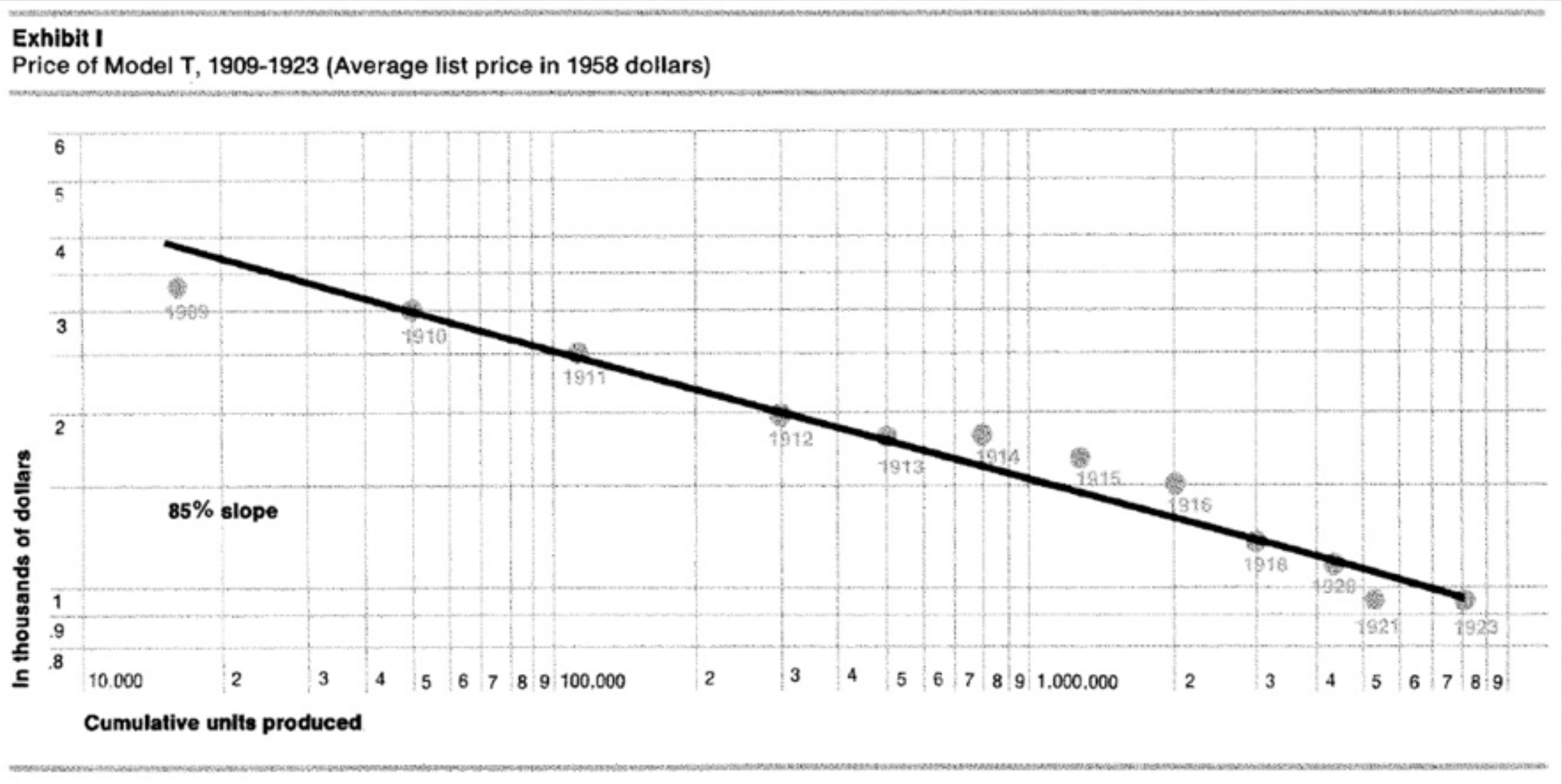
Cost vs. cumulative production = power law $y = x^{-\alpha}$

Theodore Paul Wright



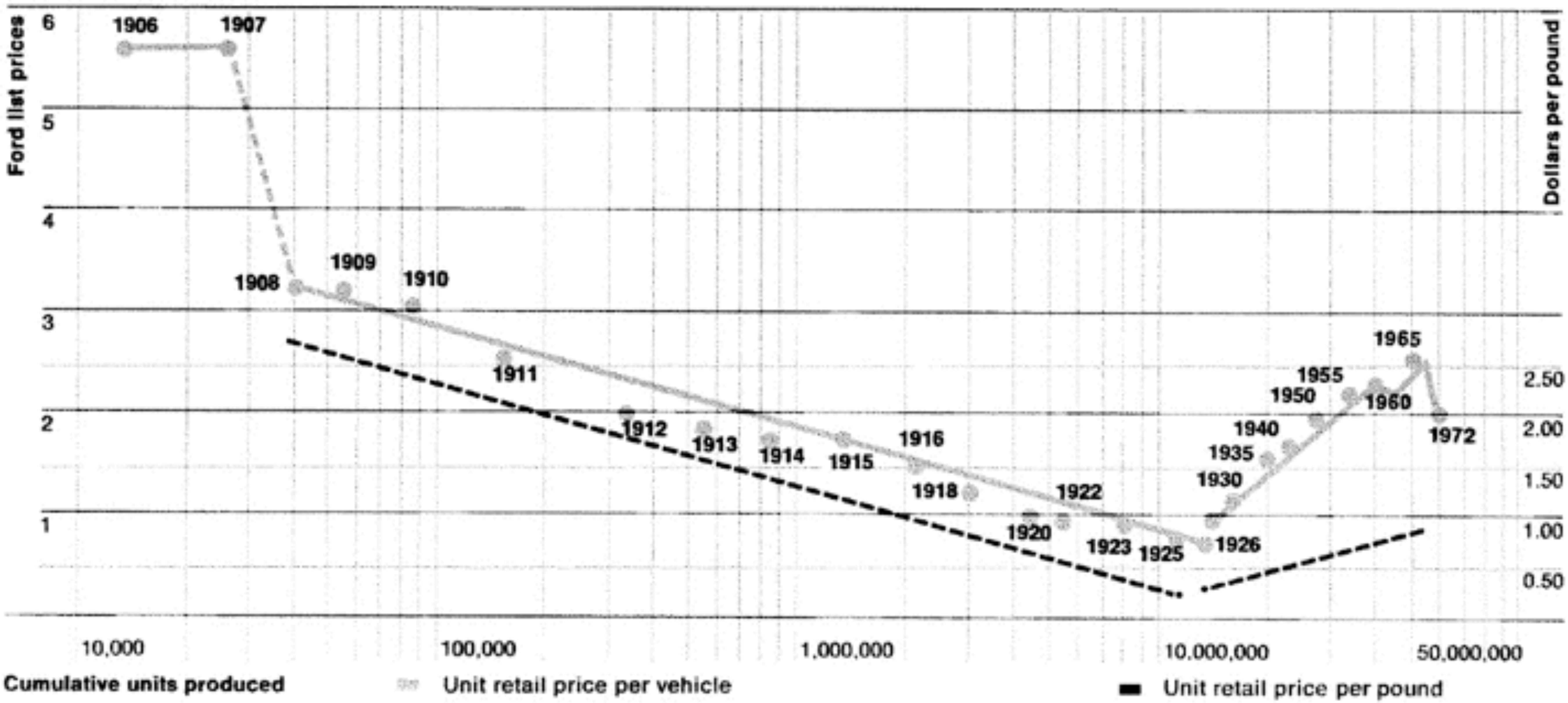

Wright
Average unit price (real $)
1e+01
1e-02
1e-05
1e-08
1e+01
1e+03
1e+05
1e+07
1e+09
Total cumulative production (# of units)
Transistor
Photovoltaics
HardDiskDrive
Ethanol

Ford's model T



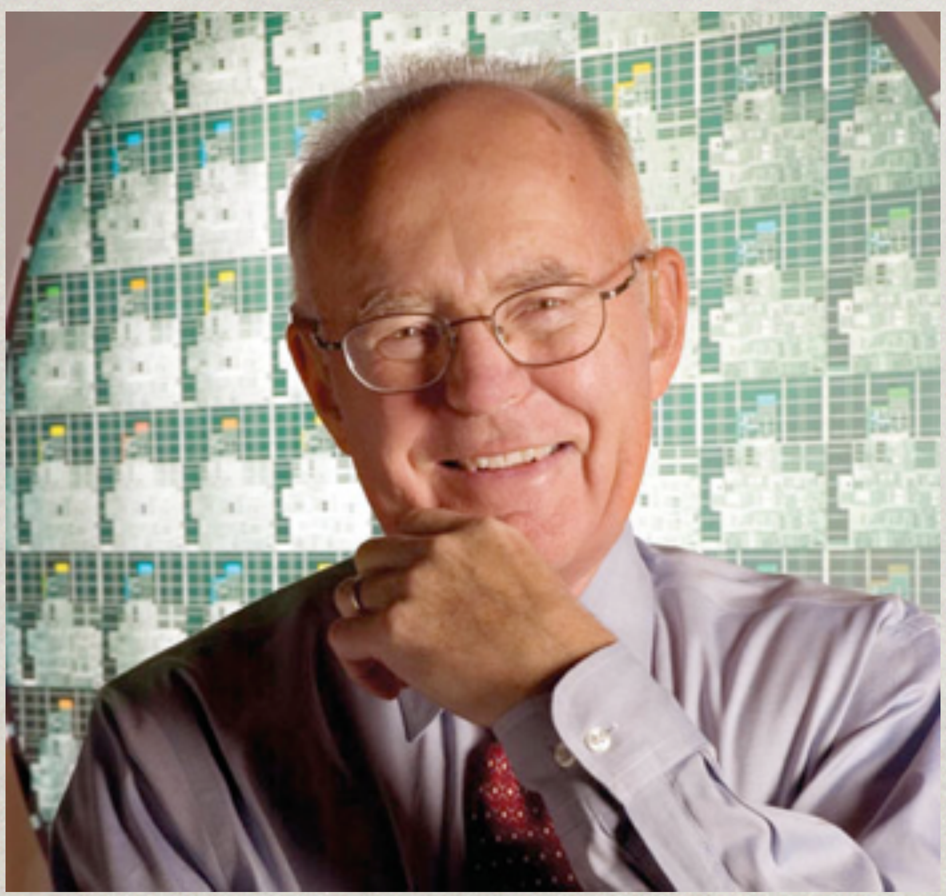
Wright's law only works when reducing cost is main objective

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)

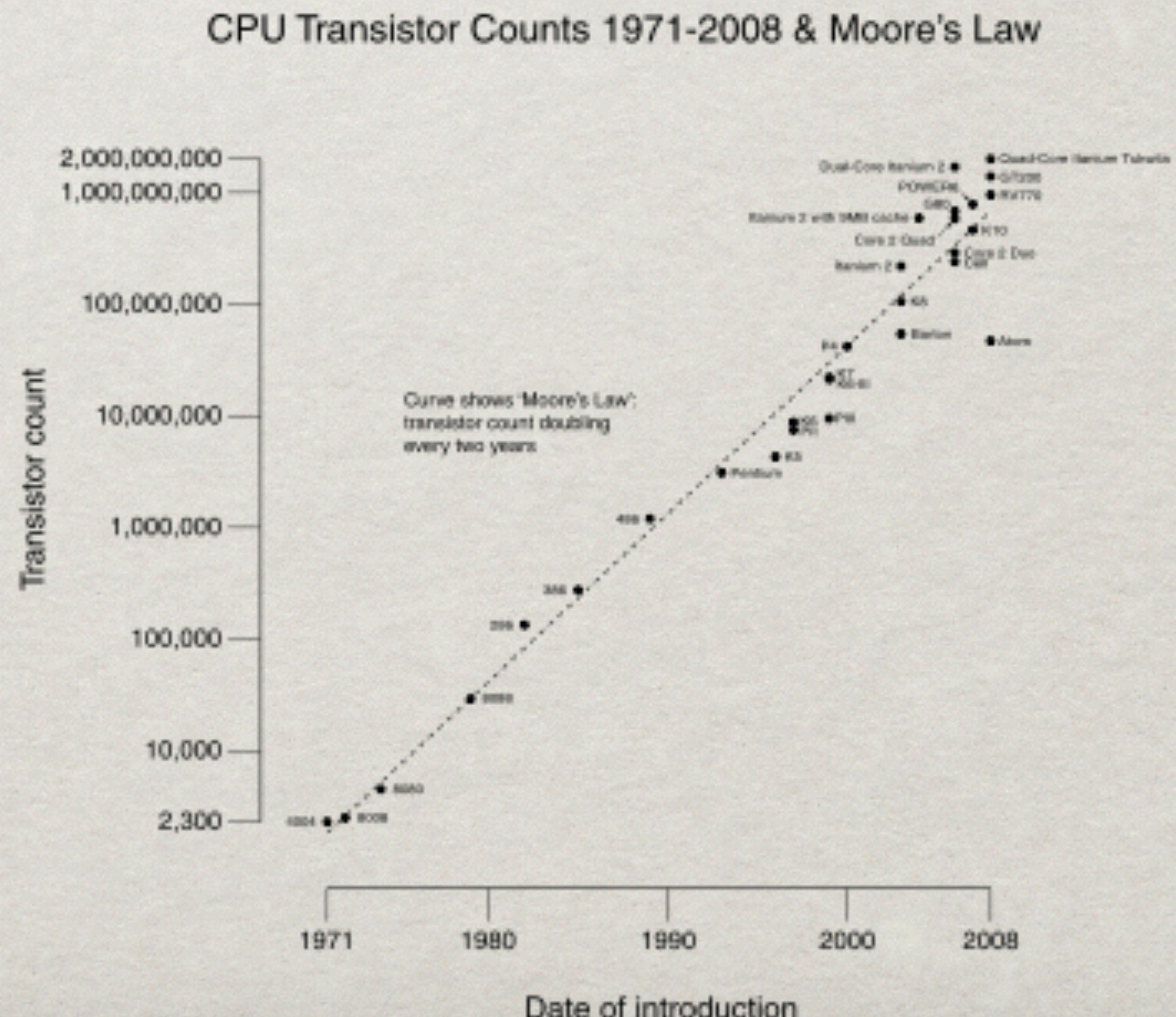


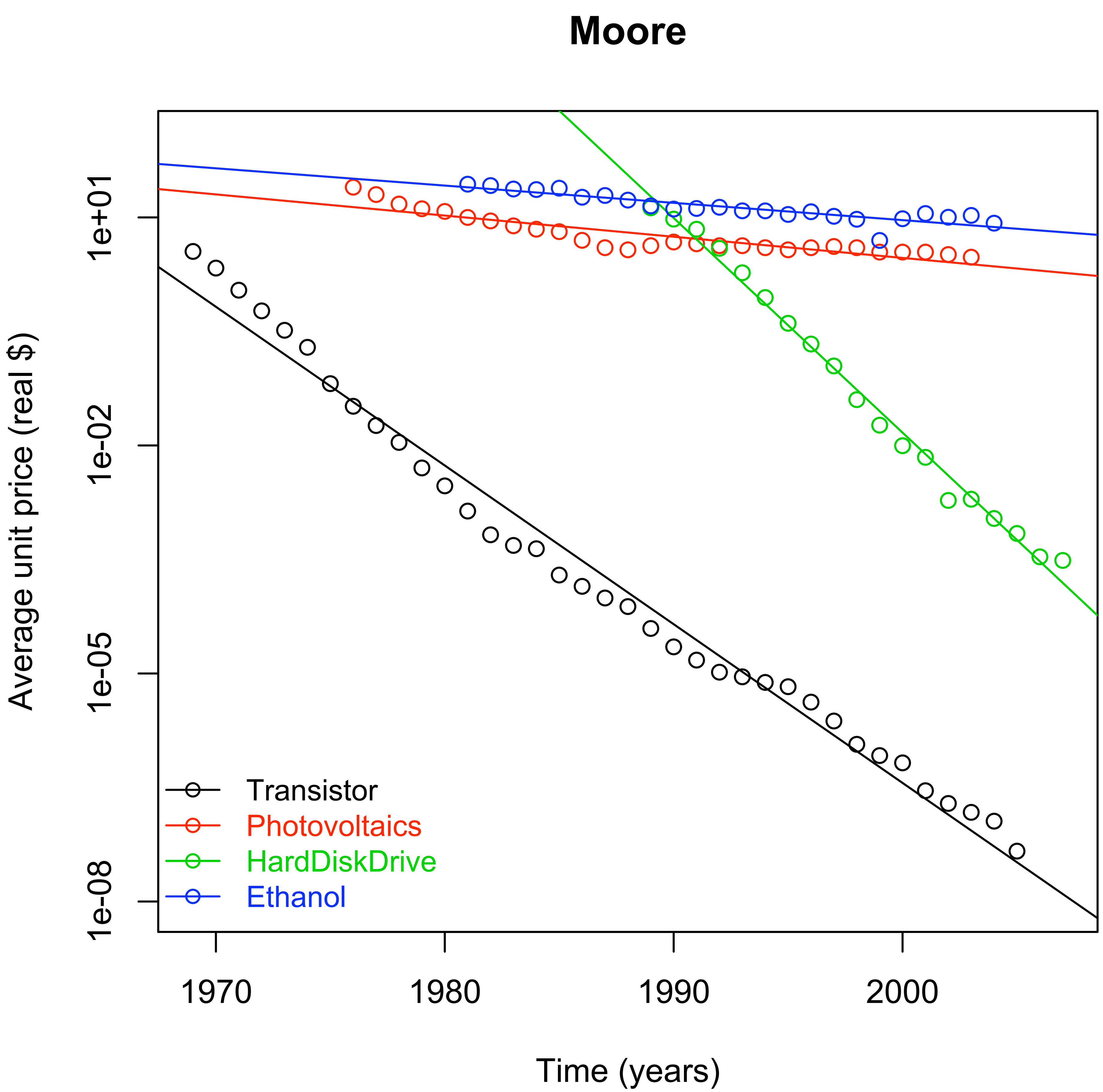
Moore's law
(1965)

Originally a statement about density of transistors
We will use to refer to the hypothesis that technological performance improves exponentially with time

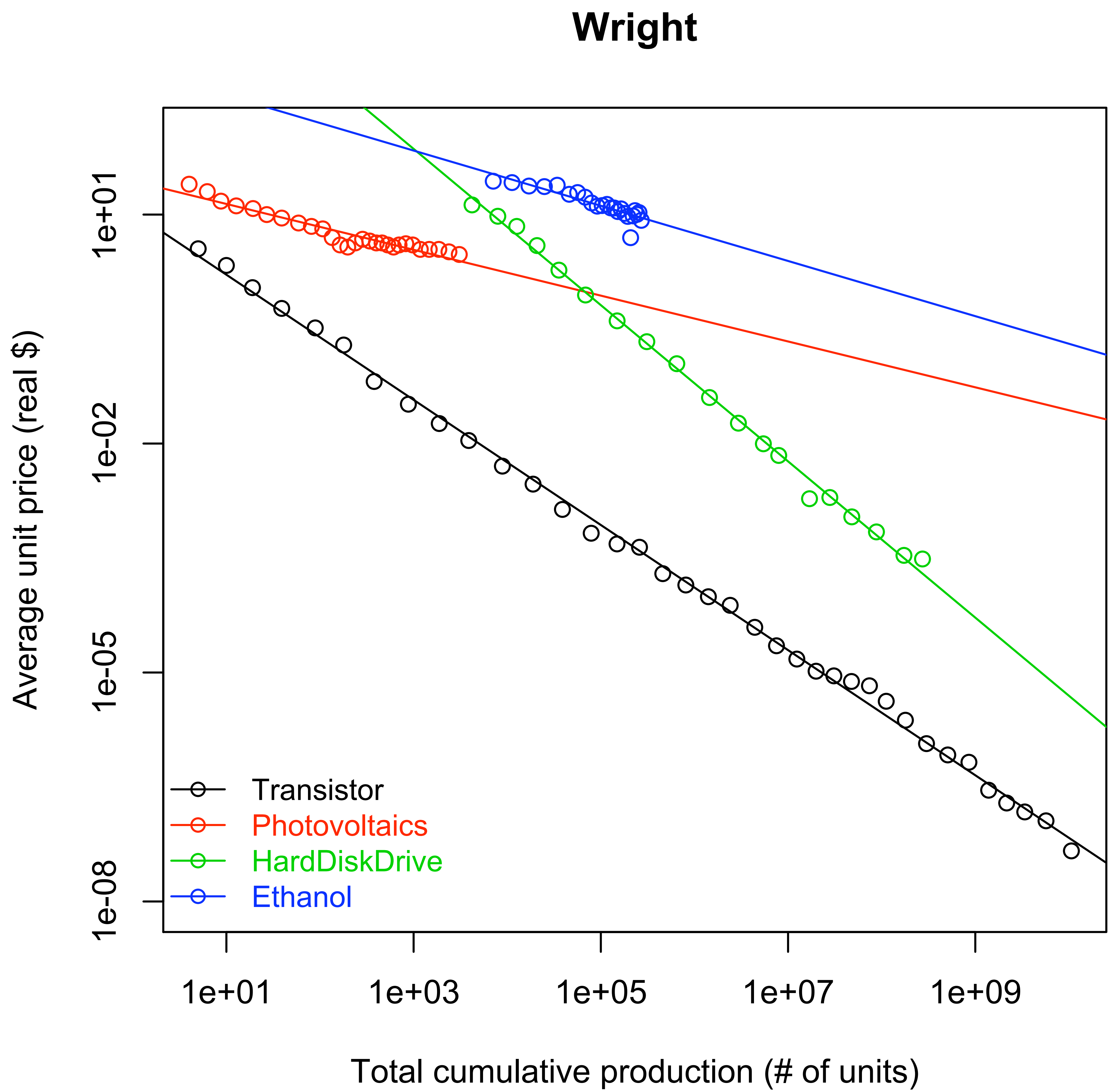


Gordon Moore



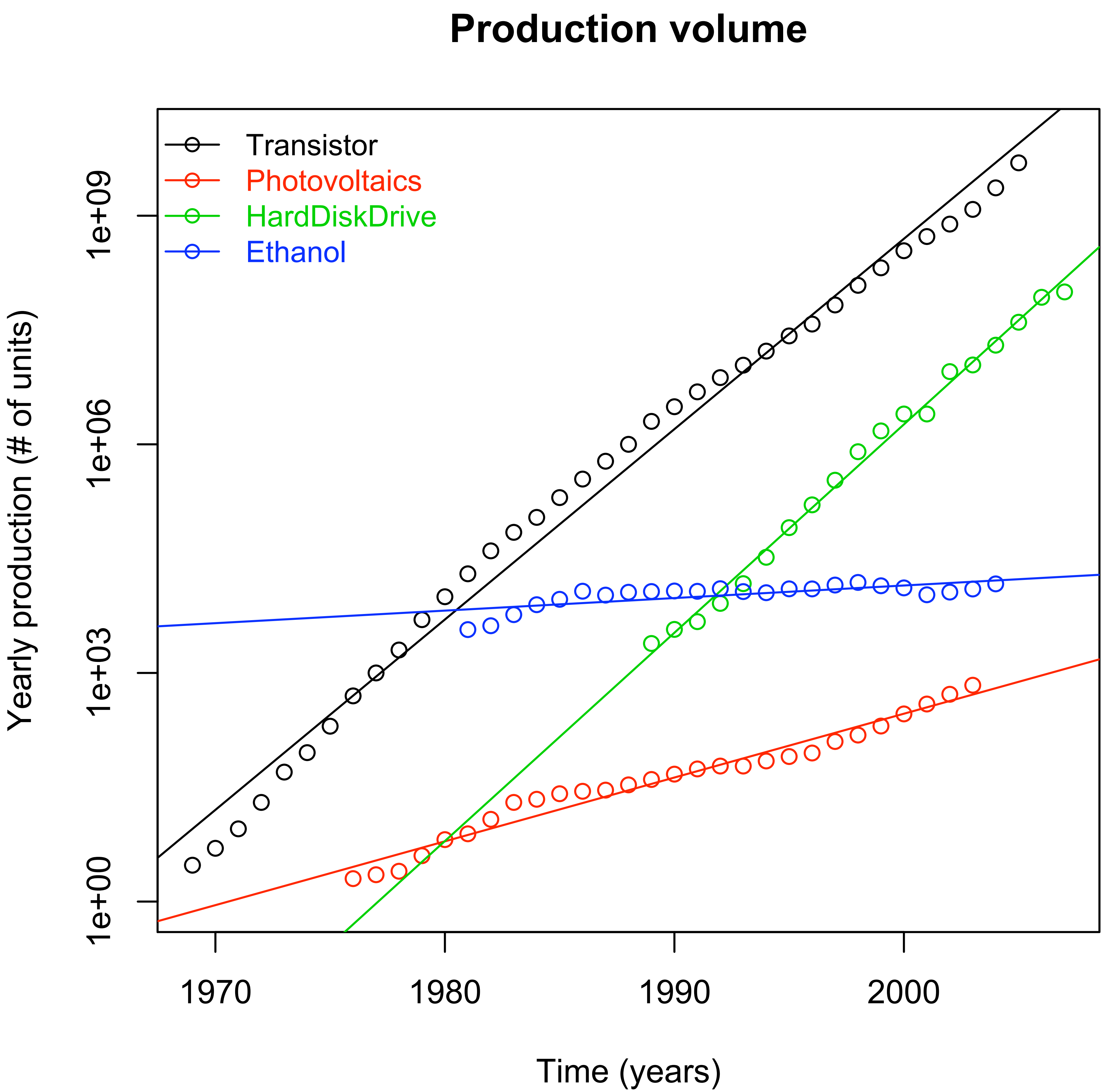


Moore
Average unit price (real $)
1e+01
1e-02
1e-05
1e-08
1970
1980
1990
2000
Time (years)
Transistor
Photovoltaics
HardDiskDrive
Ethanol


Wright
Average unit price (real $)
1e+01
1e-02
1e-05
1e-08
1e+01
1e+03
1e+05
1e+07
1e+09
Total cumulative production (# of units)
Transistor
Photovoltaics
HardDiskDrive
Ethanol

Production vs. time

- For technologies in this sample, also reasonable to postulate that production increases exponentially with time



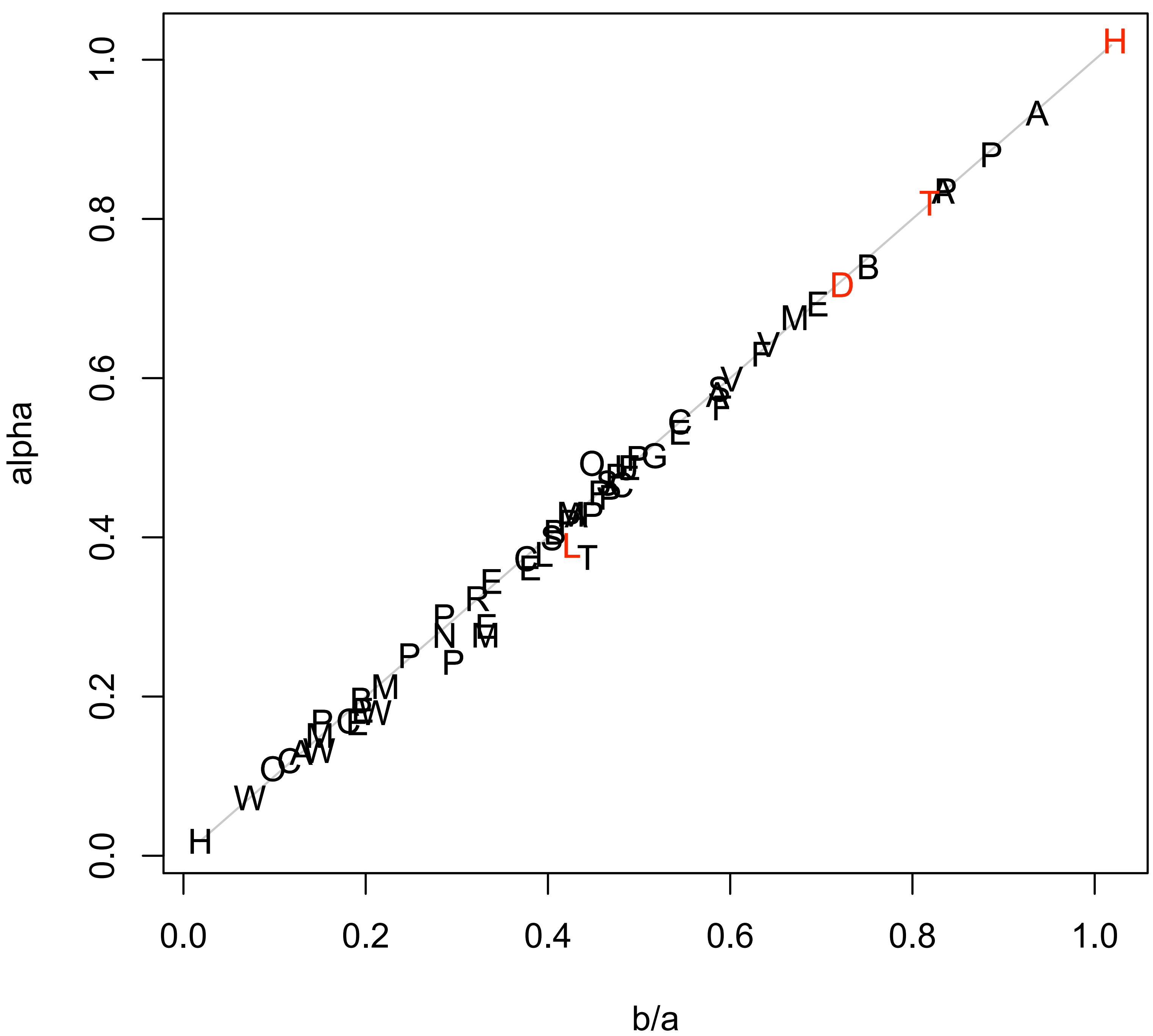
(Nagy, Farmer, Bui, Trancik, PlosOne, 2013)

Compatibility of Wright and Moore (Sahal, 1987)

If production expands exponentially and costs drop exponentially, Wright's law will hold.

$$\begin{aligned} x(t) &= \exp(at) \\ y(t) &= \exp(-bt) \\ y(x) &= x^{-b/a} \end{aligned}$$

Empirical validation of Sahal's identity: alpha = b/a



(Nagy, Farmer, Bui, Trancik, PlosOne, 2013)

Bela Nagy

Key hypothesis

All technologies obey same random process

– parameters vary across technologies

Time series models

Moore's law as a random walk with drift

$$y_{t+1} - y_t = \mu + K n_t$$

Change in log(cost) Drift Noise

Wright's law as random walk with drift dependent on cumulative production

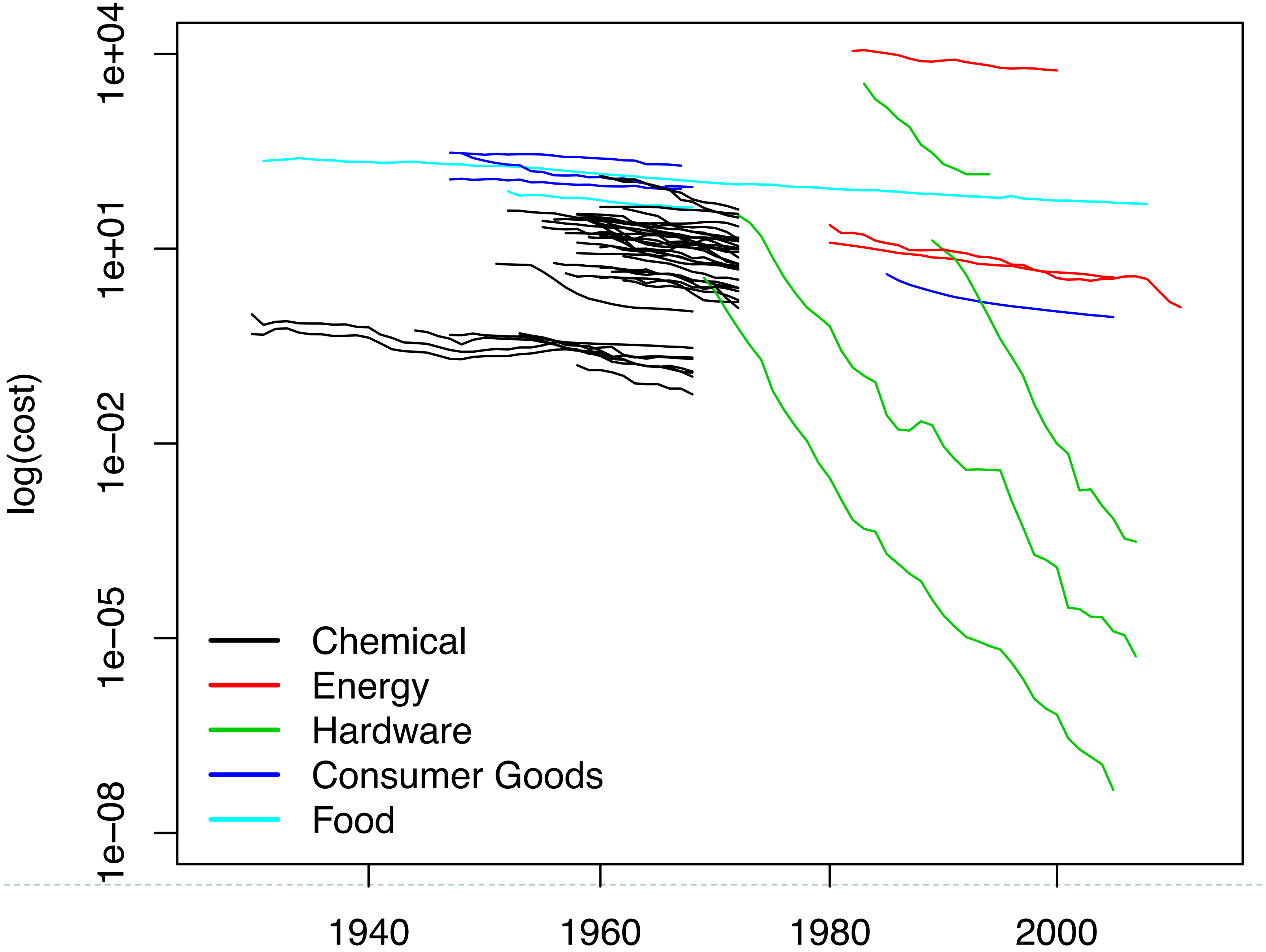
$$y_{t+1} - y_t = \omega \log\left(\frac{x_{t+1}}{x_t}\right) + S n_t$$

Testing for predictability through hind casting

(with Aimee Bailey, Jan Bakker, Francois Lafond, Patrick McSharry, Dylan Rebois,

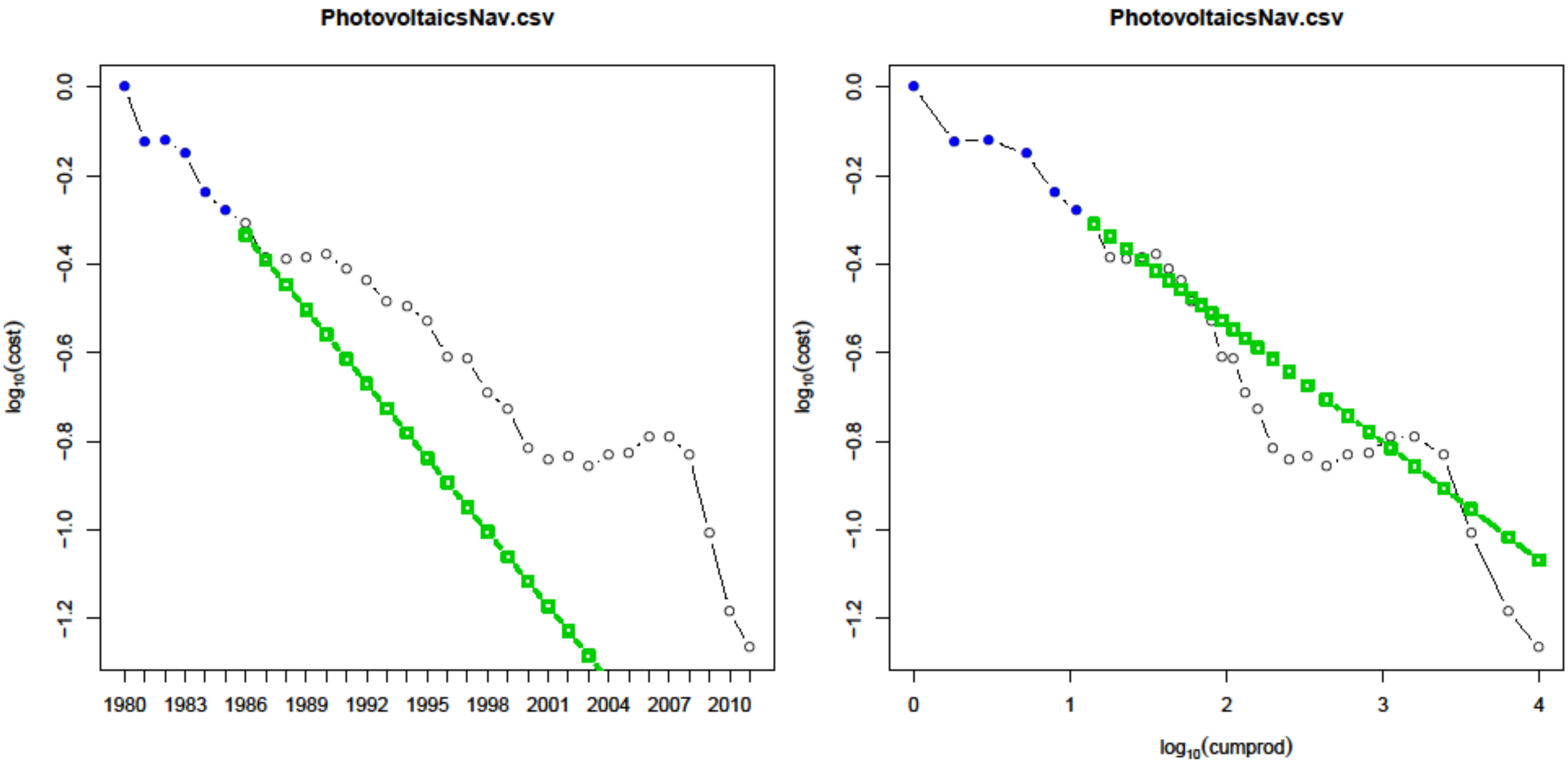
- Pretend to be at a given time in the past
- Use given method to forecast each future year
- Repeat for all past dates
- Score methods based on forecasting errors
- Make hypothesis that improvement process is the same for all technologies, except for parameters.

Data for 48 different technologies



Moore

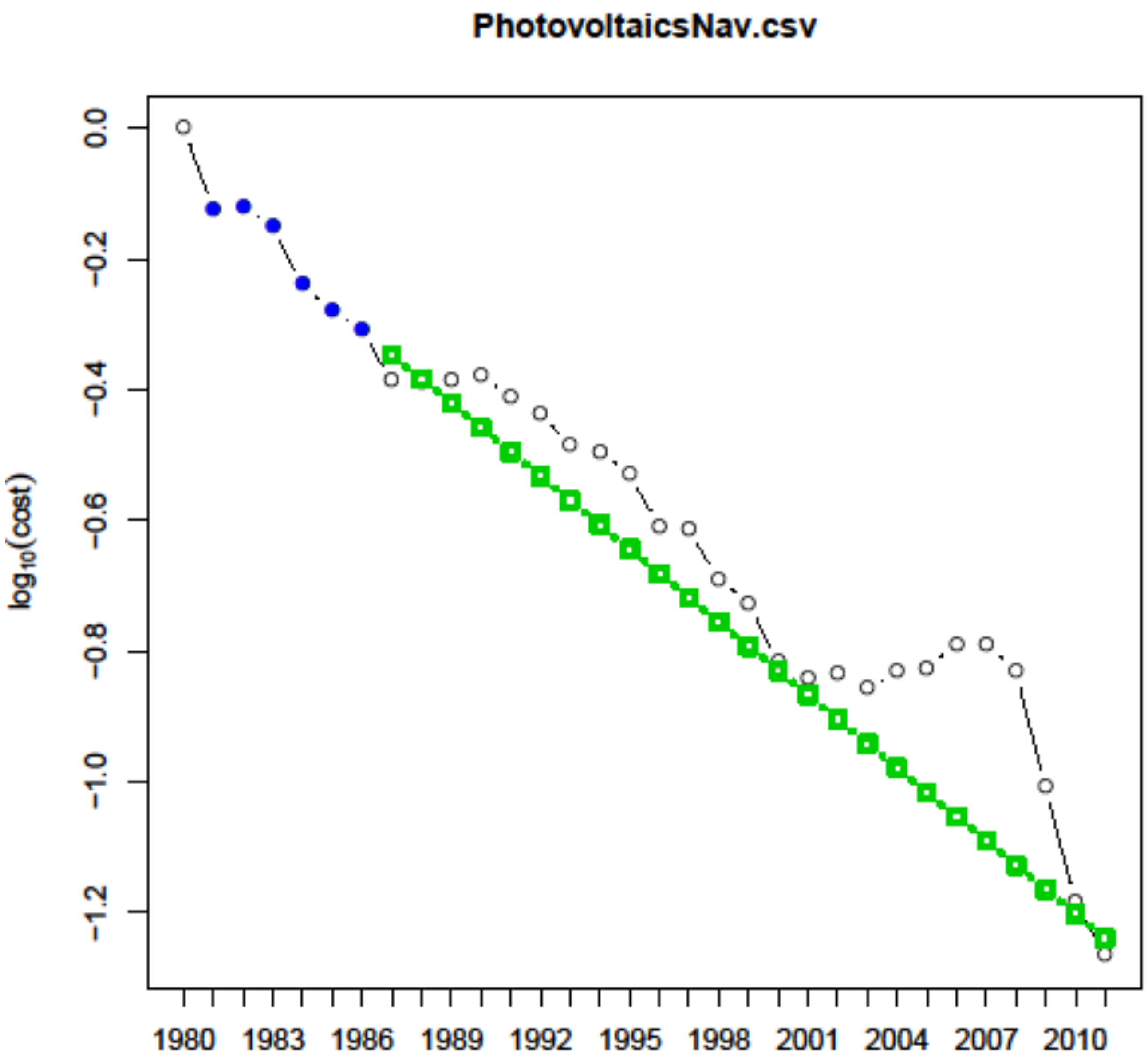
Wright

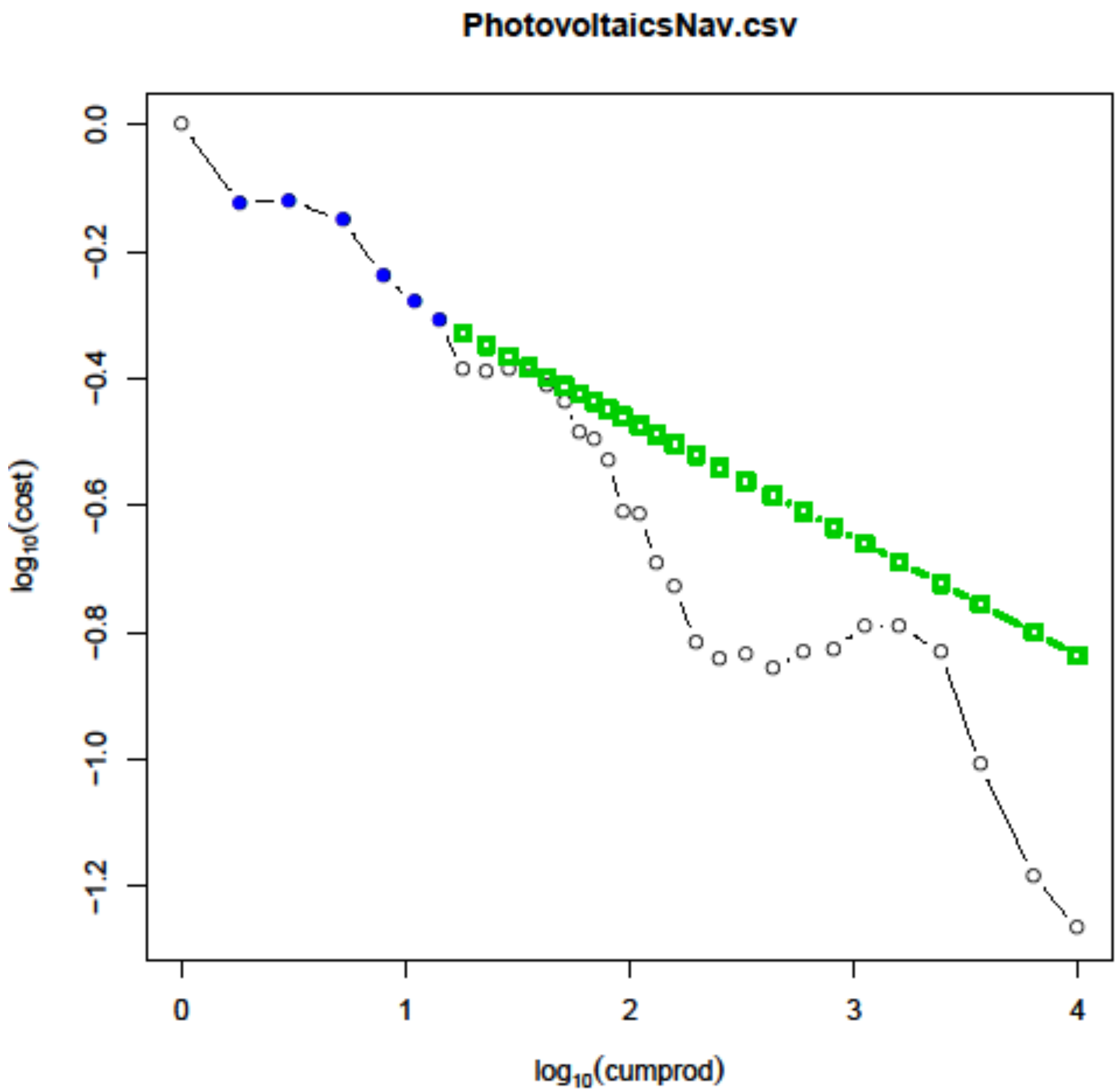


(Data are normalized by initial value; Learning Window = 6 years)

Moore

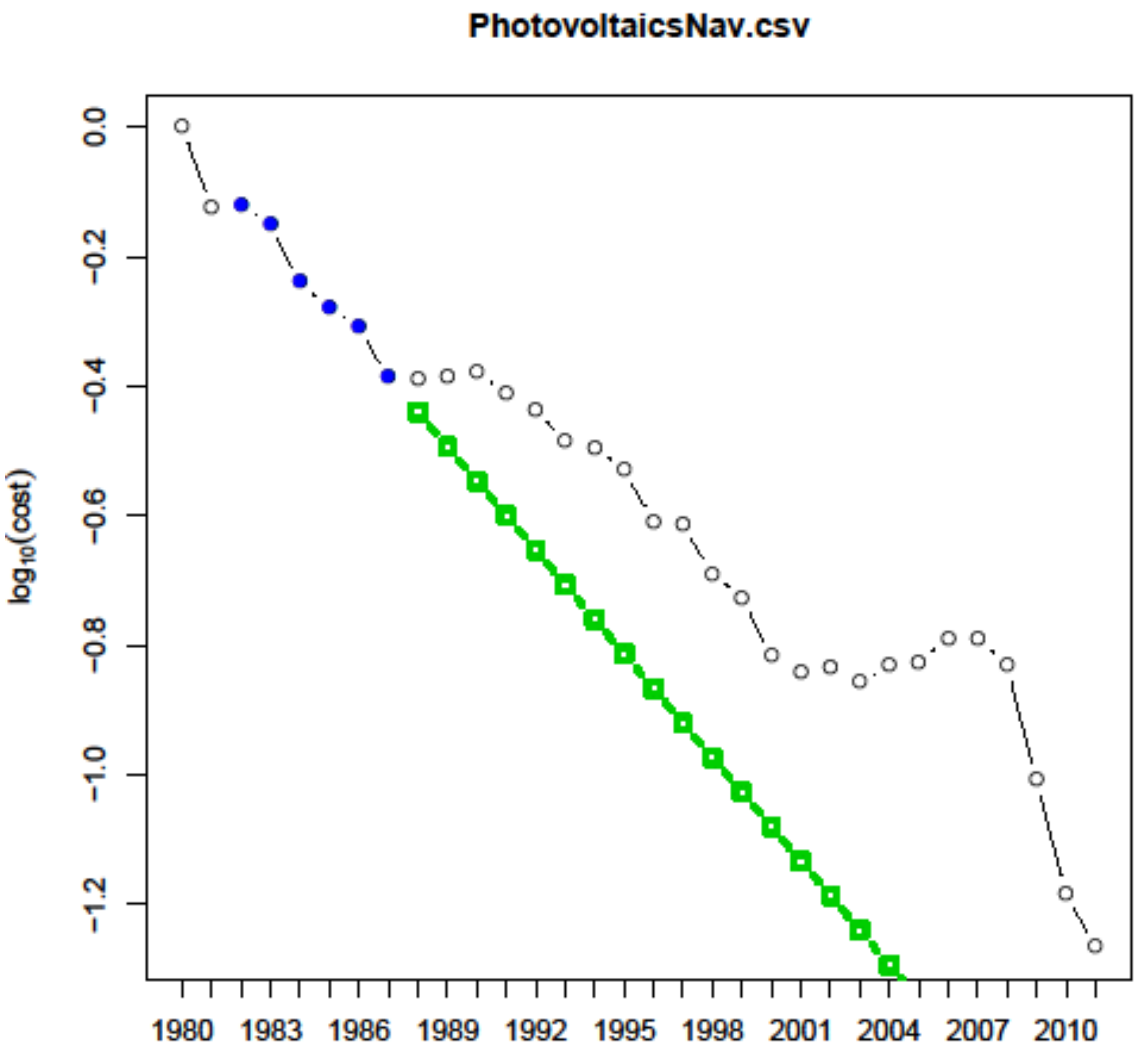
Wright

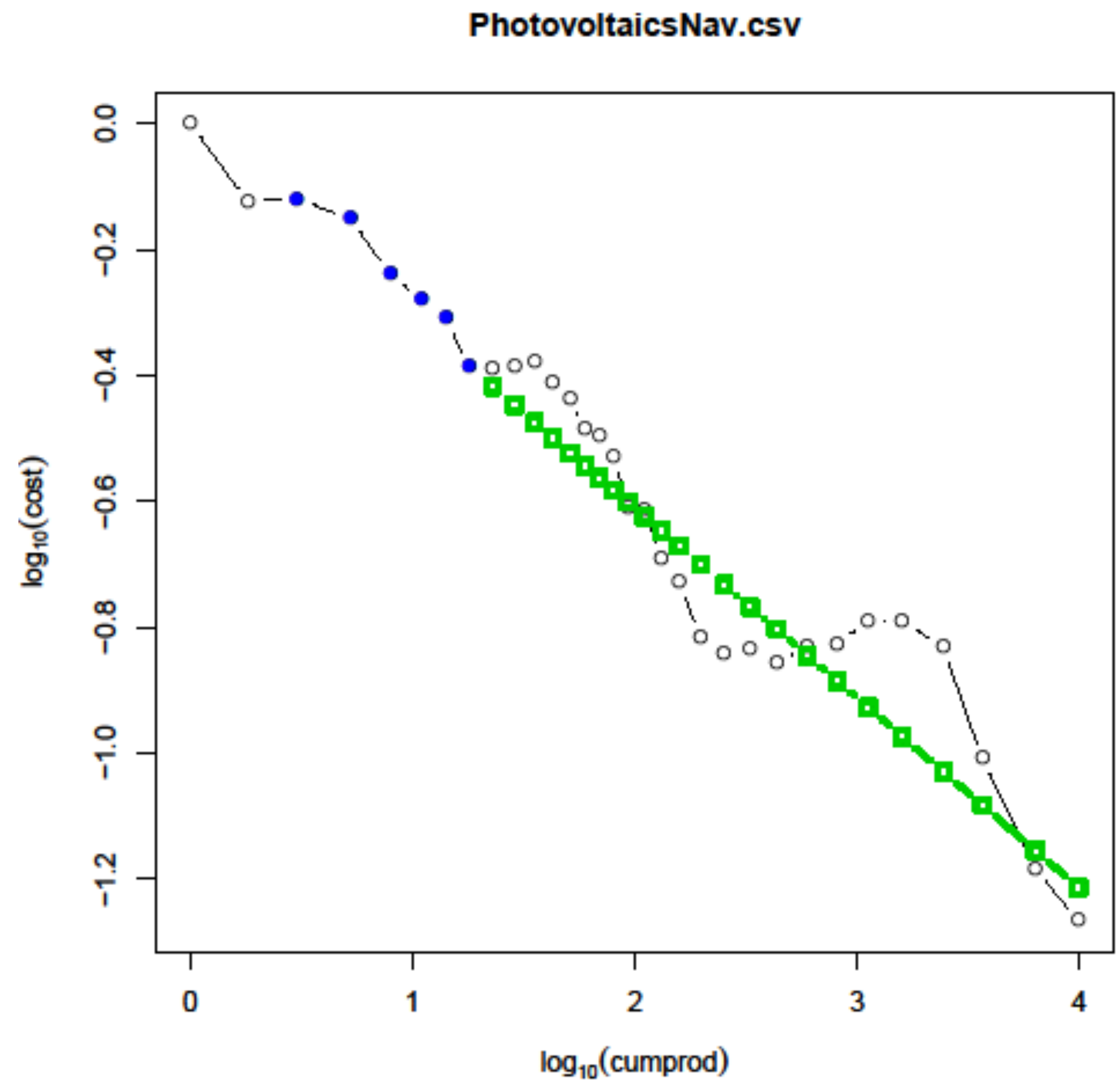




Moore

Wright





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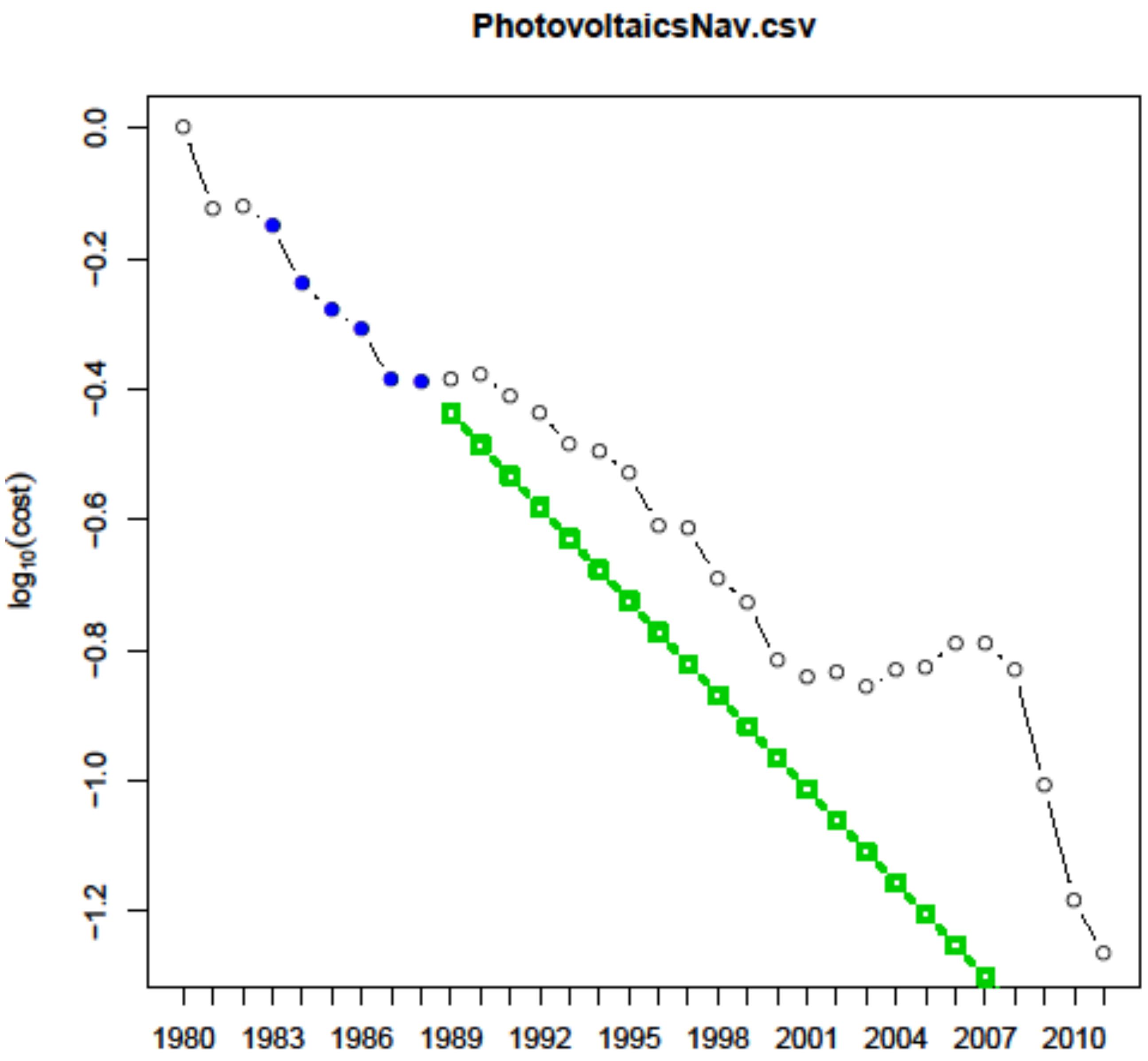

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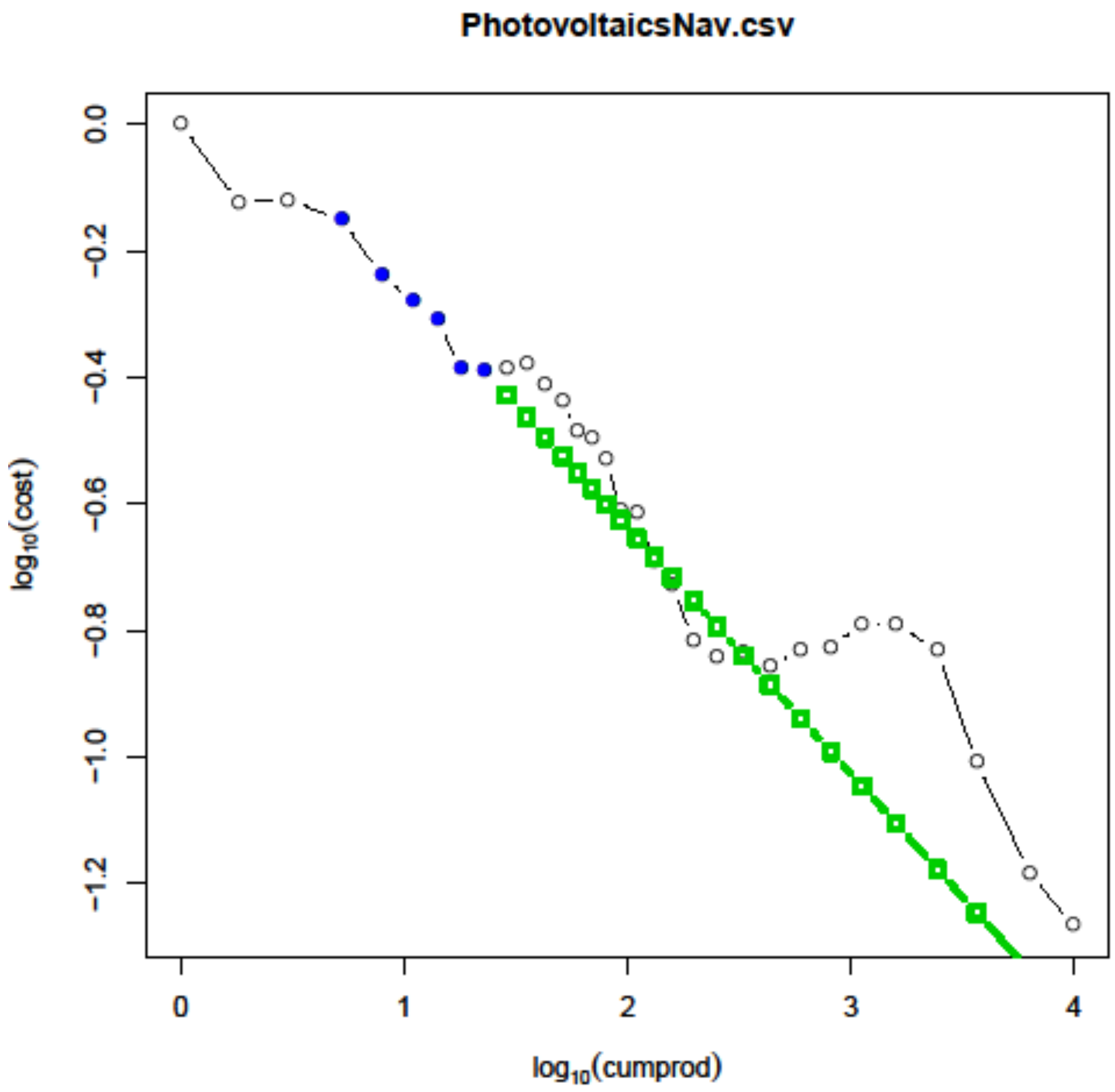

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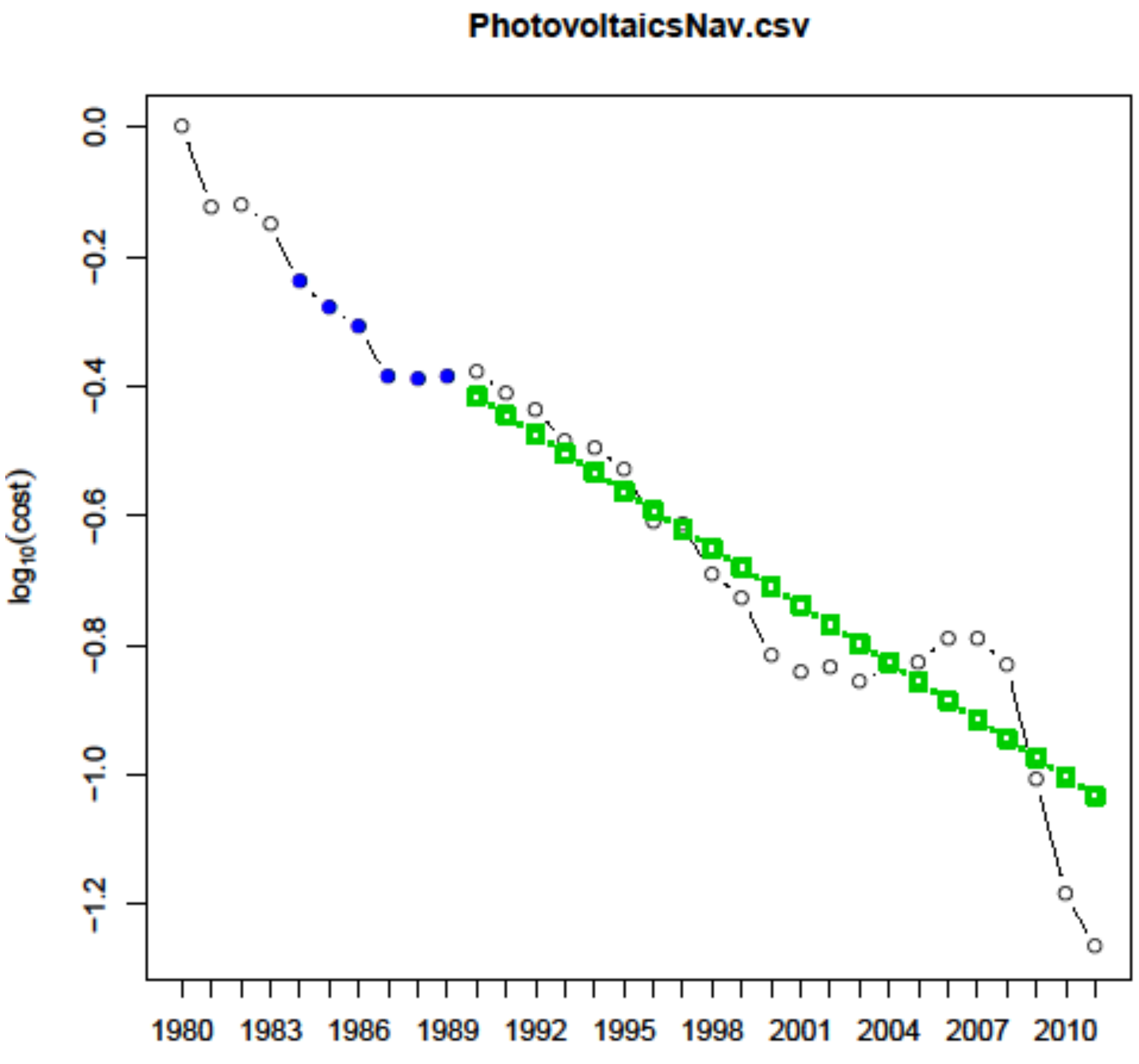

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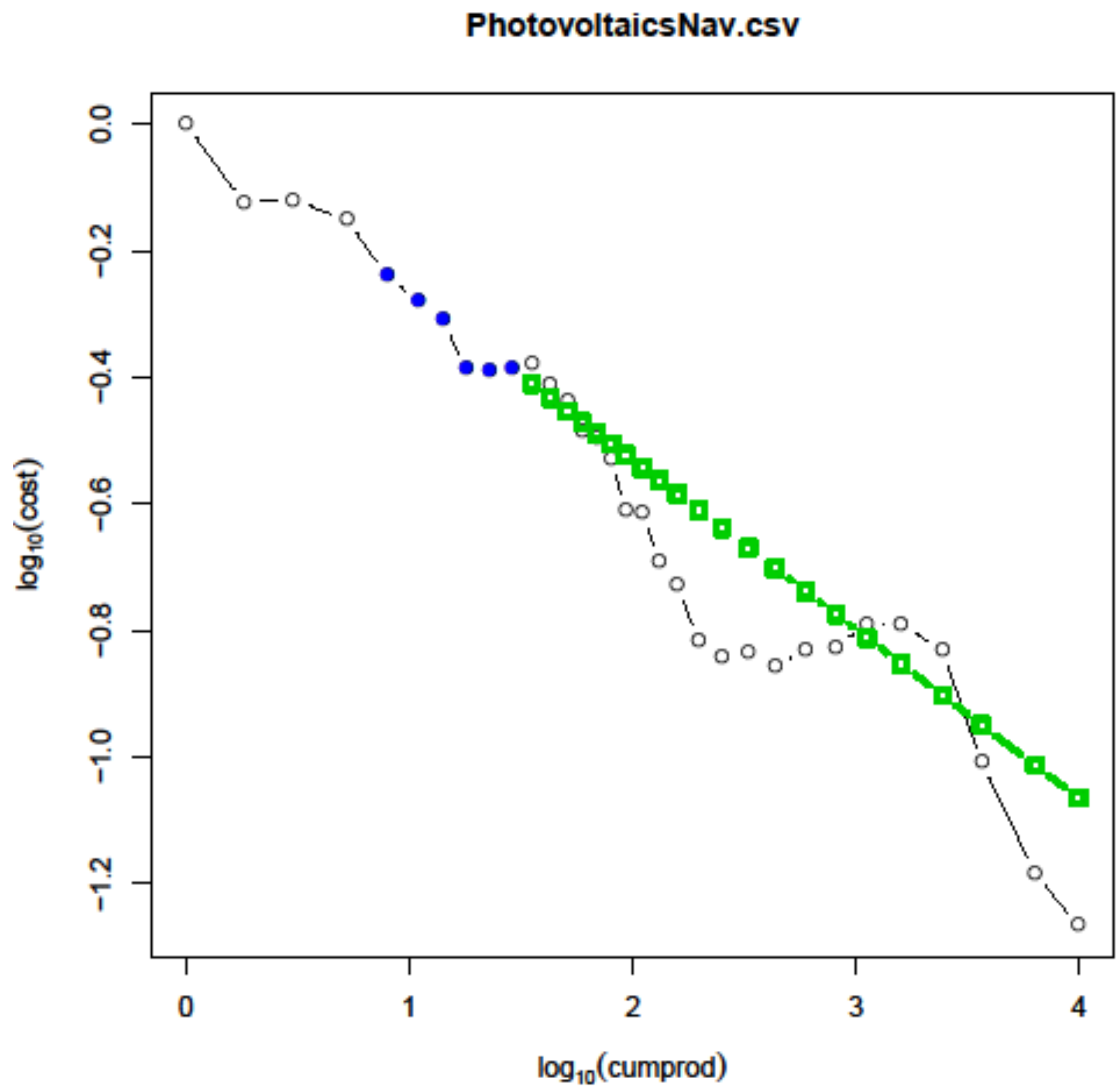

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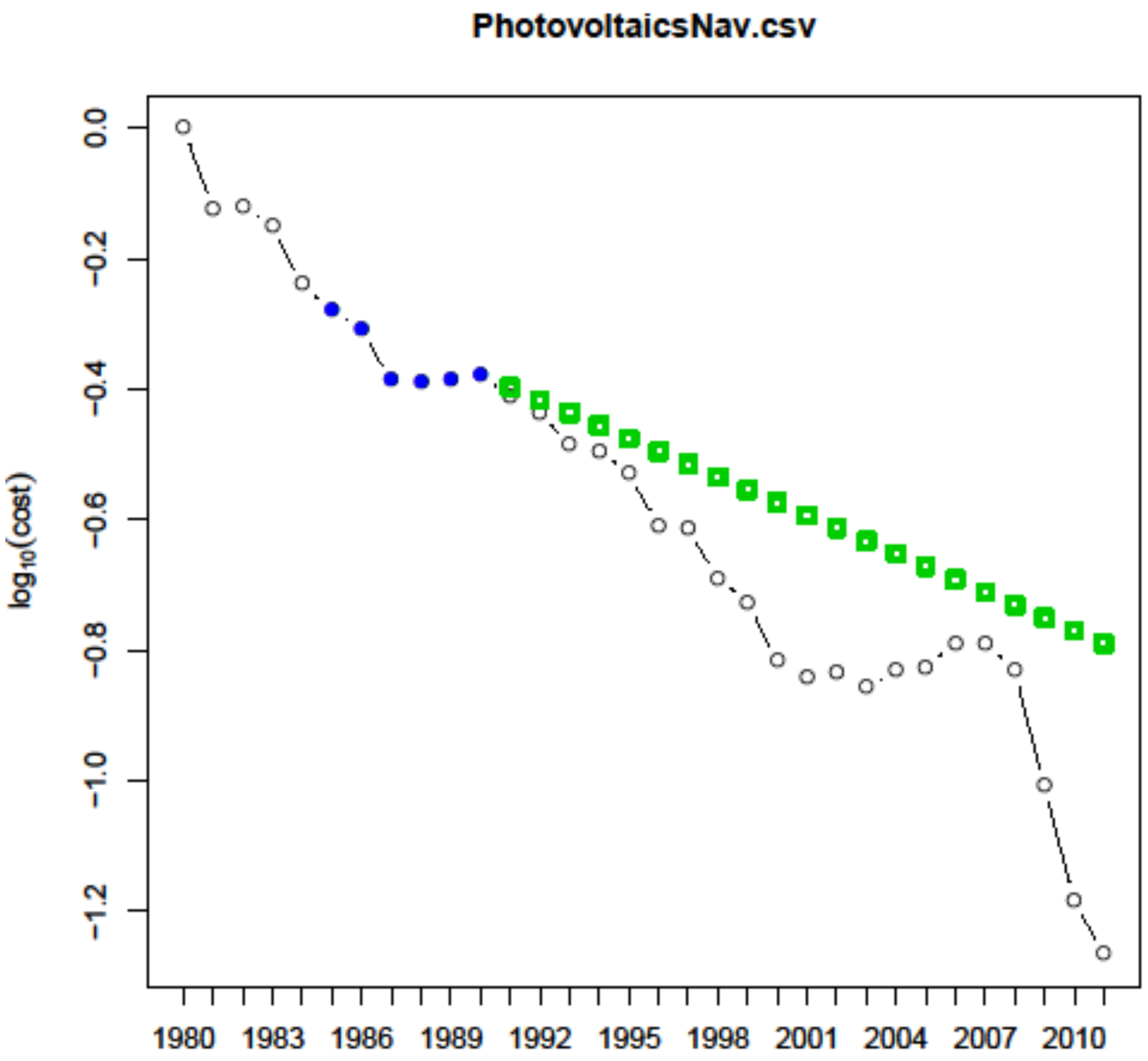
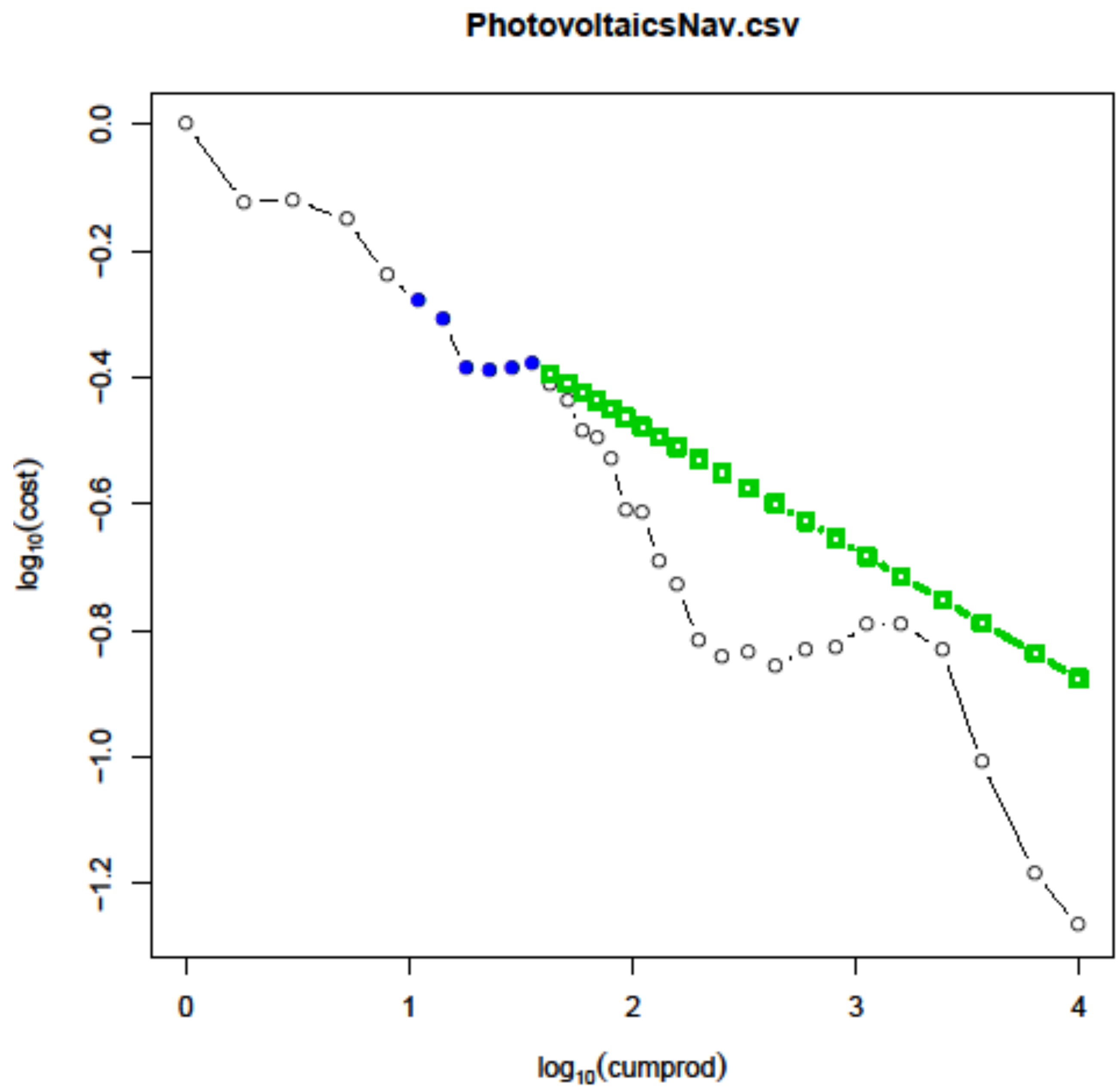
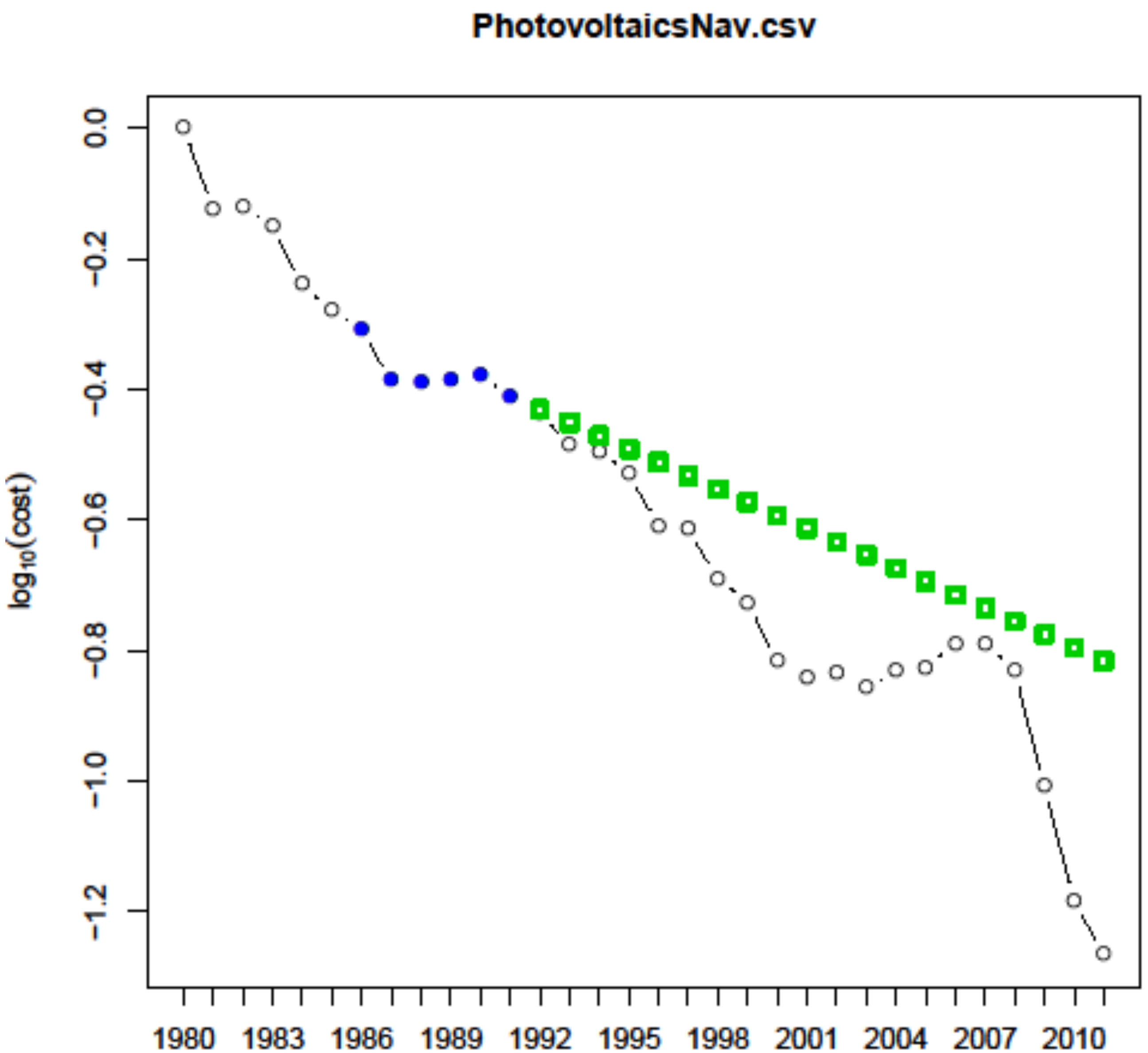
Wright

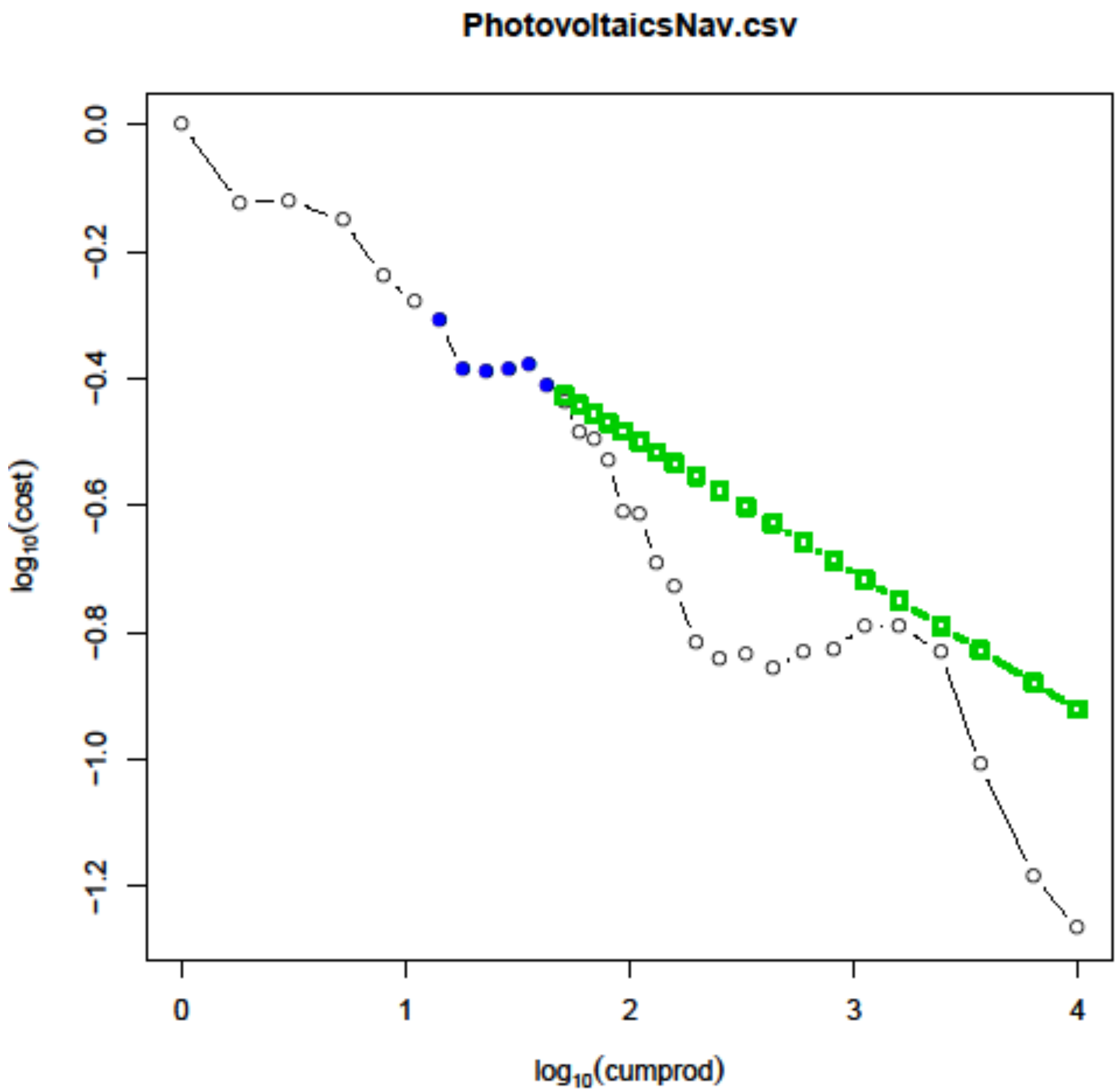




Moore

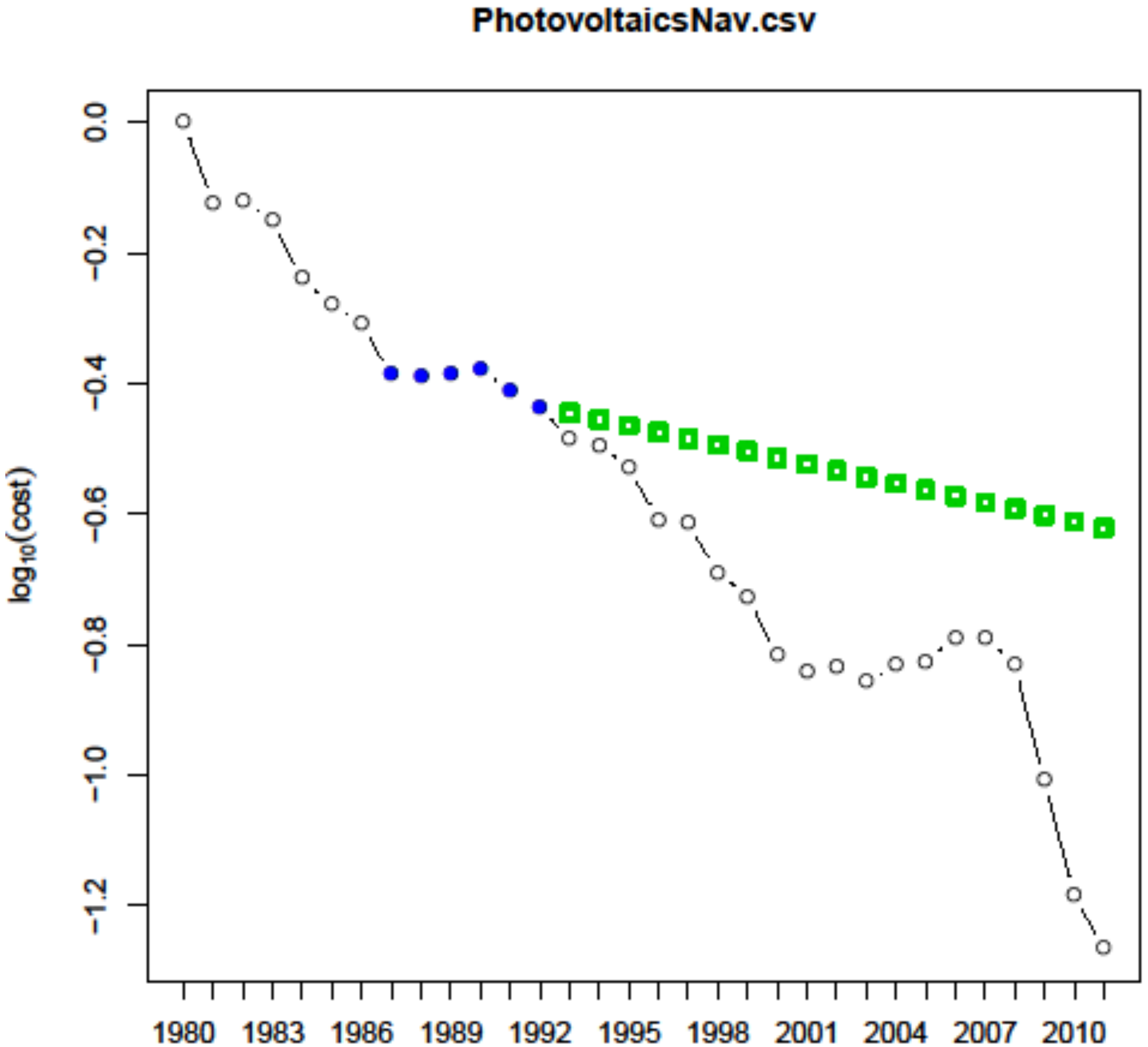
Wright

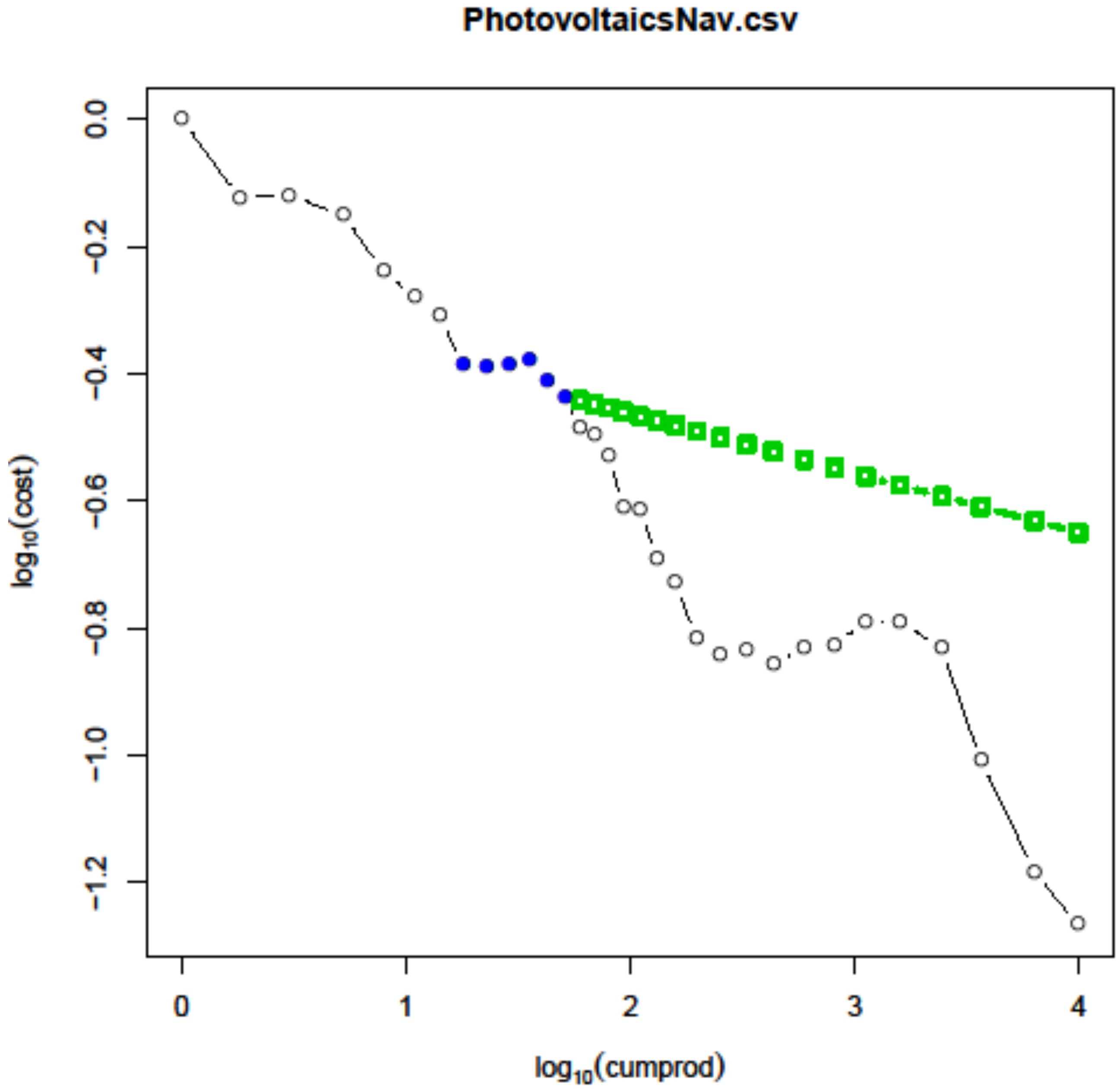


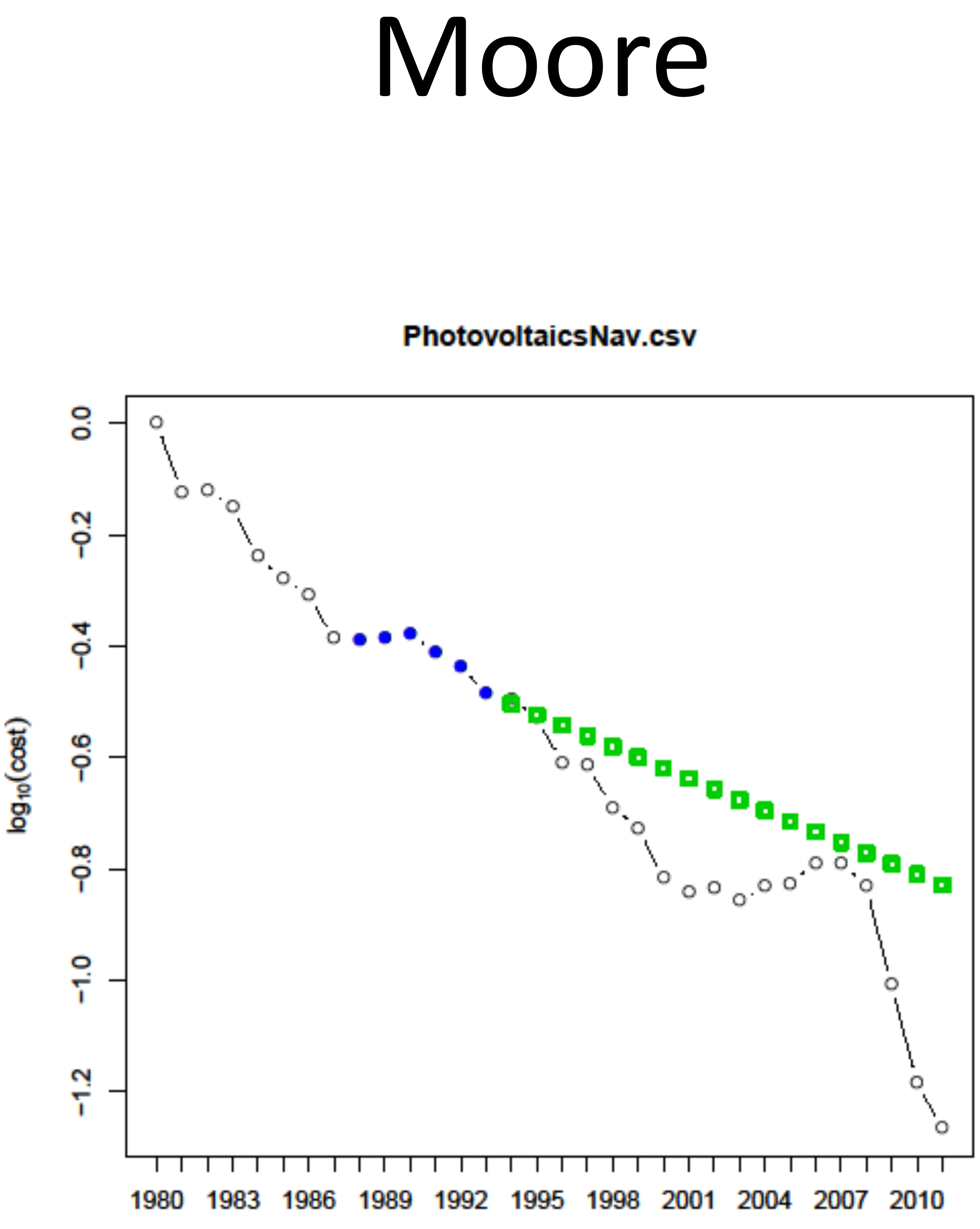


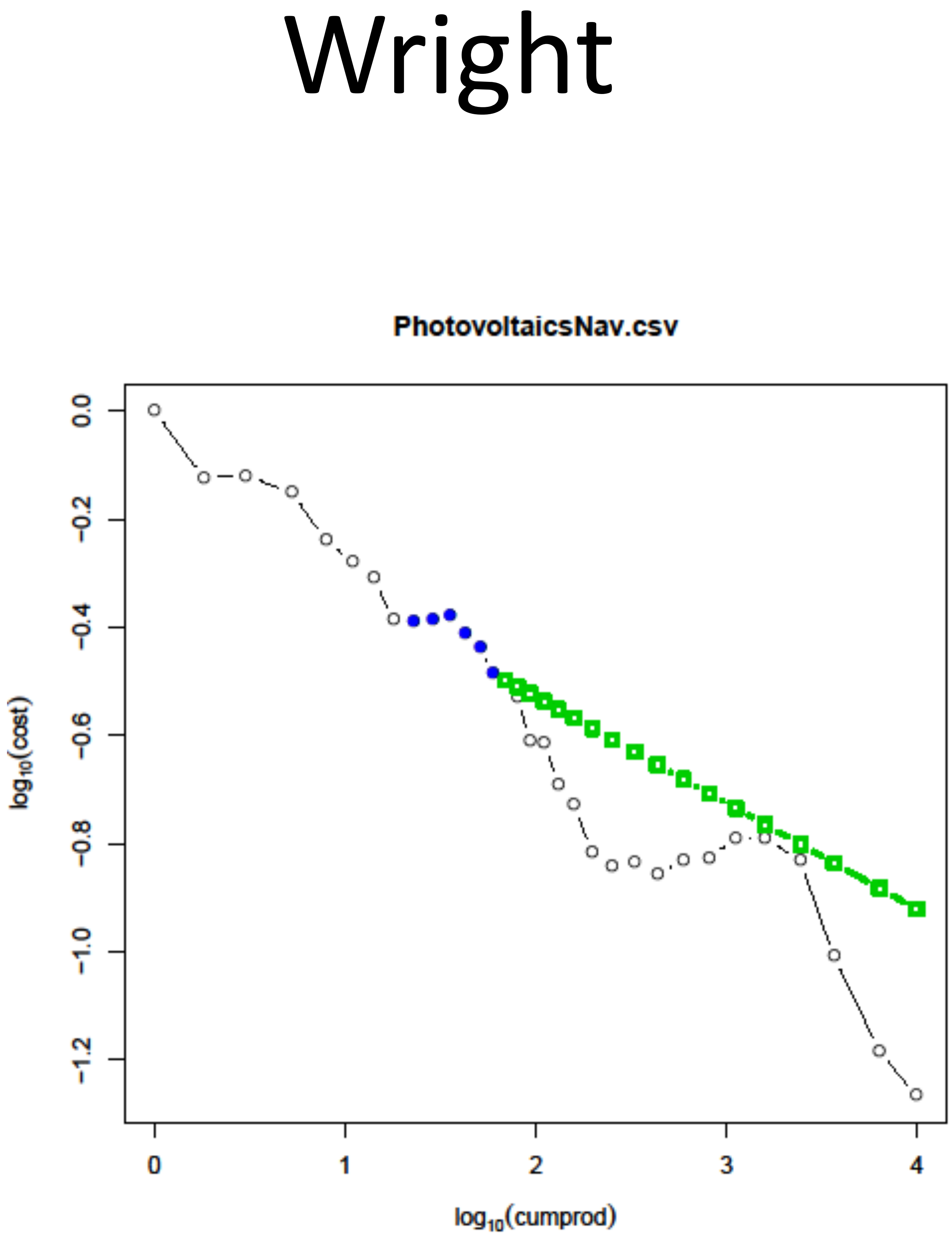
Moore

Wright



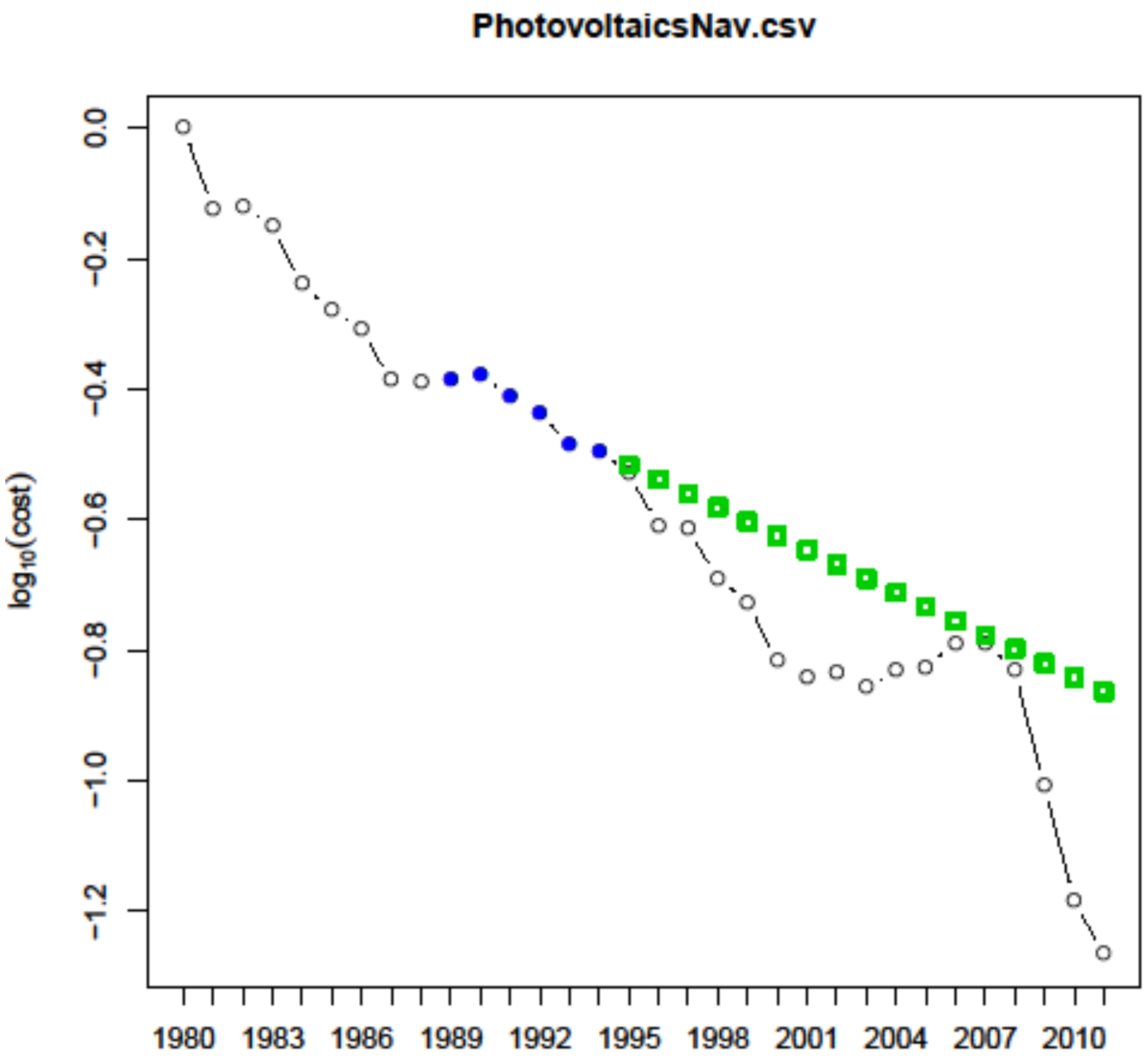


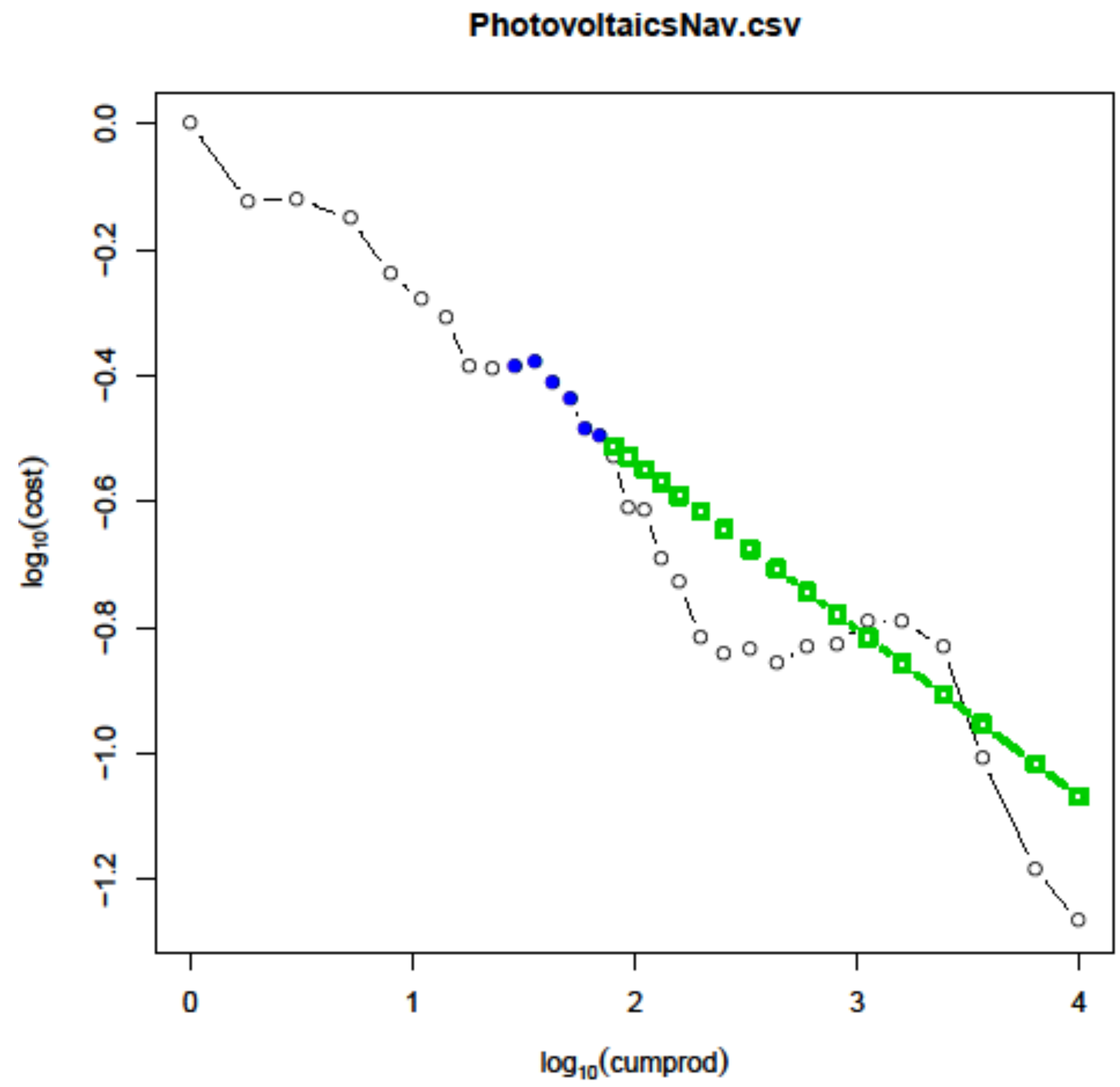

Moore
PhotovoltaicsNav.csv
log10(cost)
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
1980
1983
1986
1989
1992
1995
1998
2001
2004
2007
2010


Wright
PhotovoltaicsNav.csv
log10(cost)
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
0
1
2
3
4
log10(cumprod)

Moore

Wright





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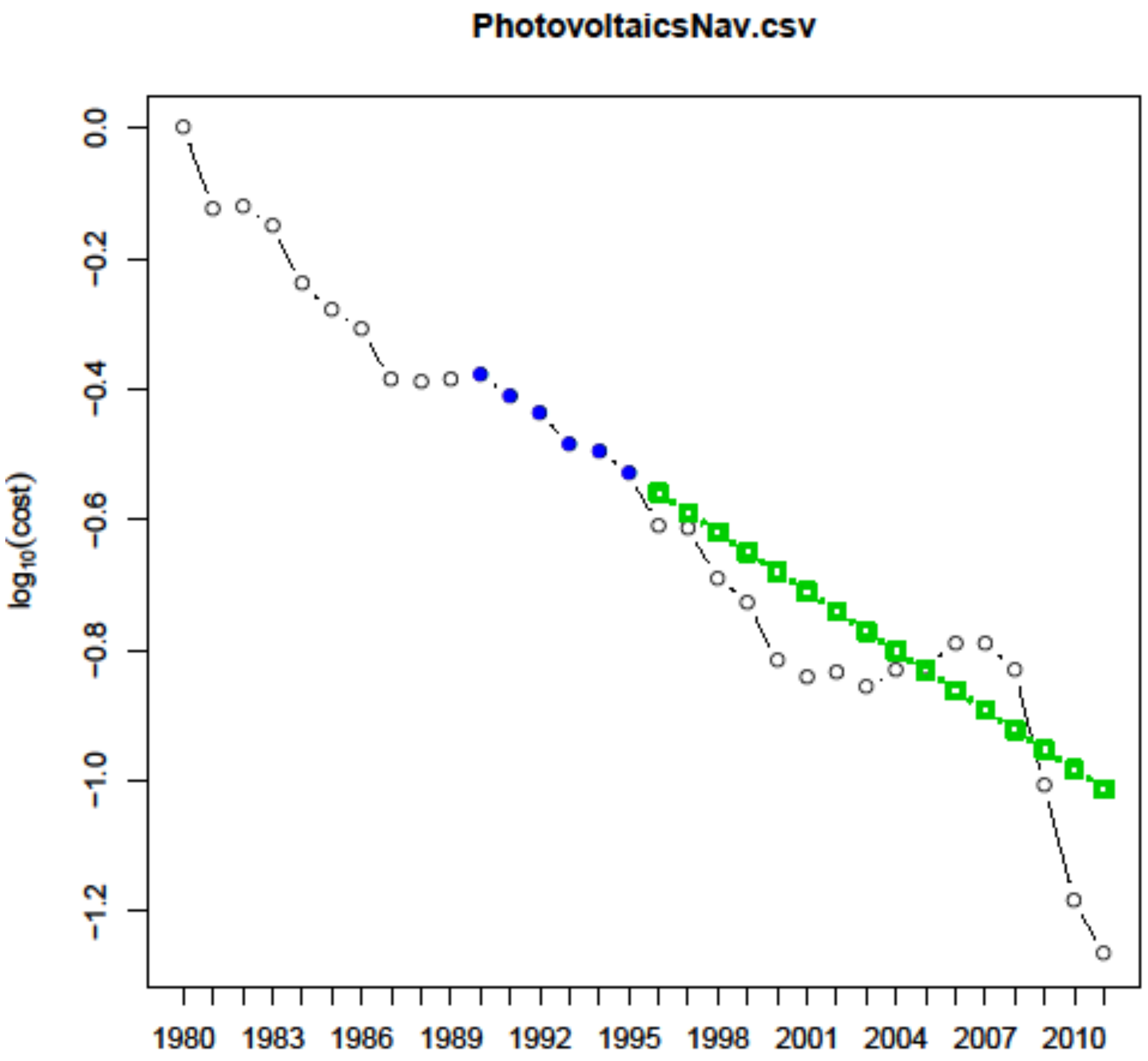

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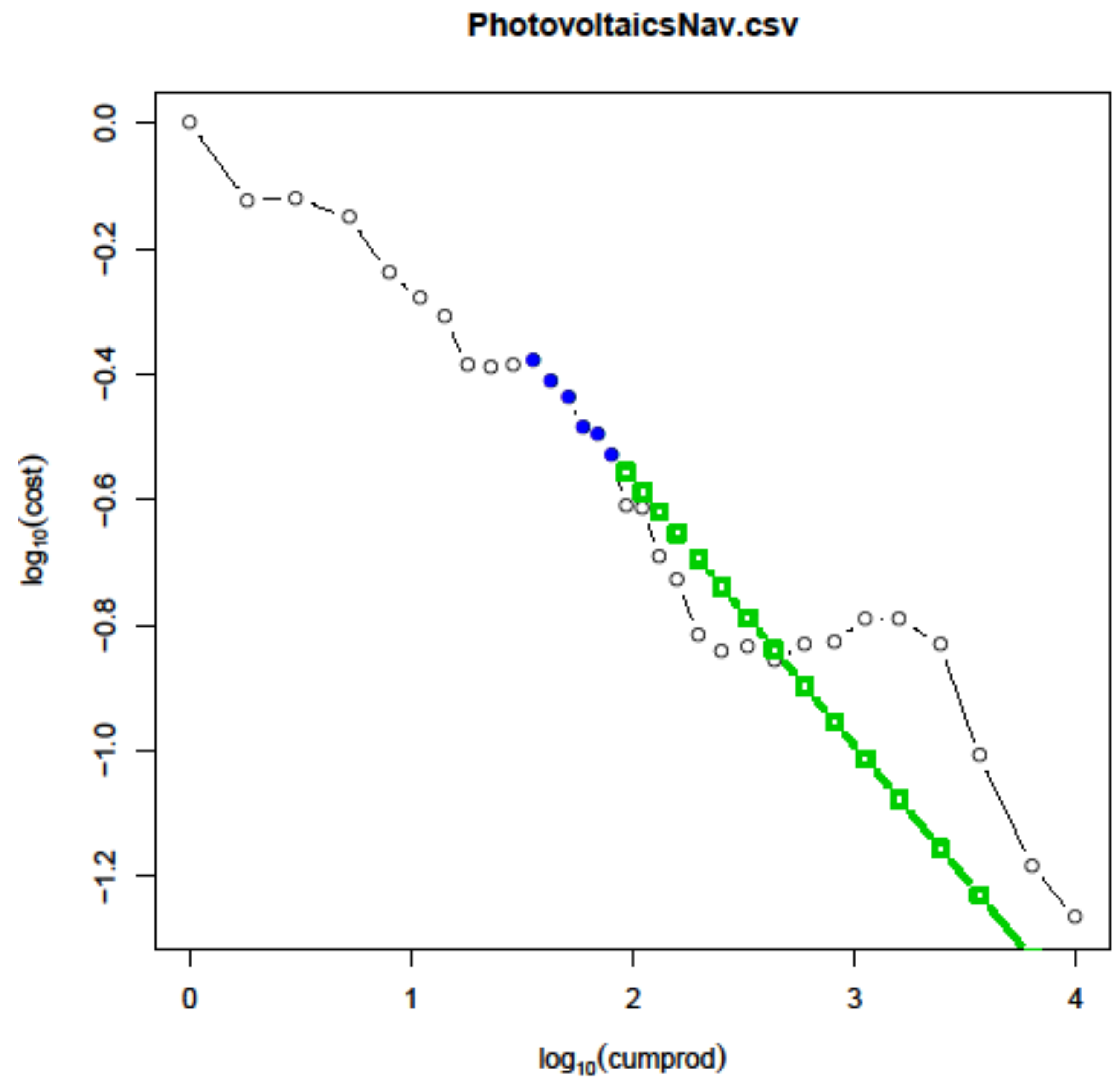

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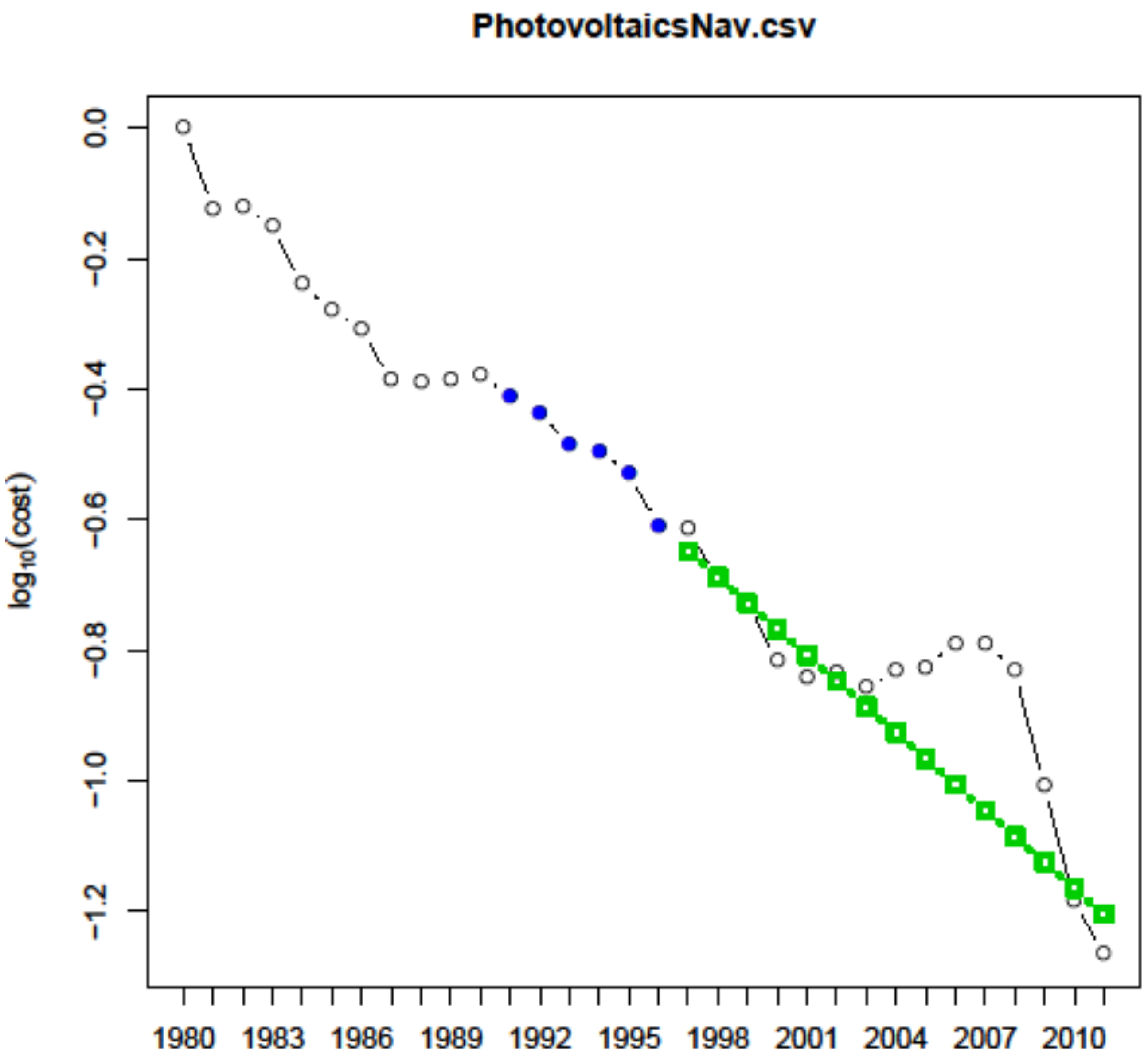

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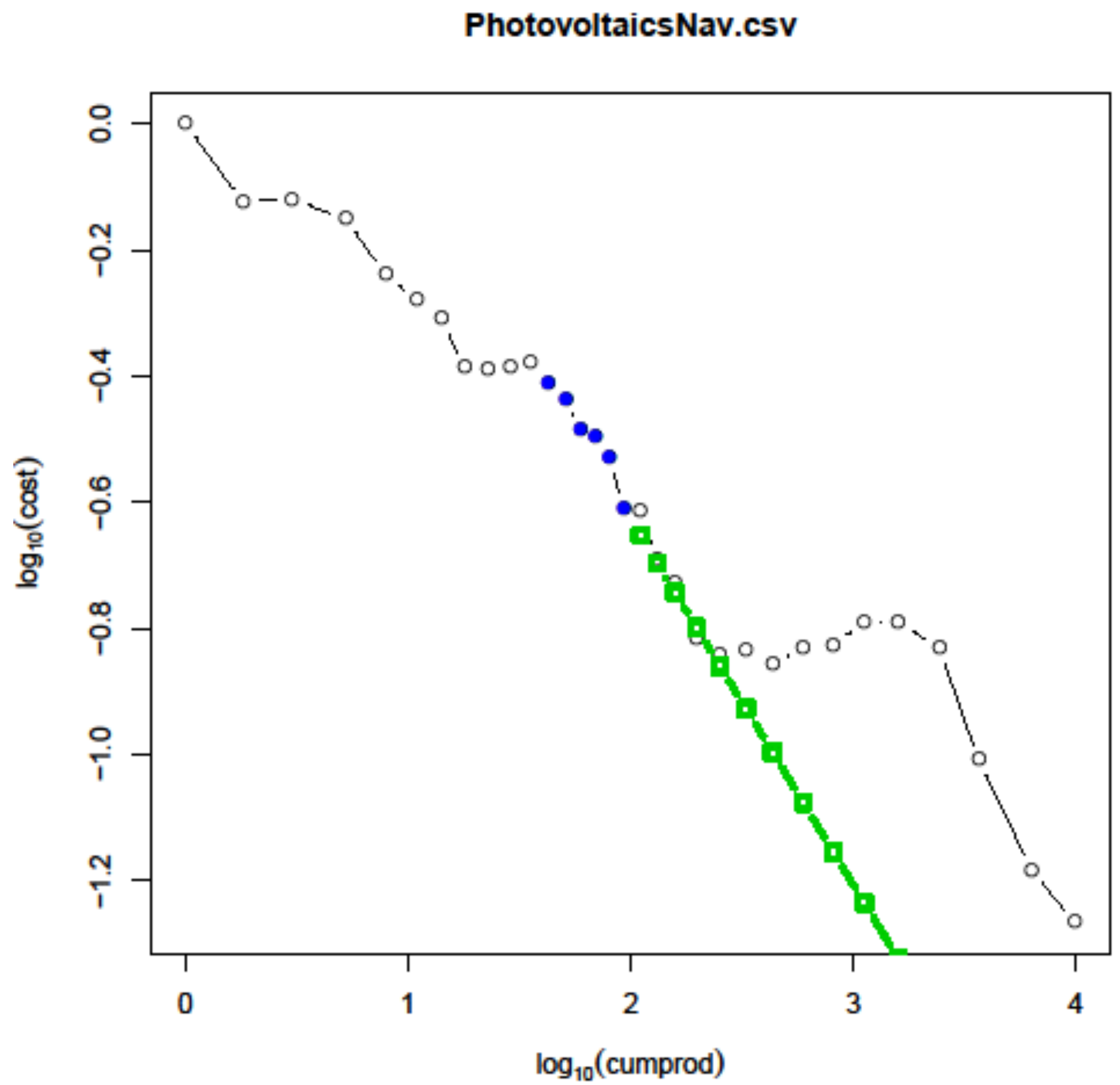

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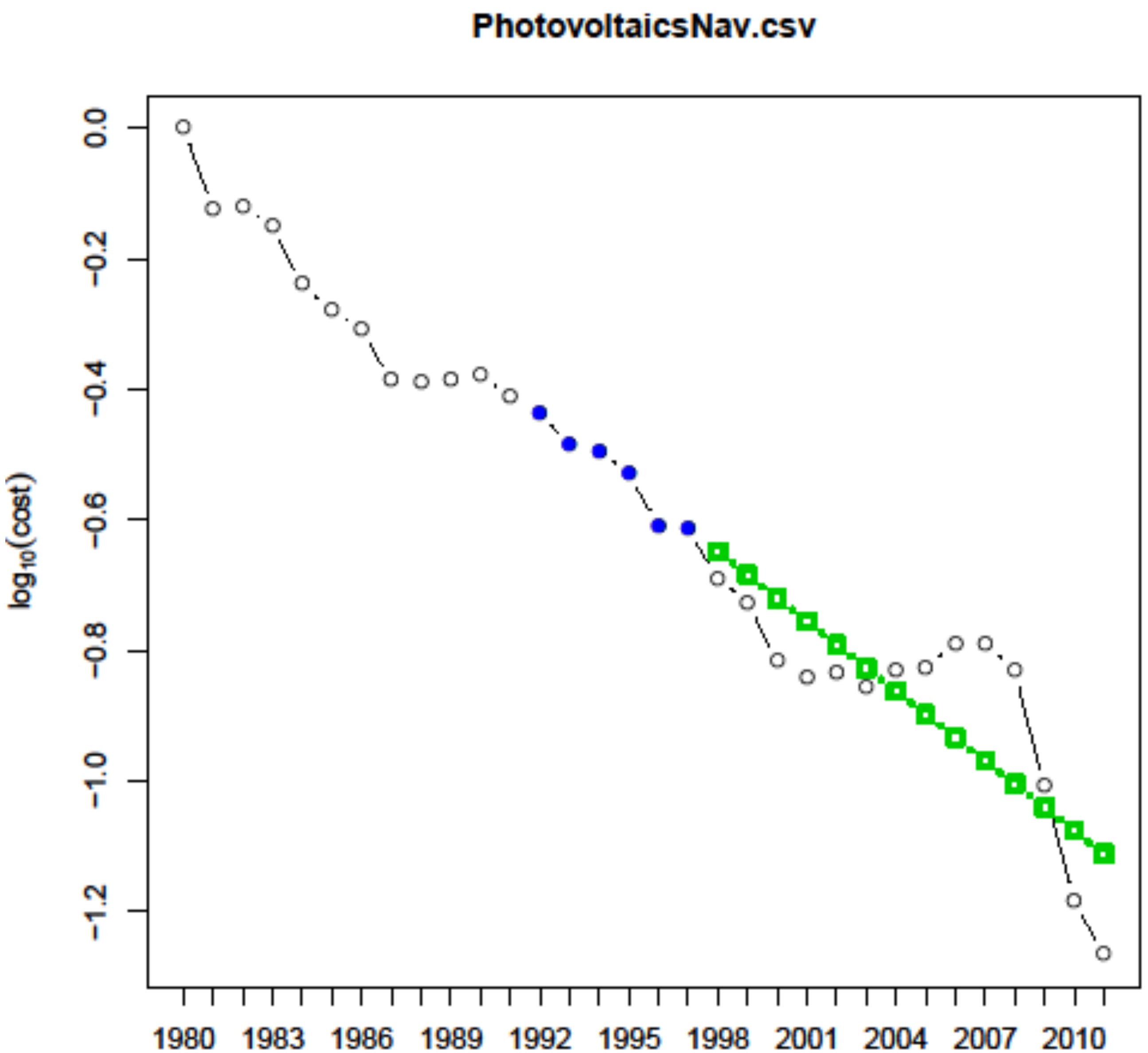

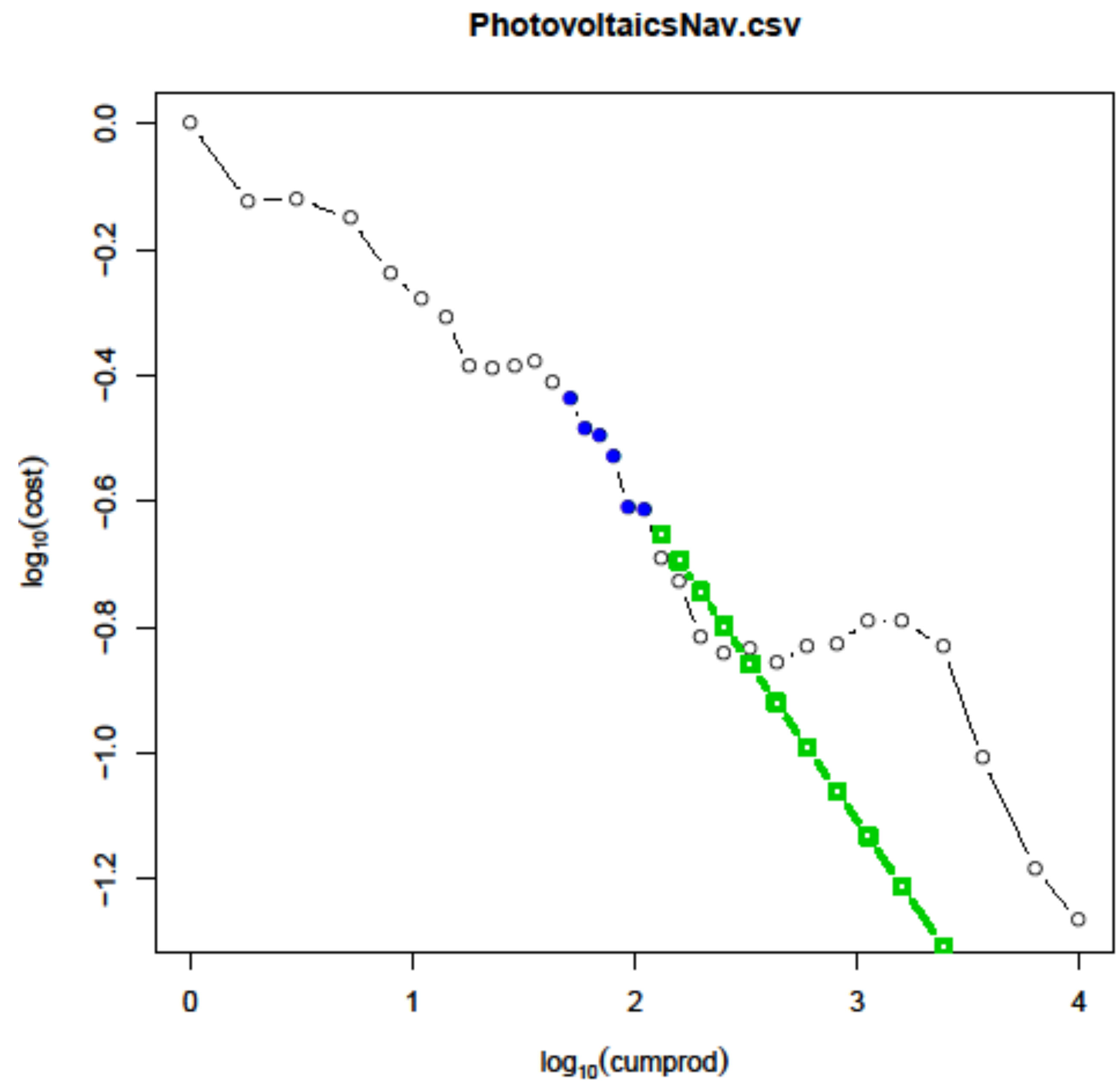

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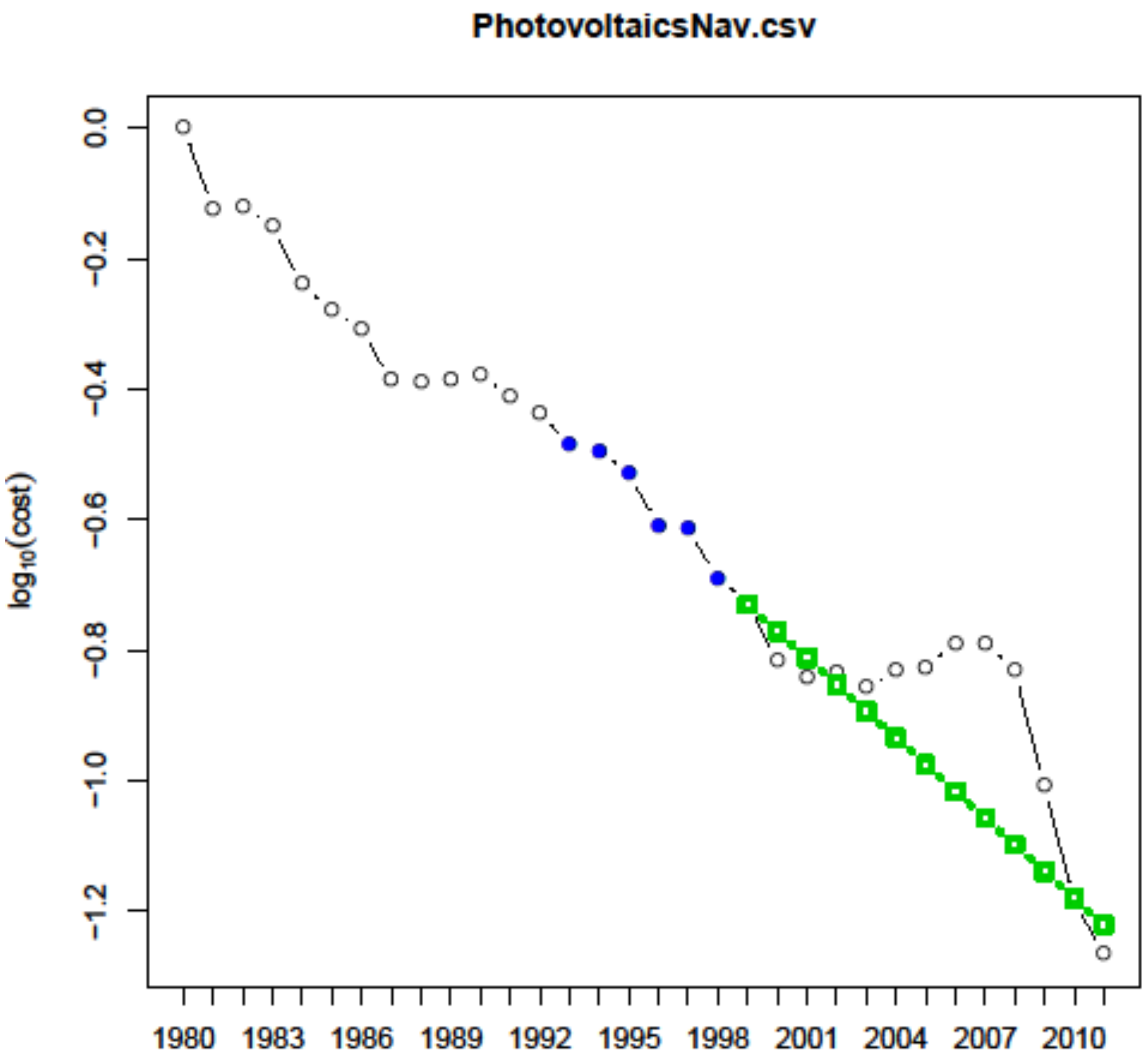

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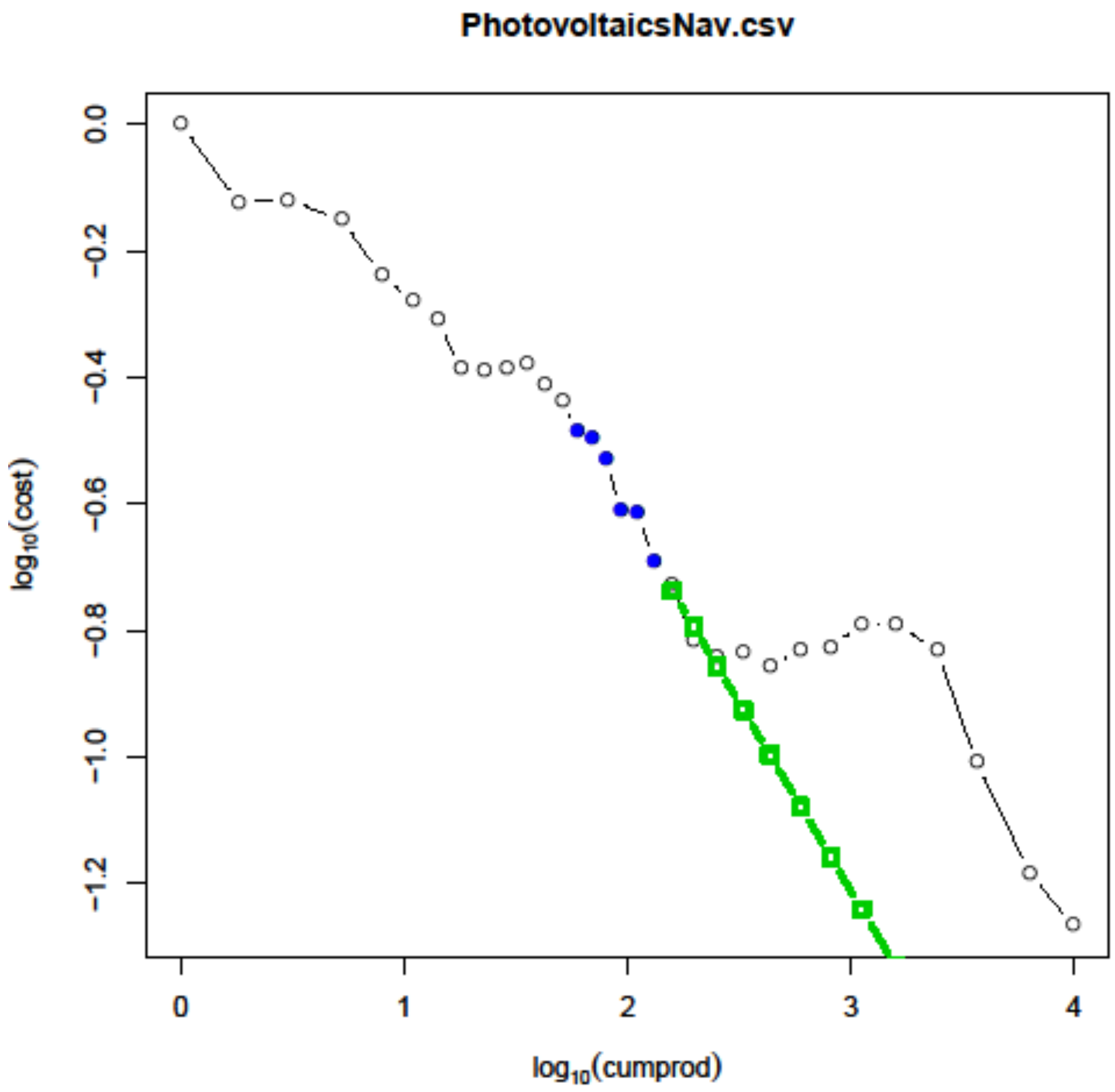

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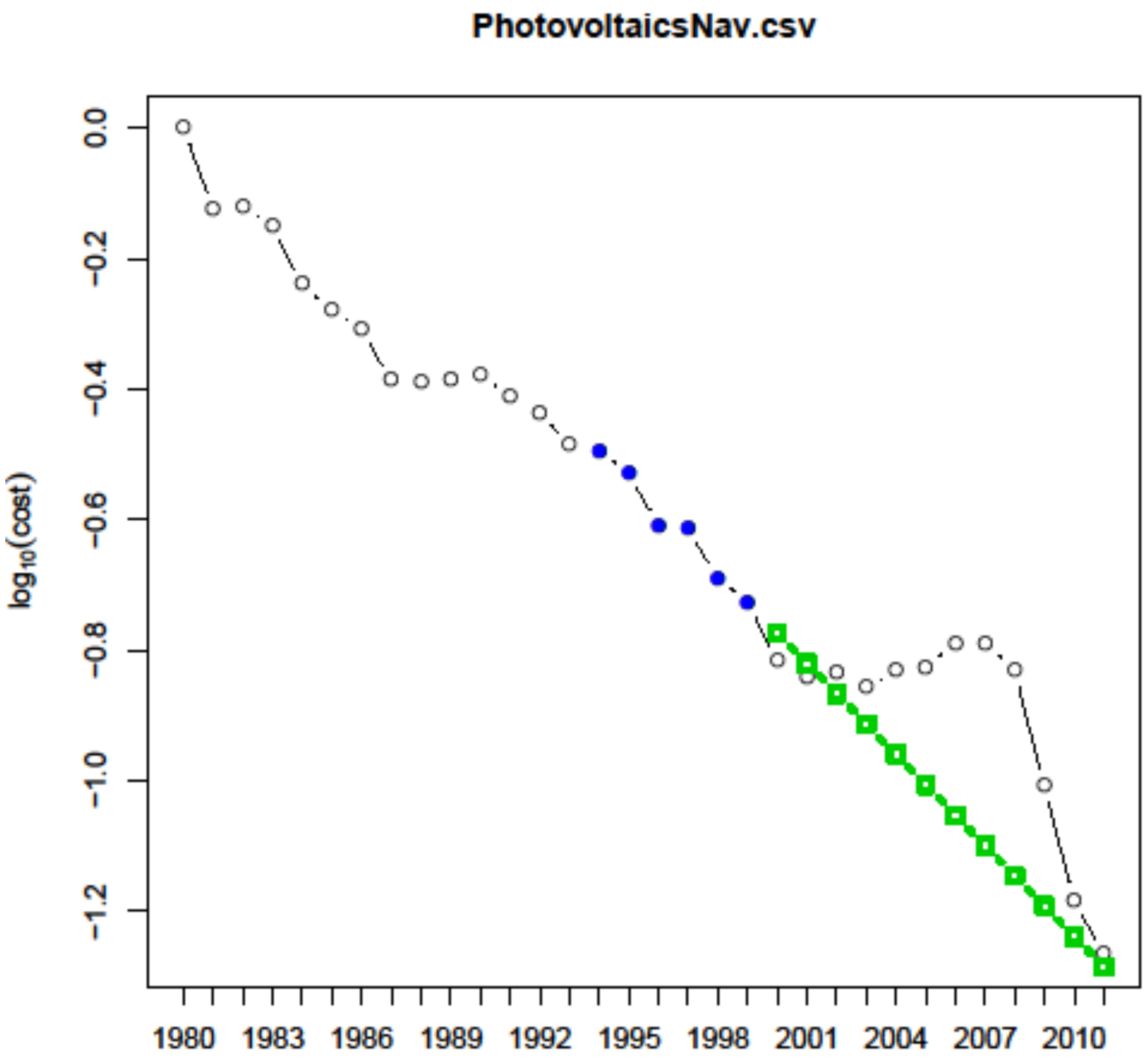

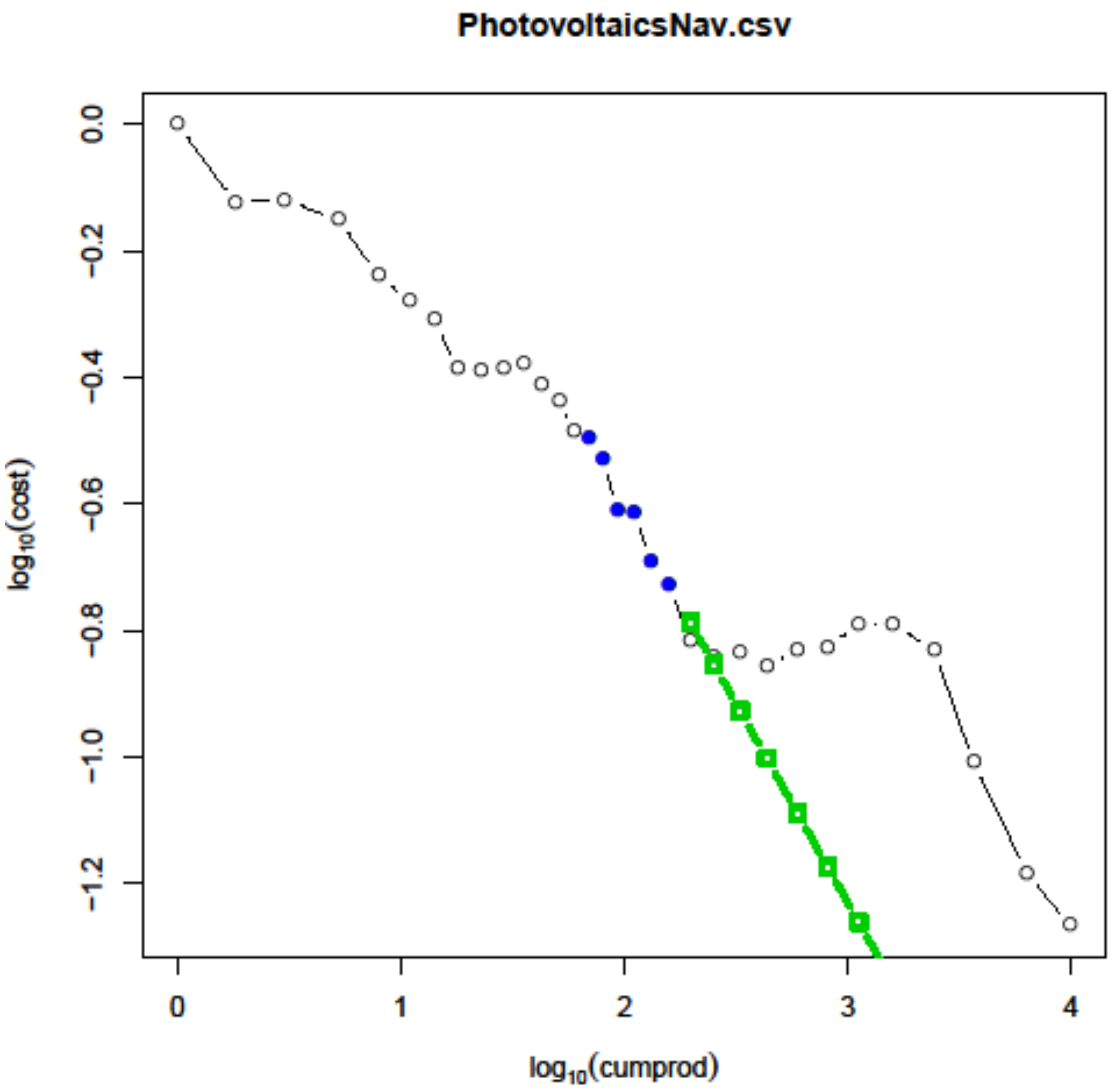

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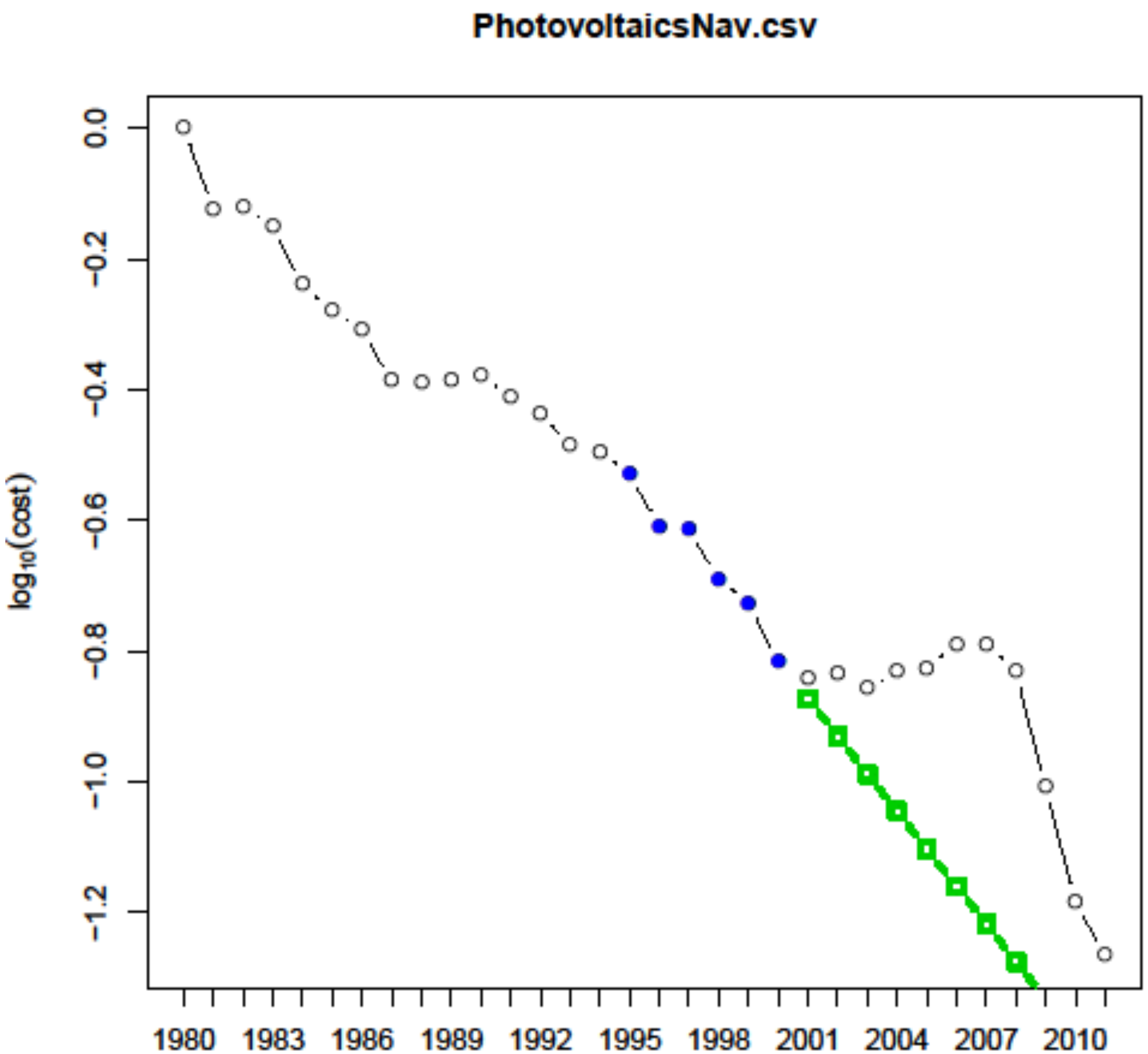

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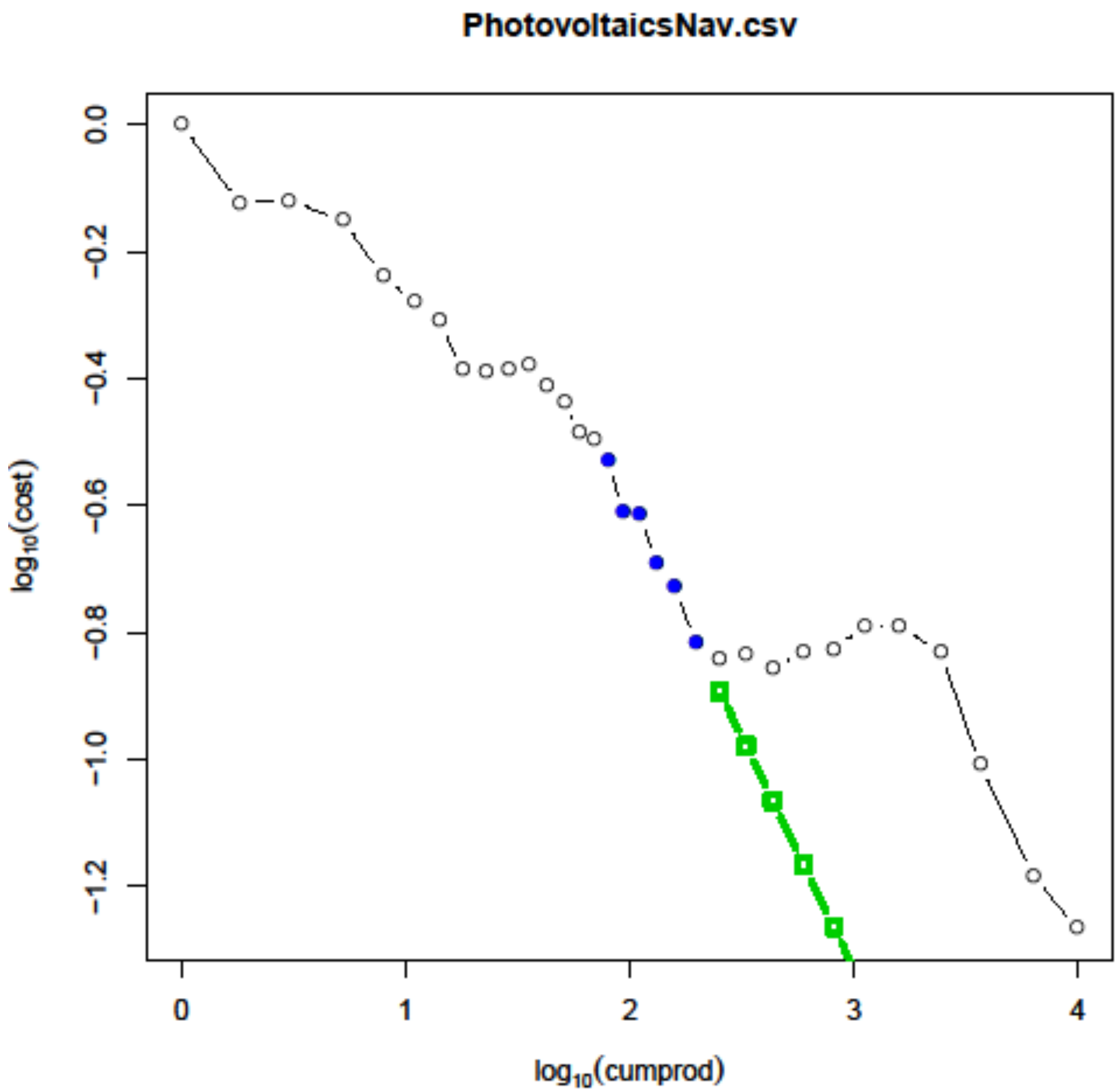

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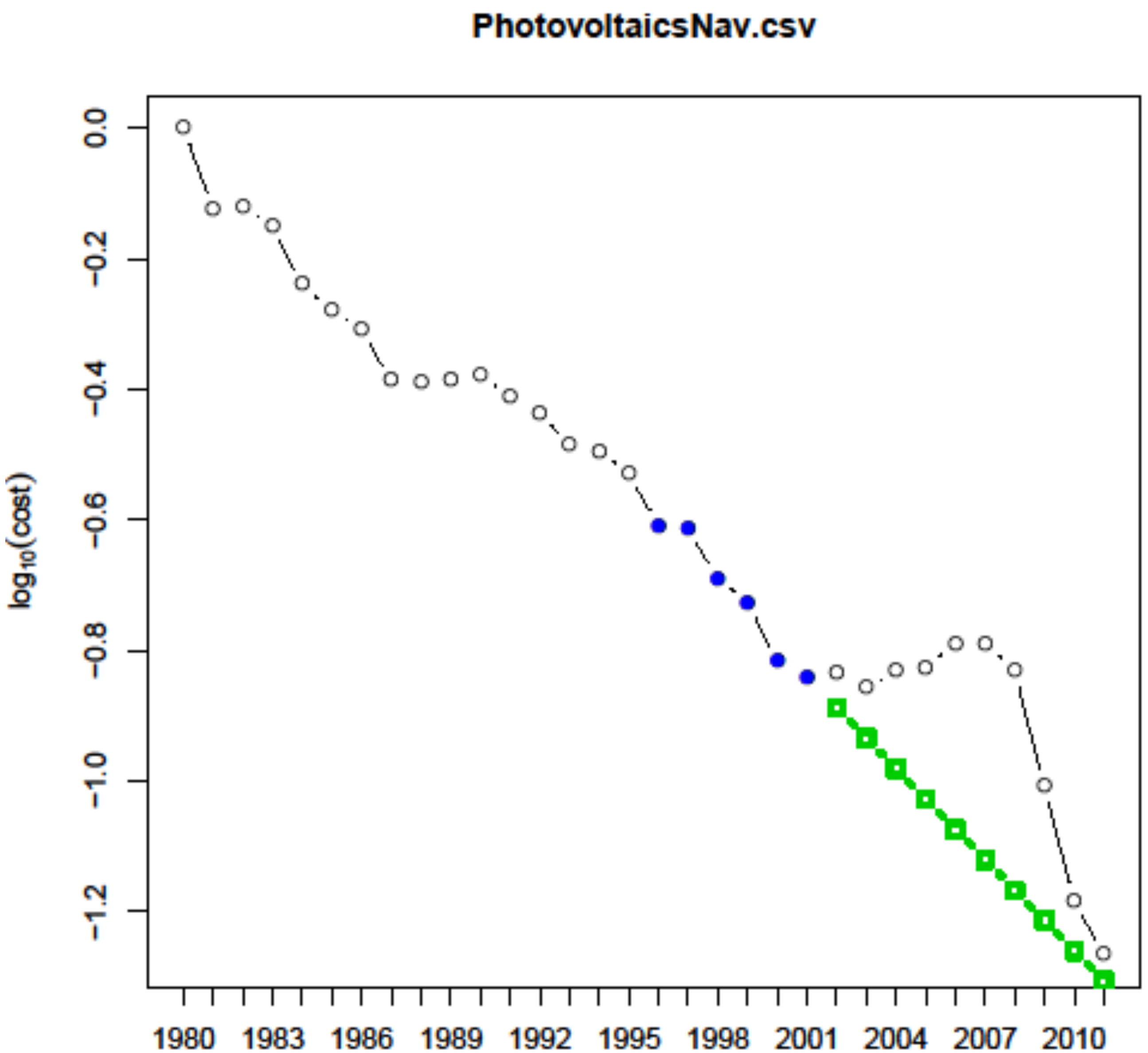

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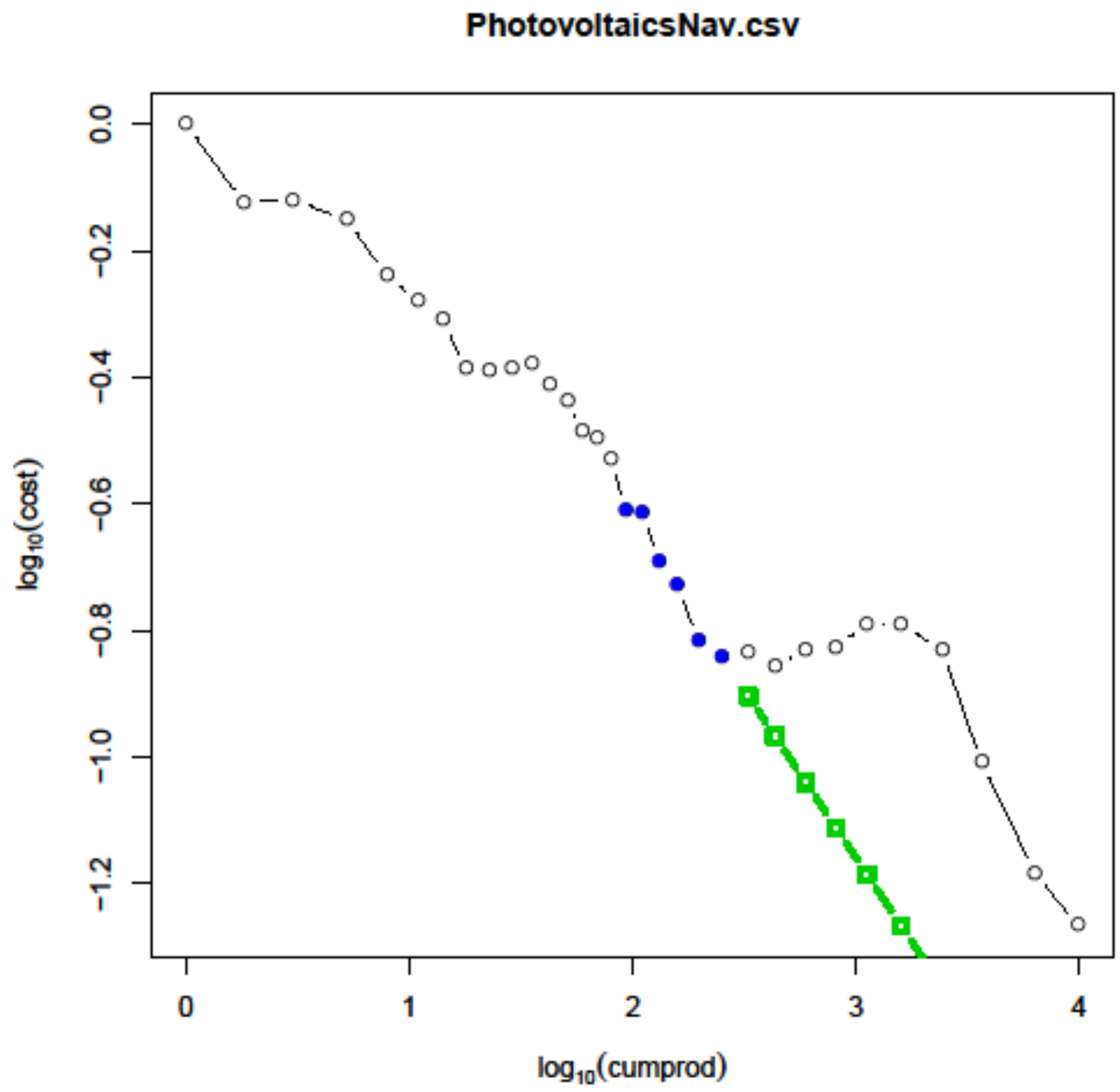

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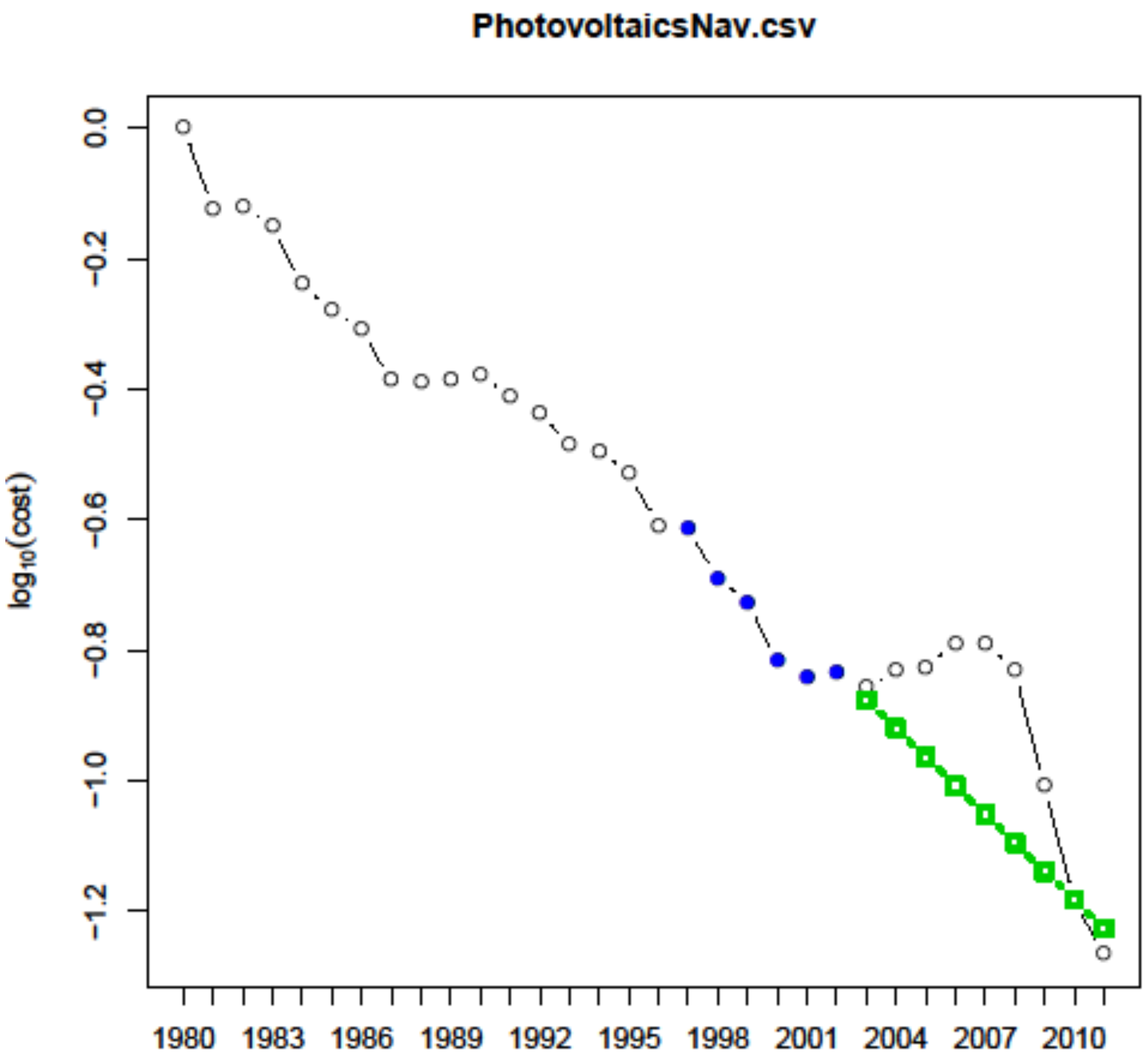

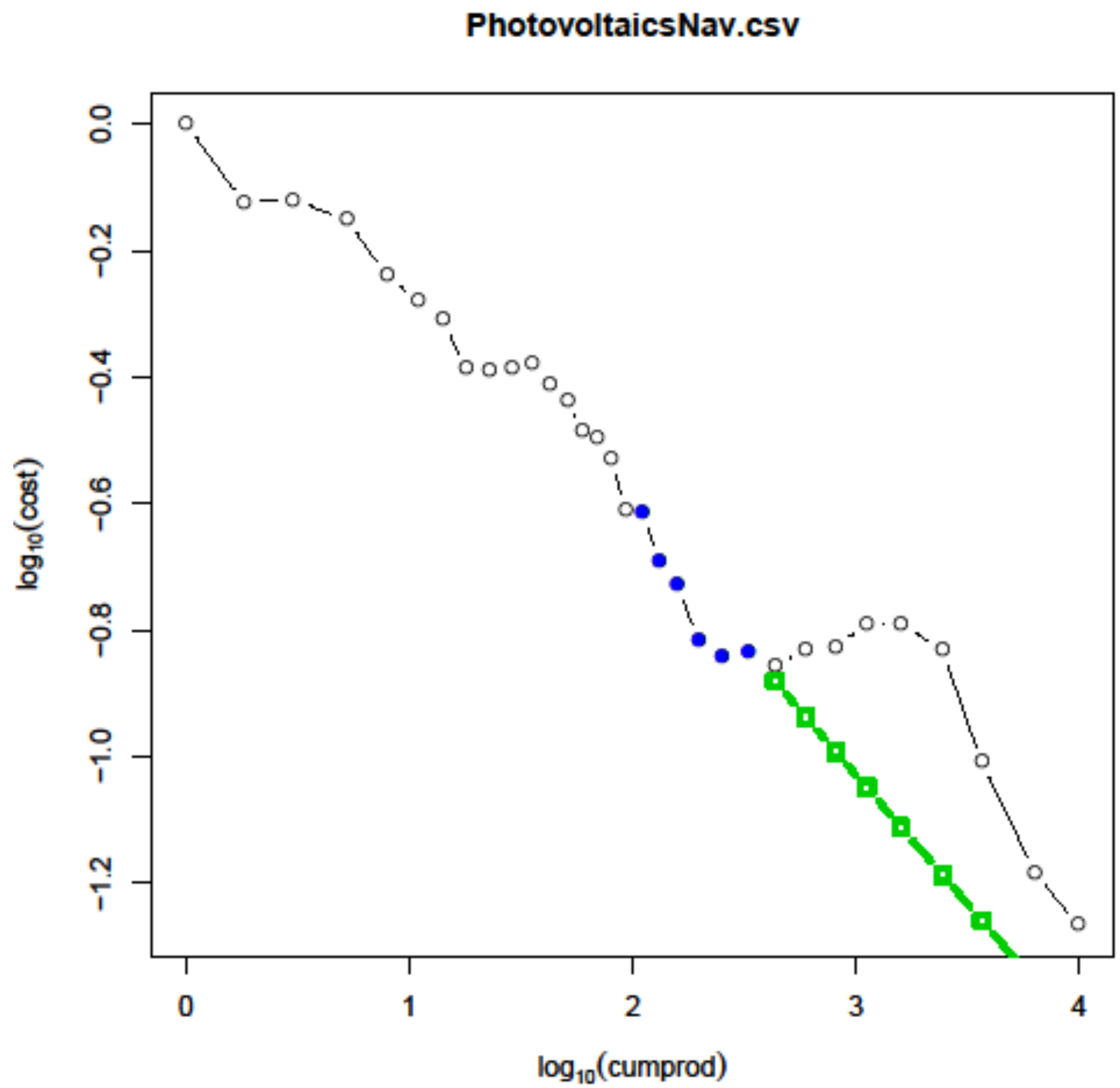

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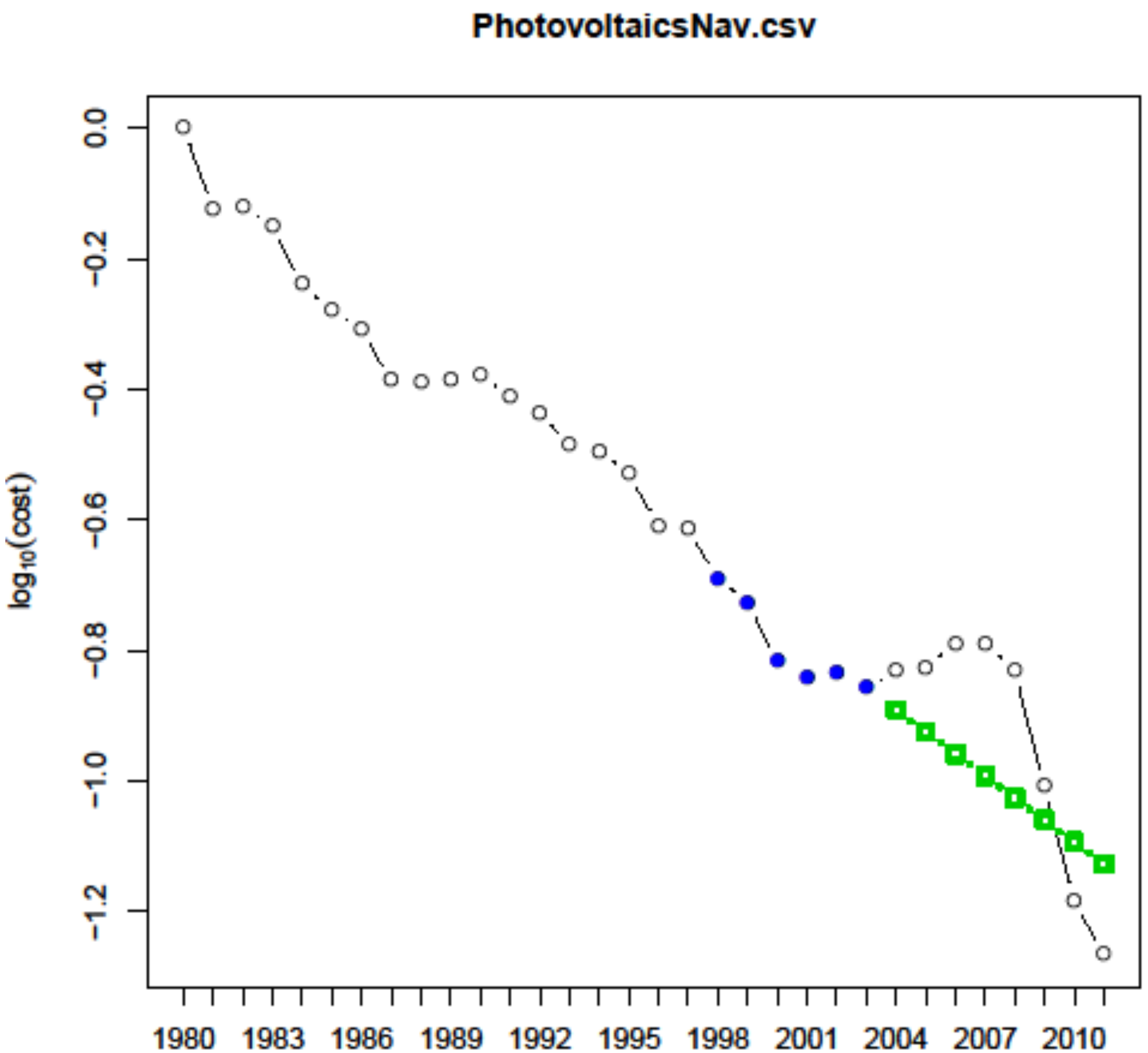

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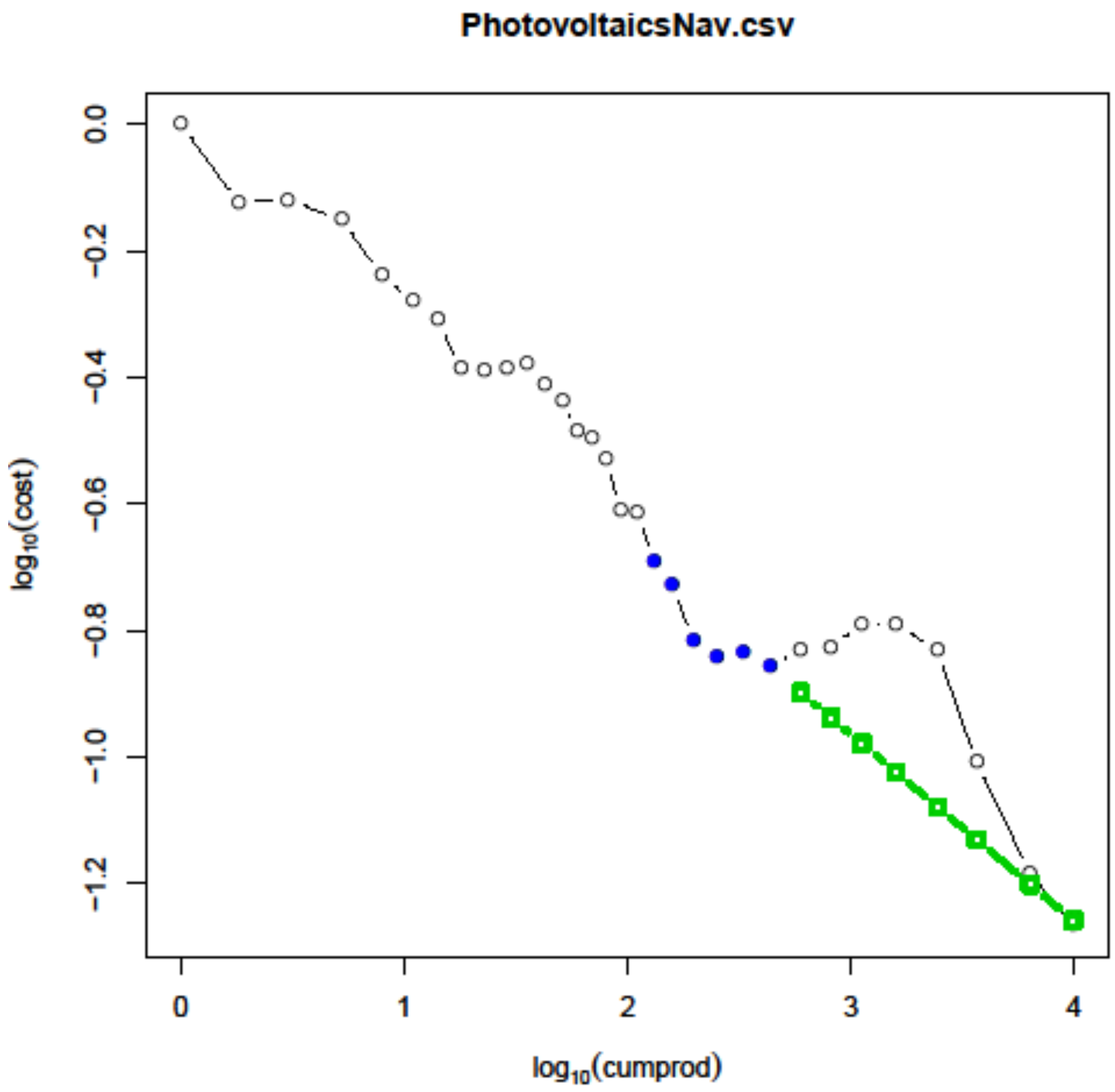

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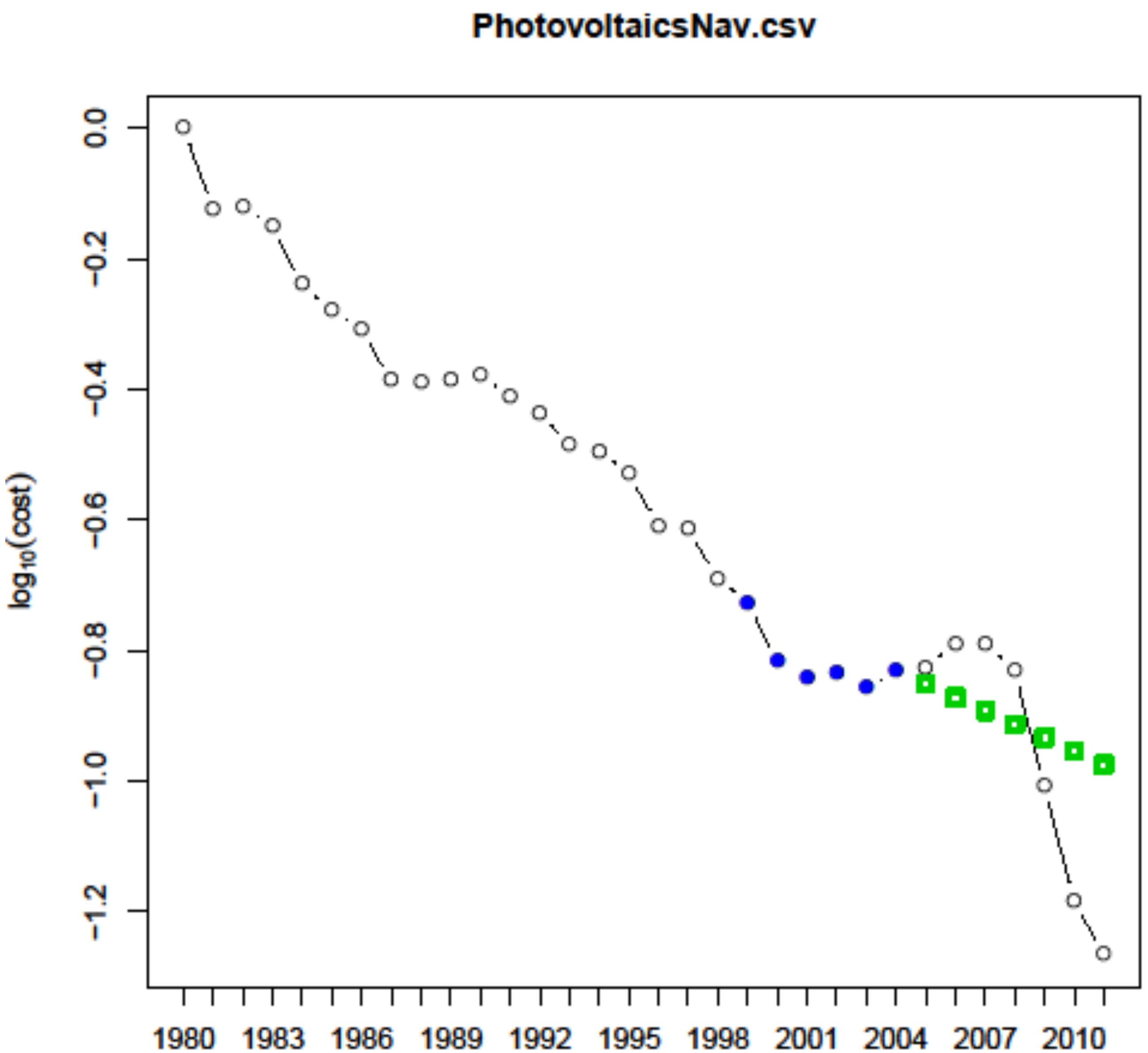

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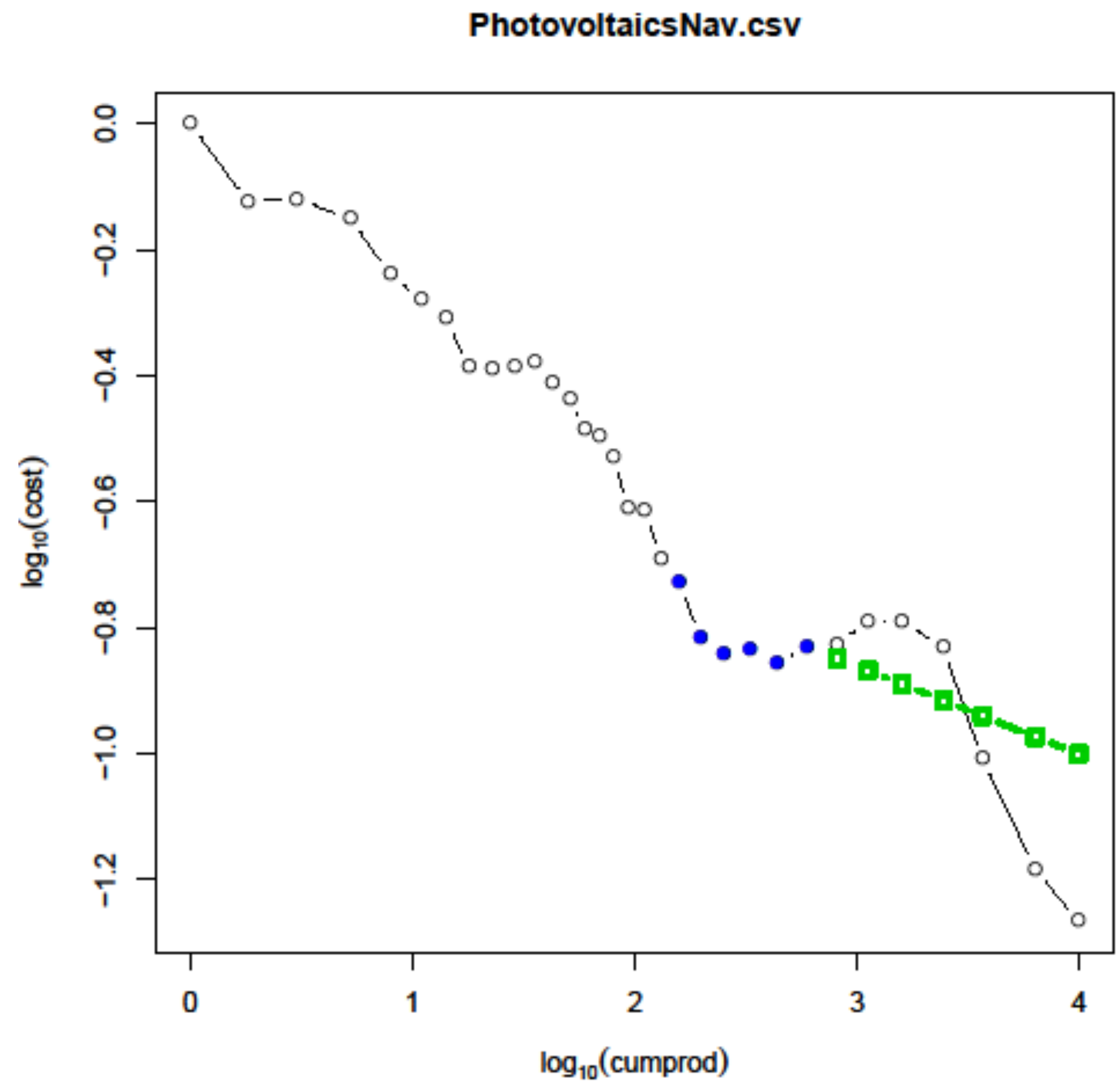
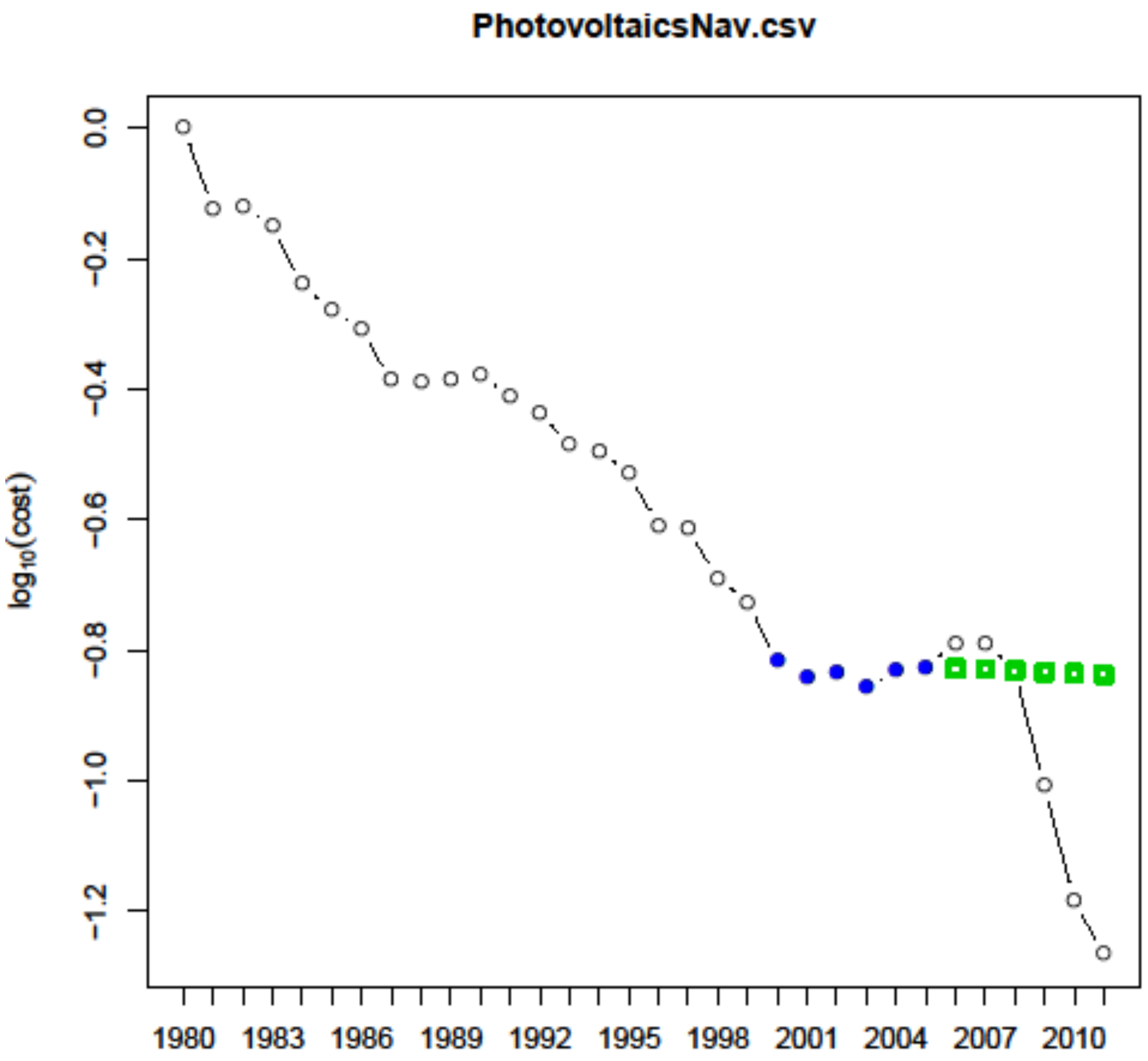
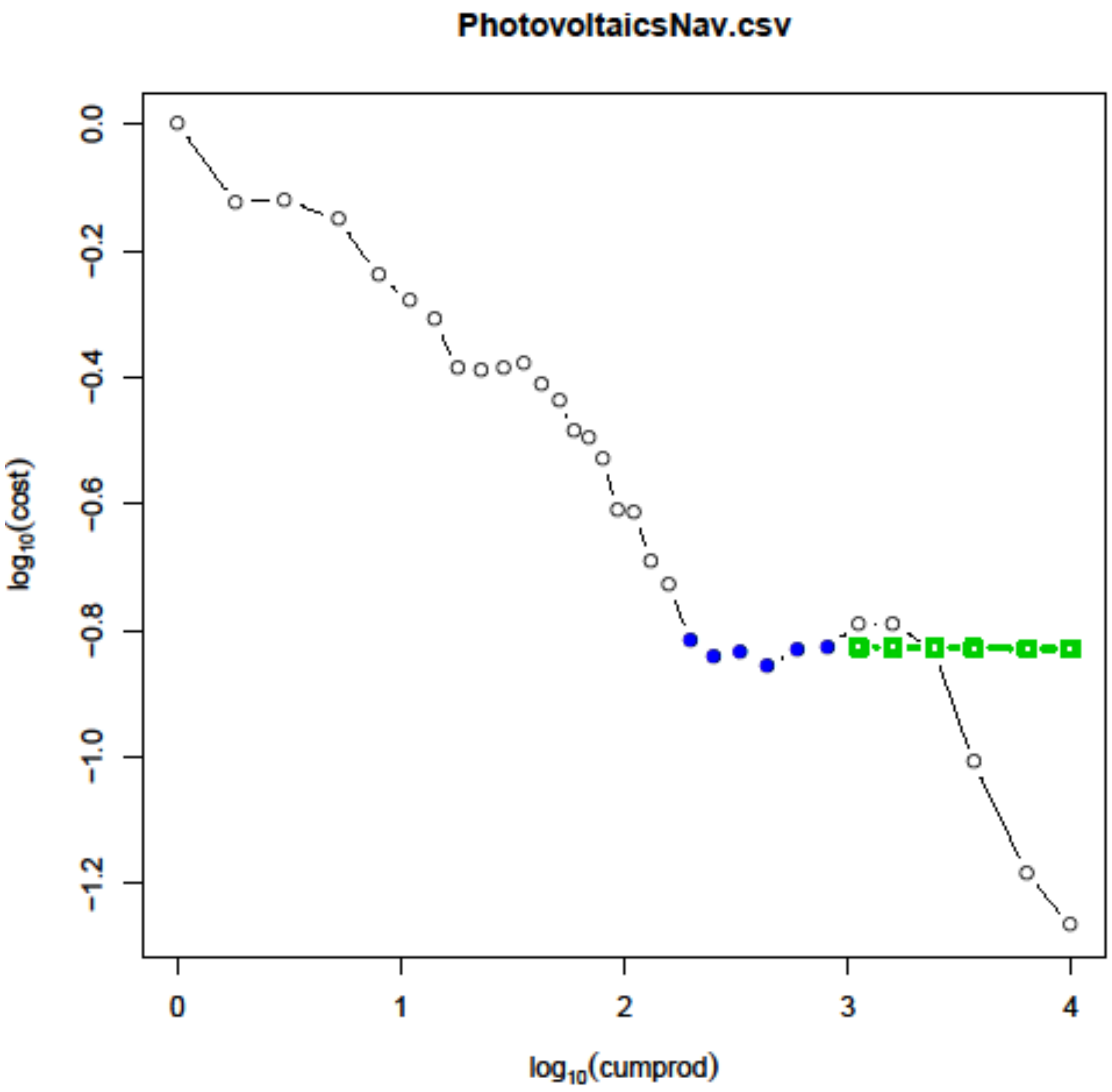


Moore

Wright





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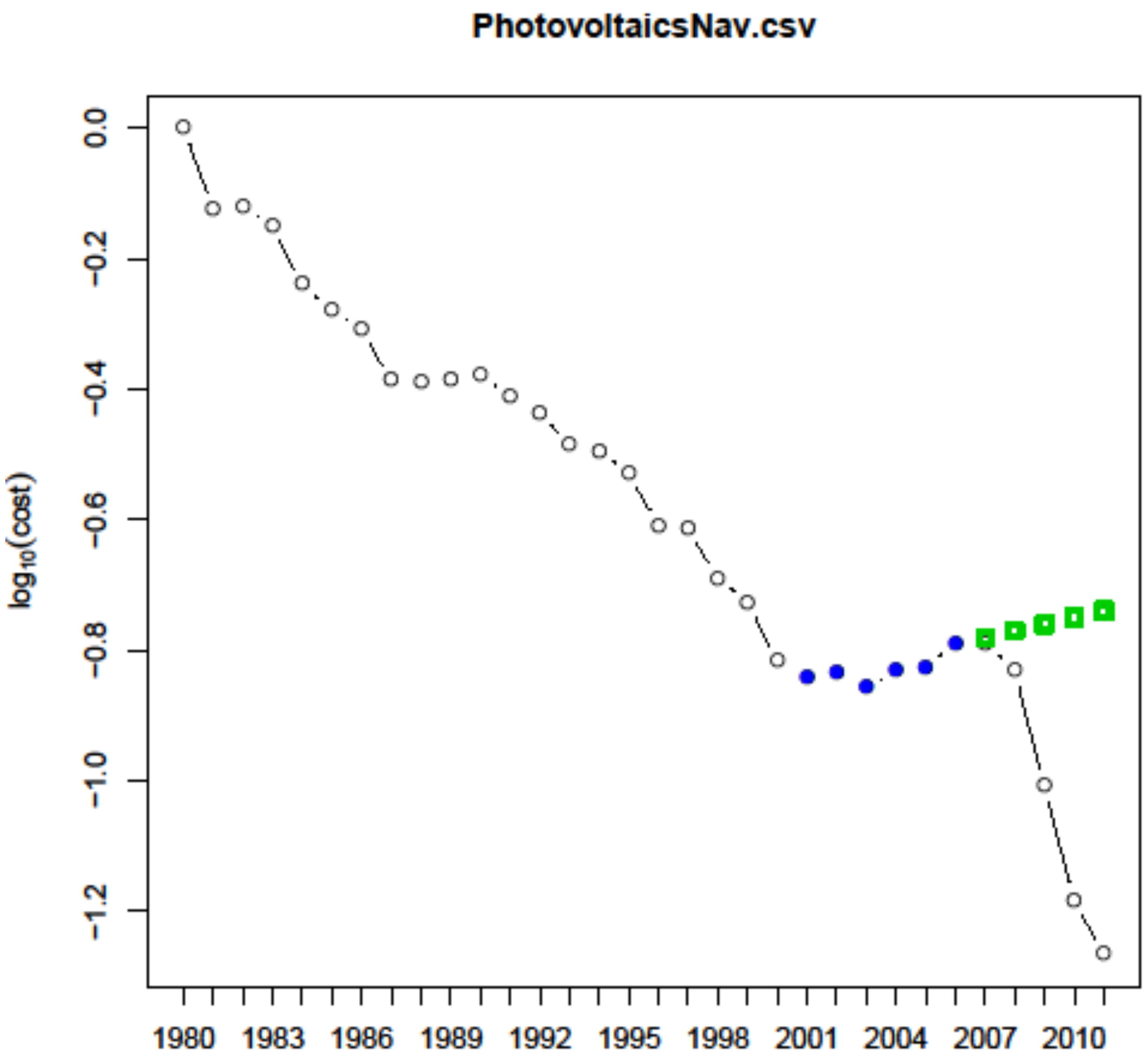
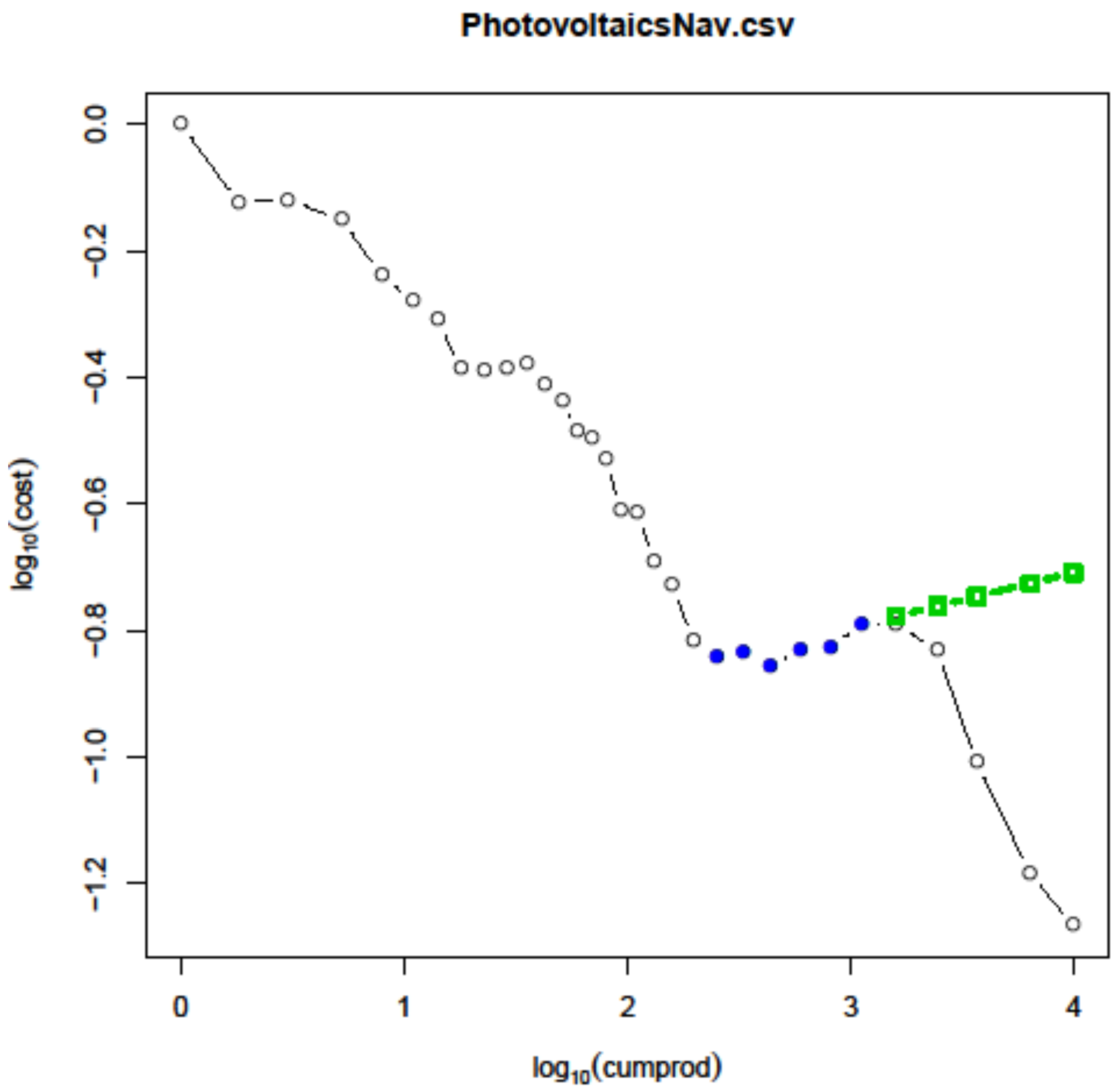
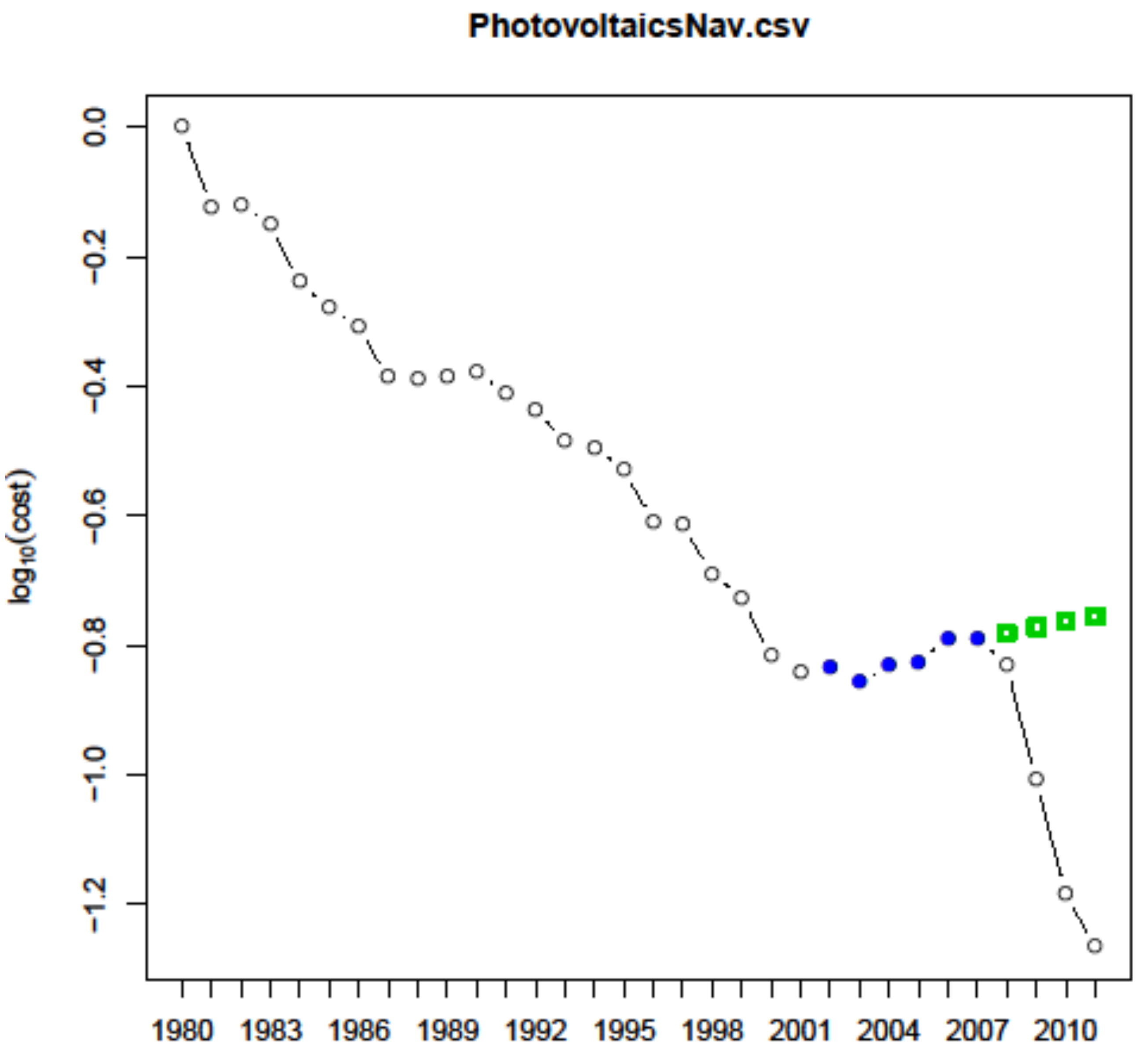
Wright

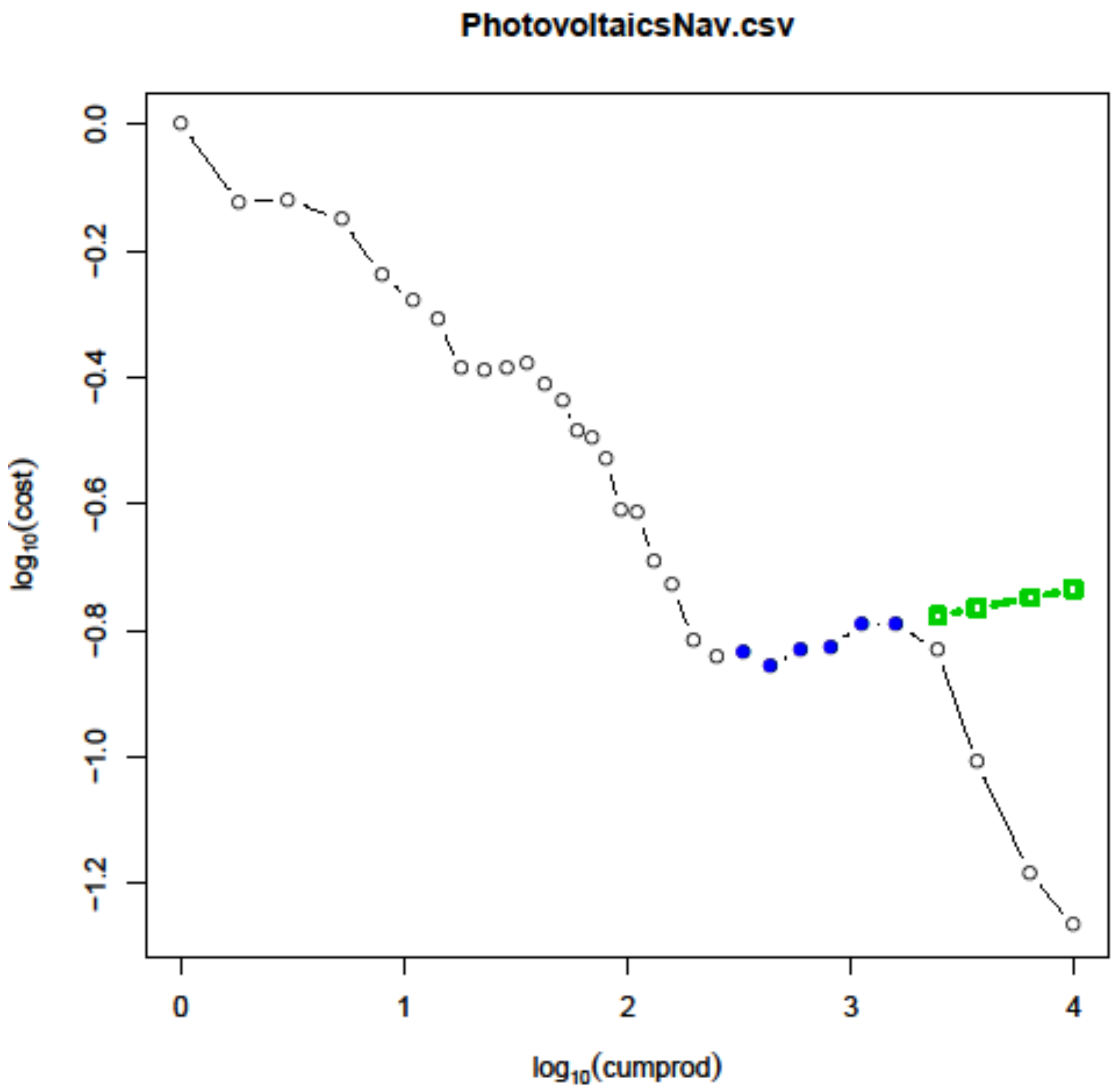




Moore

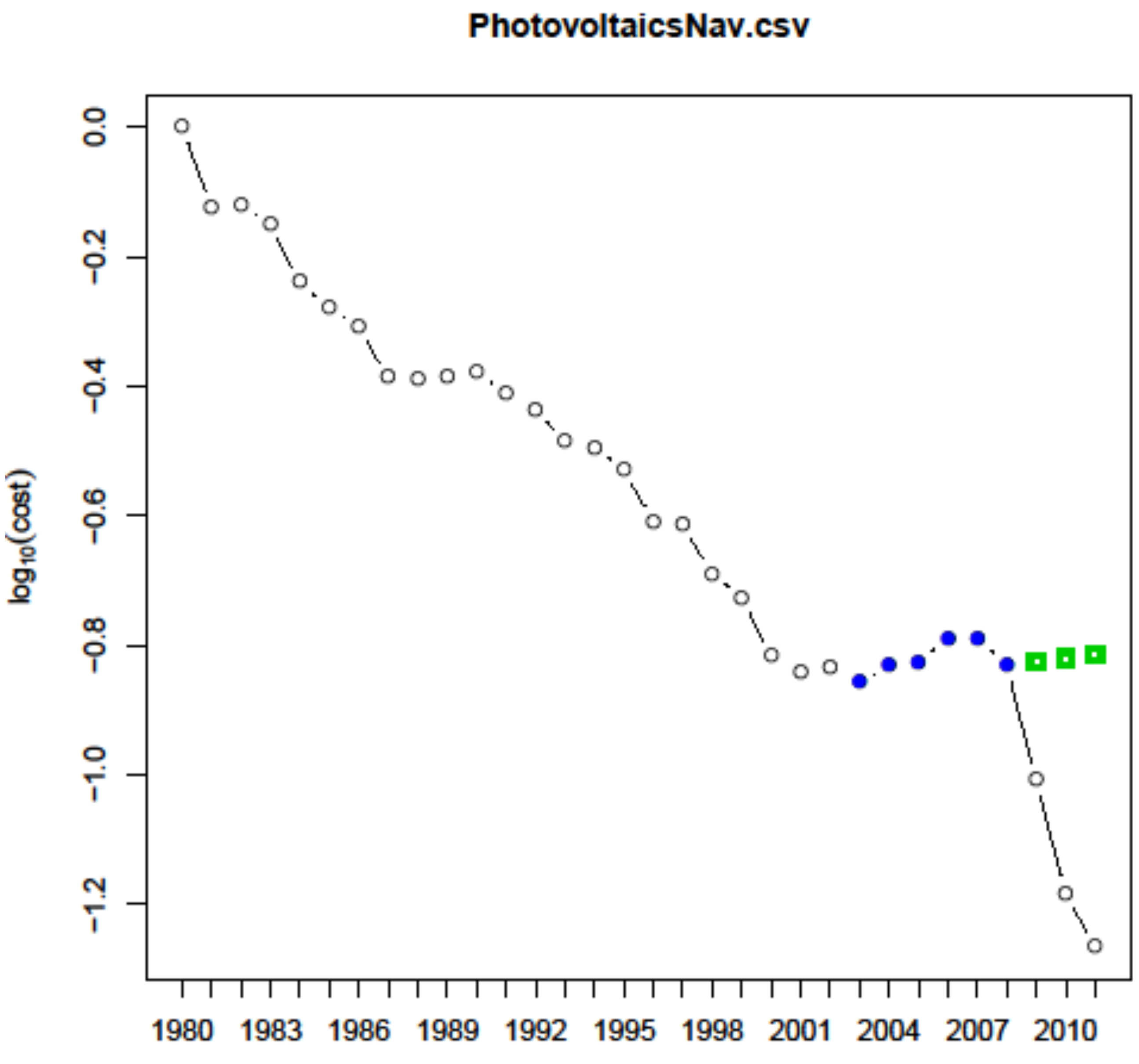
Wright

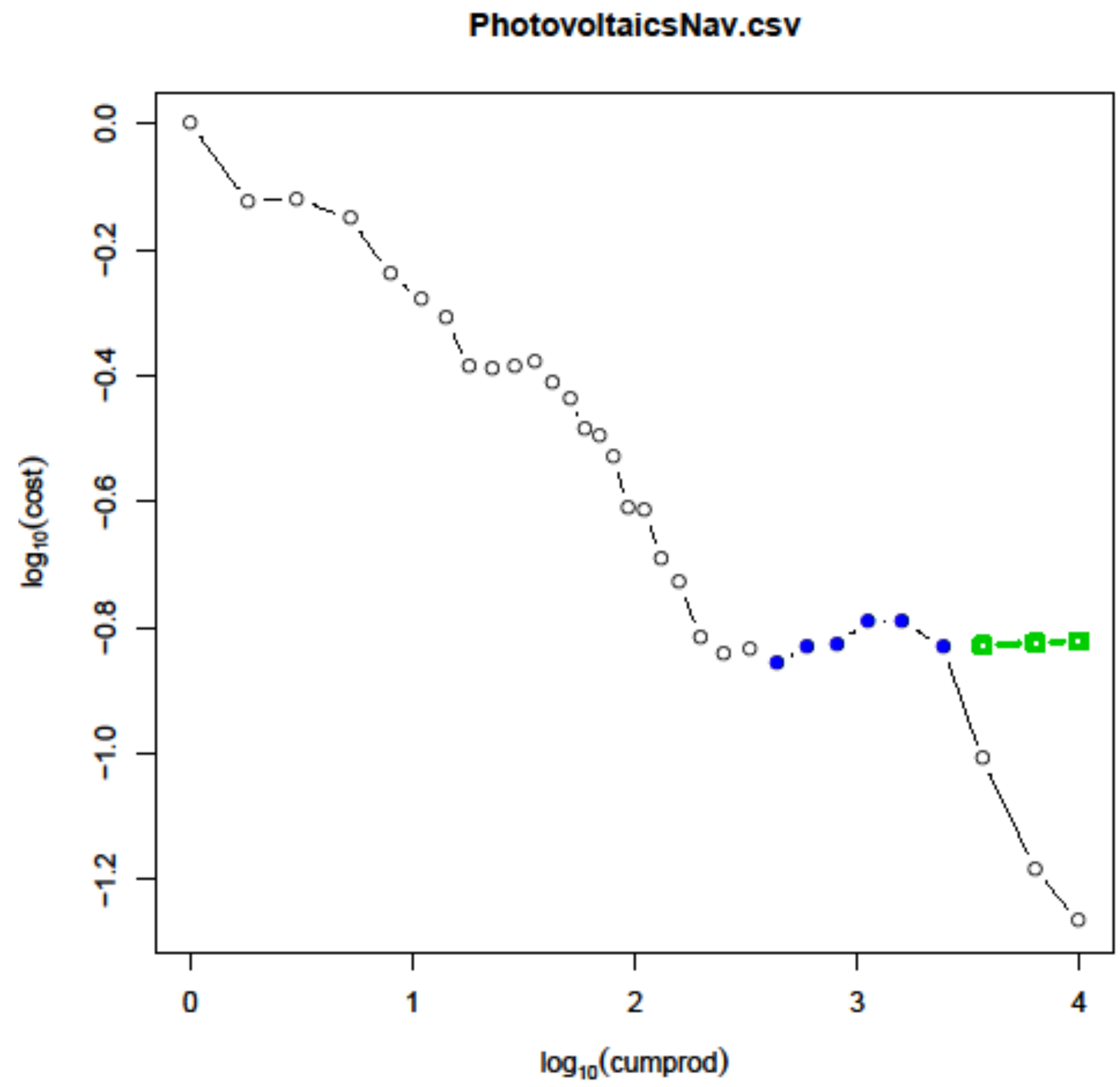




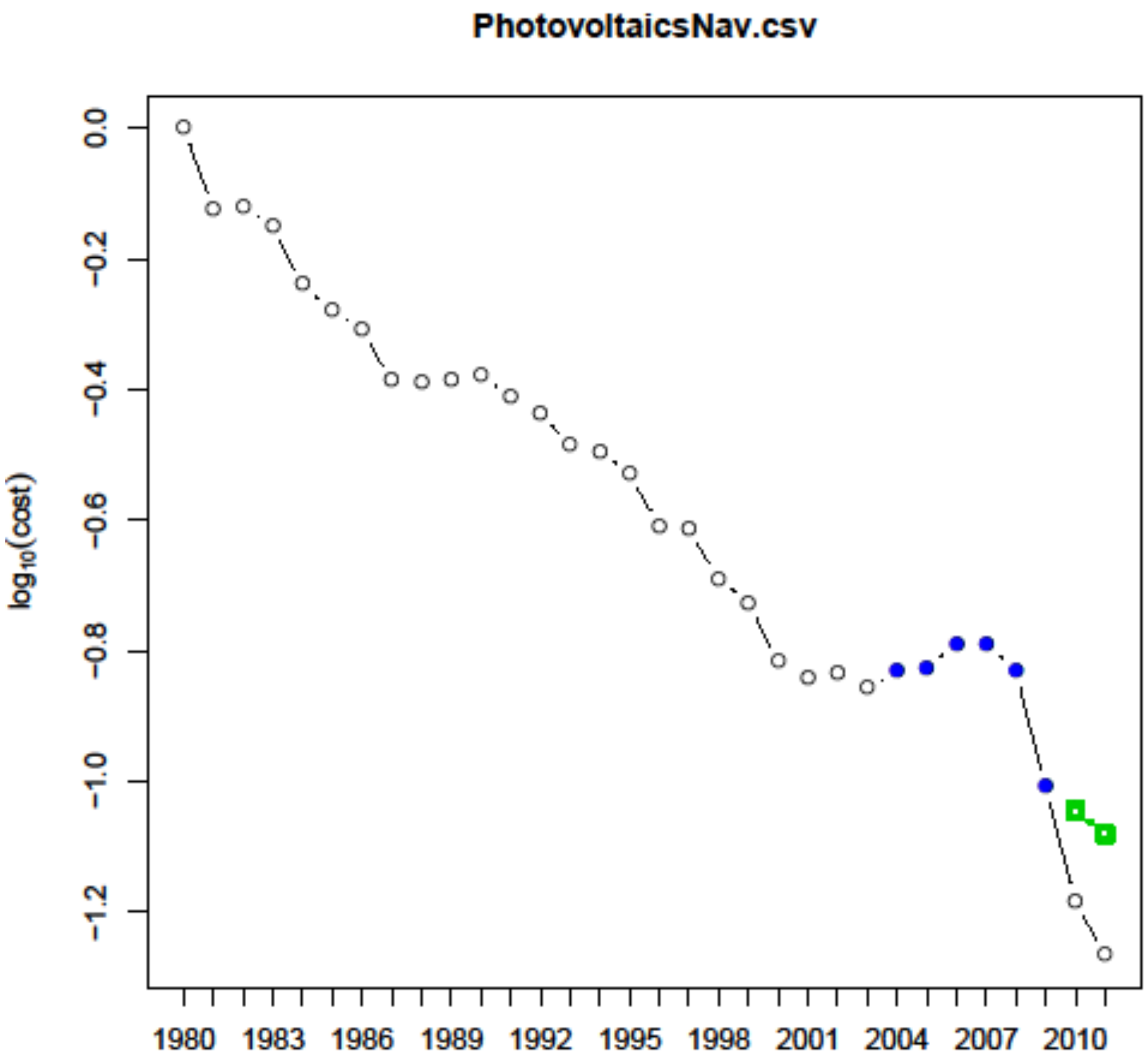
Moore

Wright

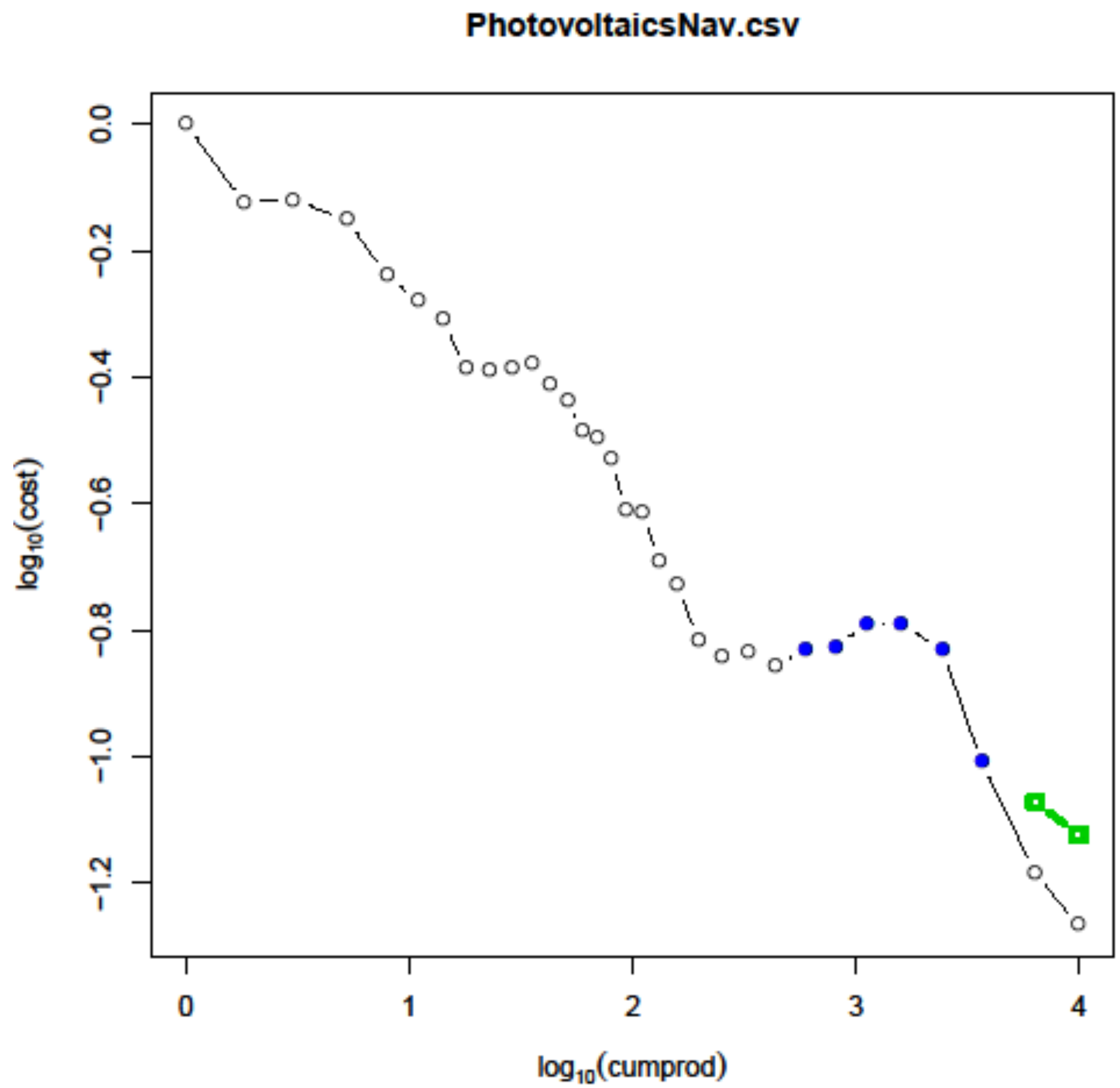




Moore

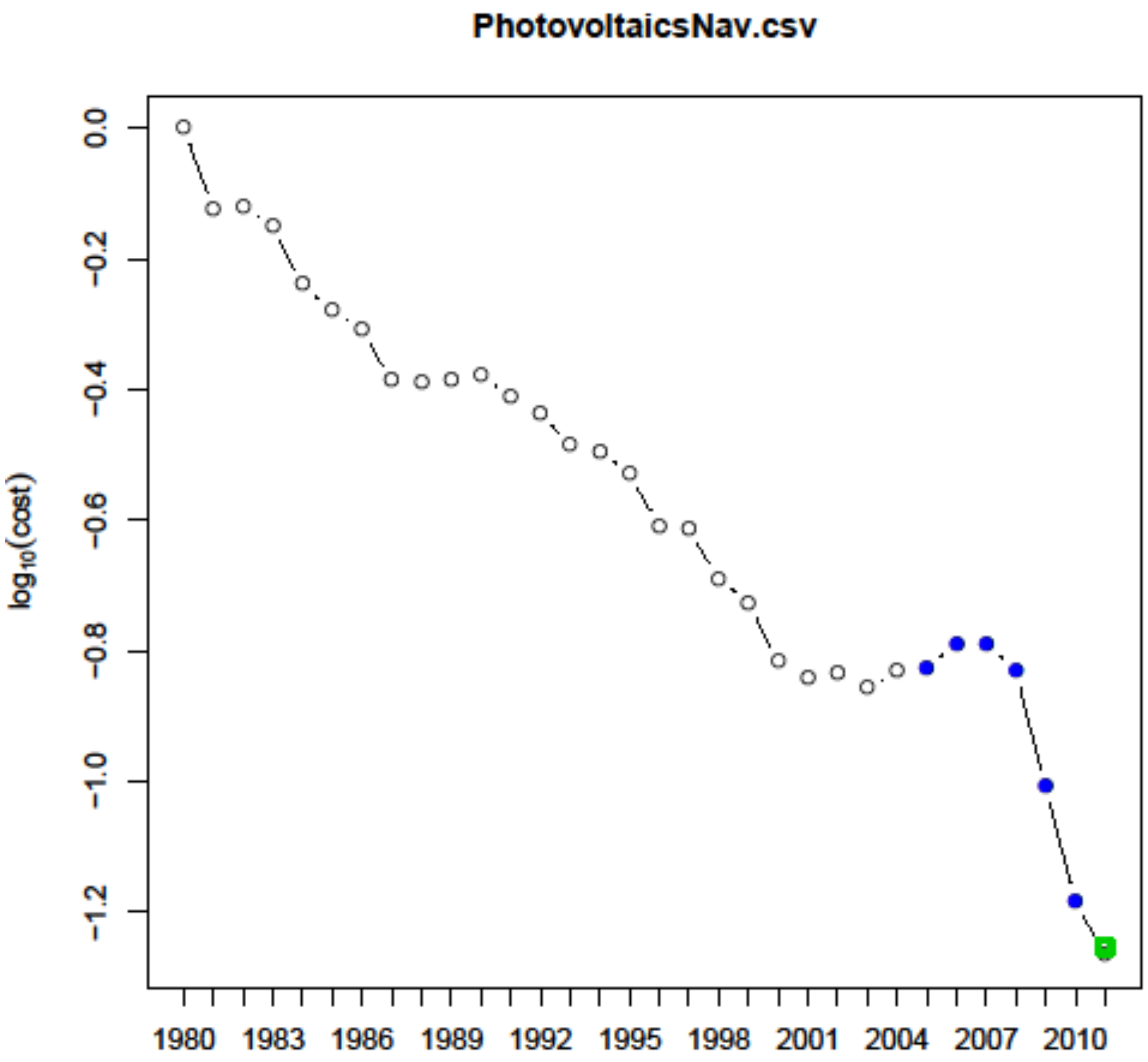


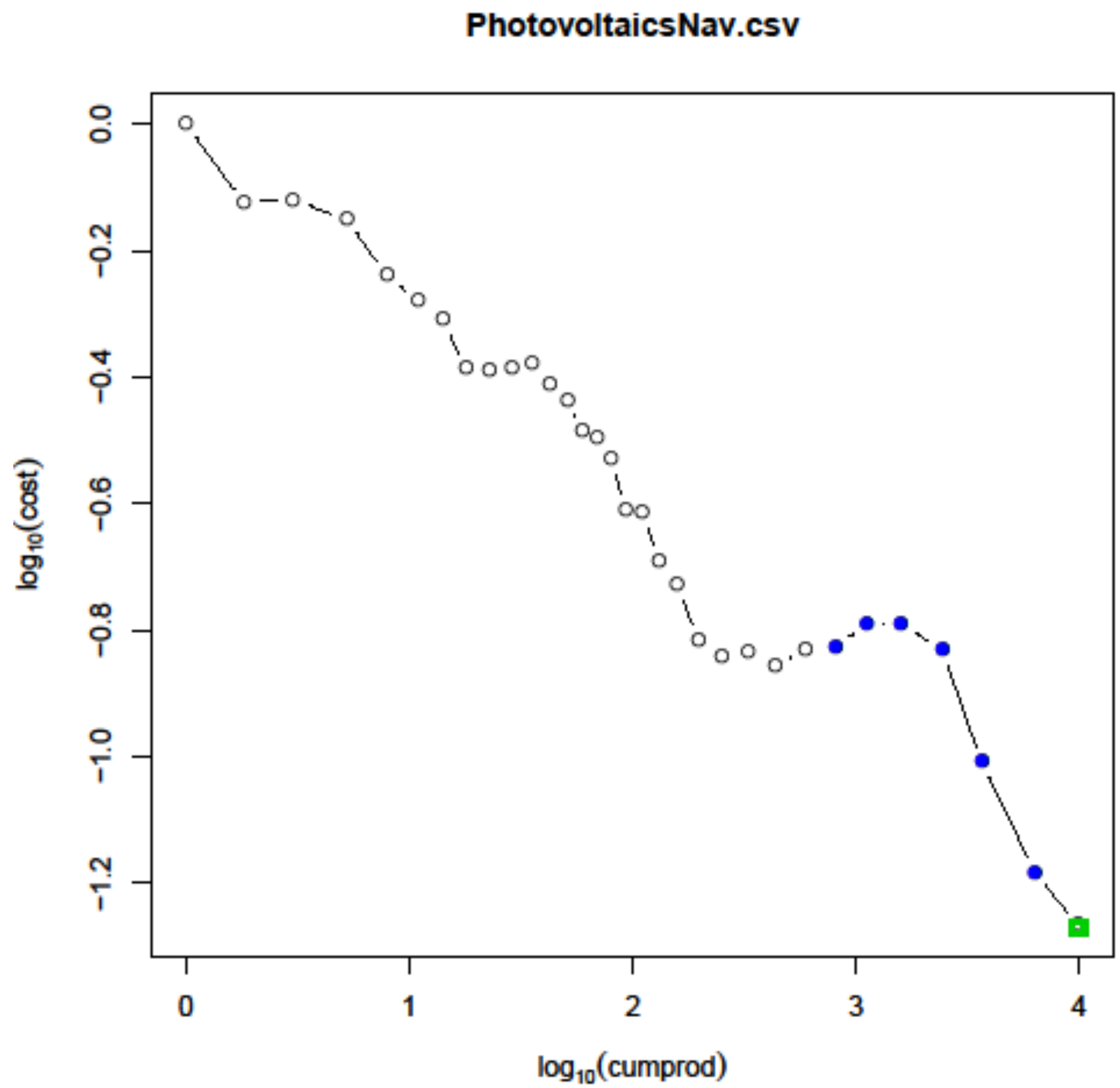
Wright



Moore

Wright





How good are the forecasts?

Forecasts without error bars
are not very useful.

Time series models

Moore's law as a random walk with drift

$$y_{t+1} - y_t = \mu + K n_t$$

Change in log(cost) Drift Noise

Wright's law as random walk with drift
dependent on cumulative production

$$y_{t+1} - y_t = \omega \log\left(\frac{x_{t+1}}{x_t}\right) + S n_t$$

Predicted forecasting error for Moore's law assuming normally distributed IID noise

$$\mathcal{E} = y_{t+\tau} - \hat{y}_{t+\tau}$$

$$\frac{1}{\sqrt{A}}\left(\frac{\mathcal{E}}{\hat{K}}\right) \sim t(m-1)$$

$$A = \tau(1 + \tau/m)$$

$\hat{y}_{t+\tau}$ = prediction for time $t+\tau$

$\hat{K}$ = estimated noise amplitude

m = number of points used to estimate μ

t = Student's "t" distribution

This works surprisingly well

However, it is possible to do better by taking correlations into account

Random process with correlated noise

$$y_{t+1} - y_t = \mu + v_t + \theta v_{t-1}$$

v_t = noise at time t

θ = parameter describing correlation

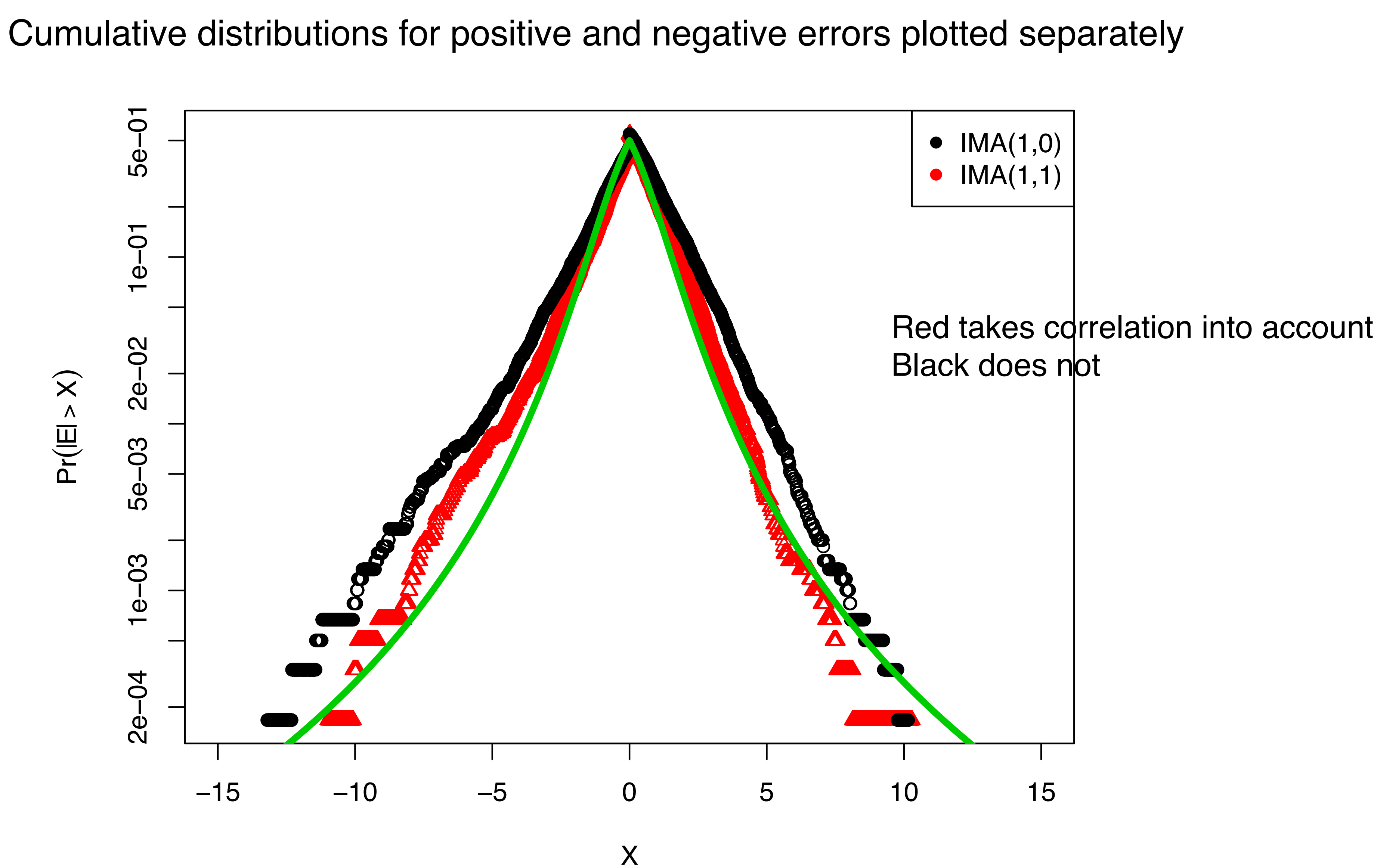
$$\frac{1}{\sqrt{A^*}}\left(\frac{\mathcal{E}}{\hat{K}}\right) \sim t(m-1)$$

A^* = 2^{nd} degree polynomial in τ

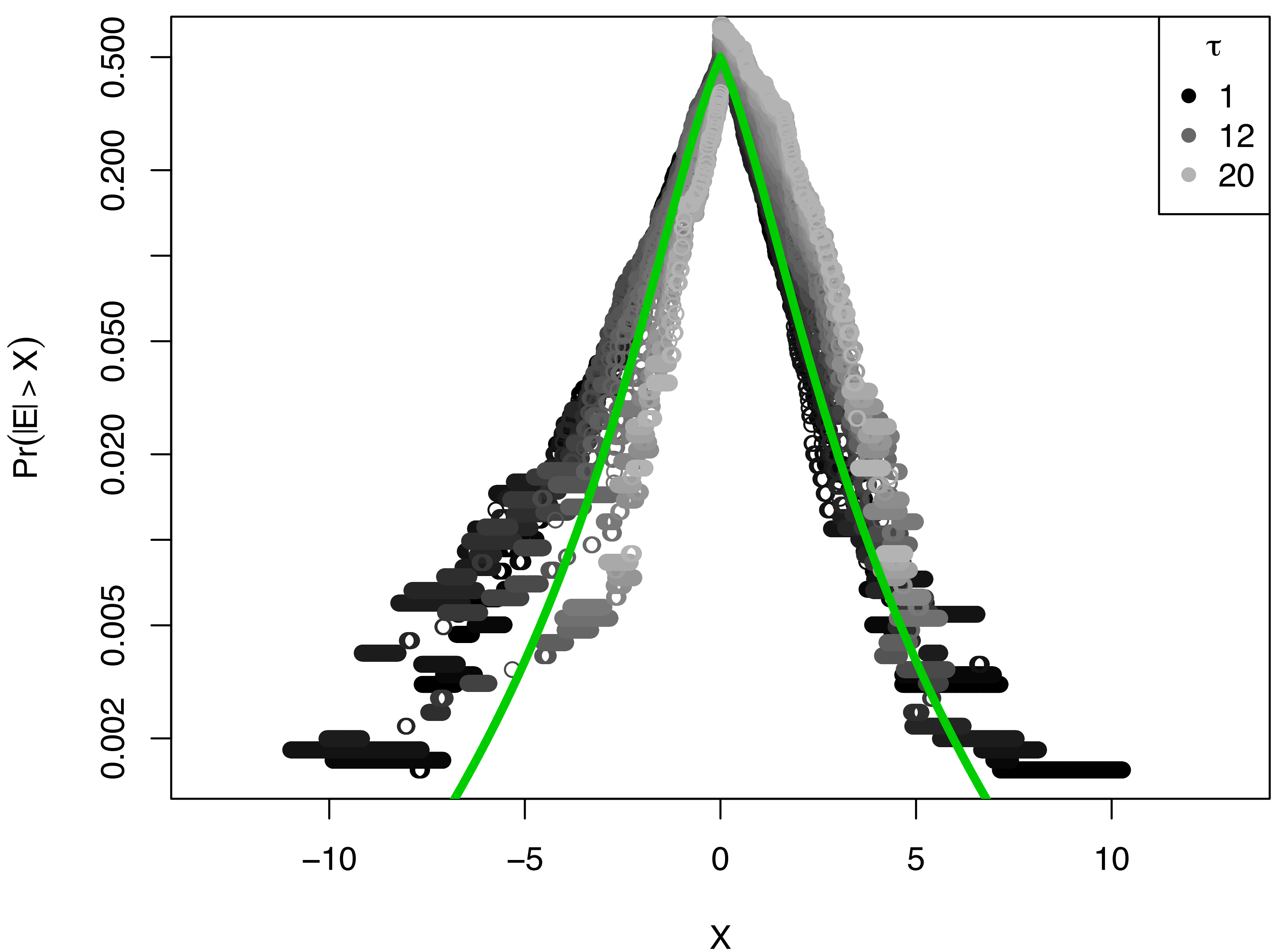
whose coefficients depend on θ and m

Comparison to empirical data for 48 different technologies

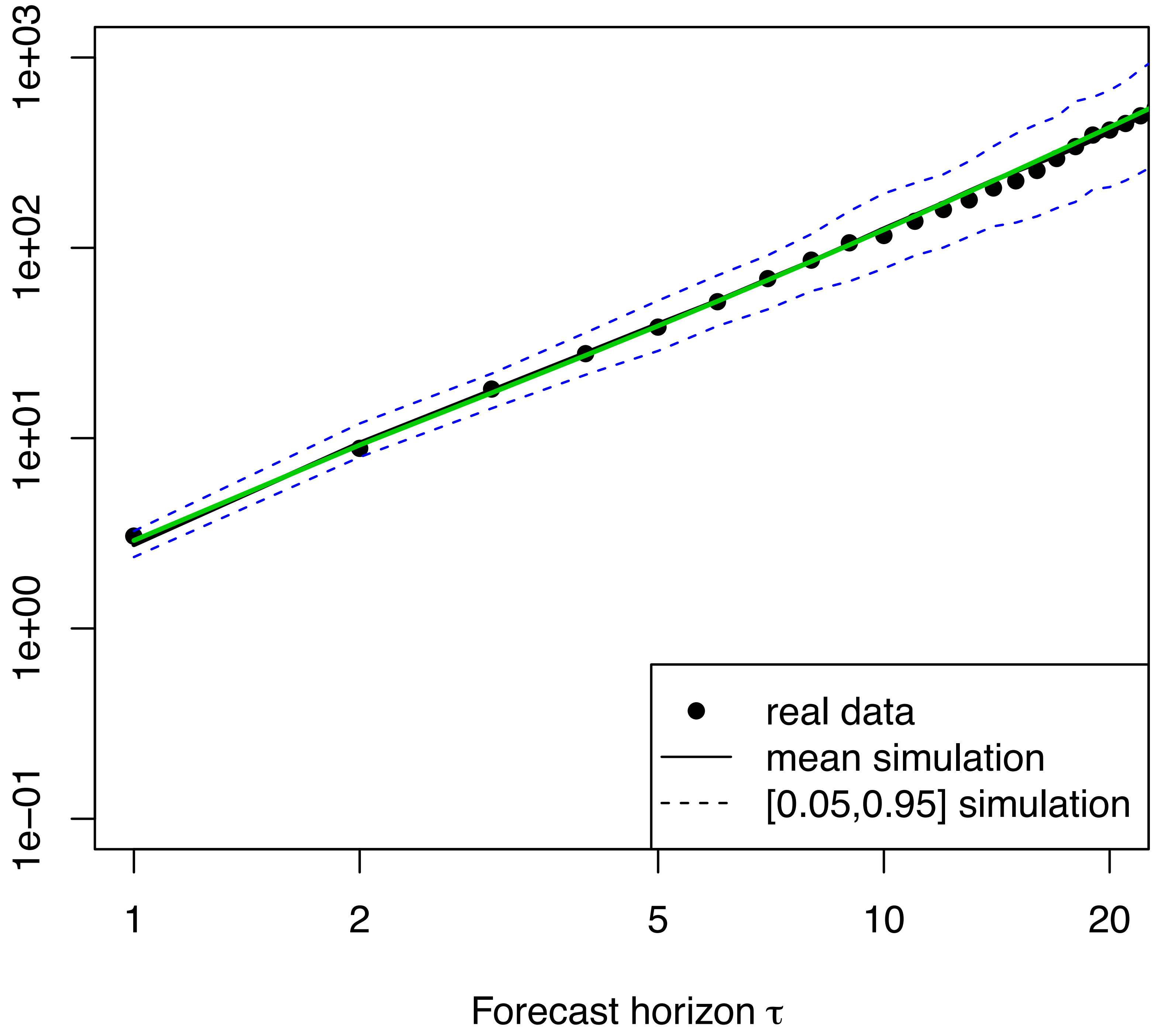
5,973 annual forecasts, all τ with $\tau < 20$



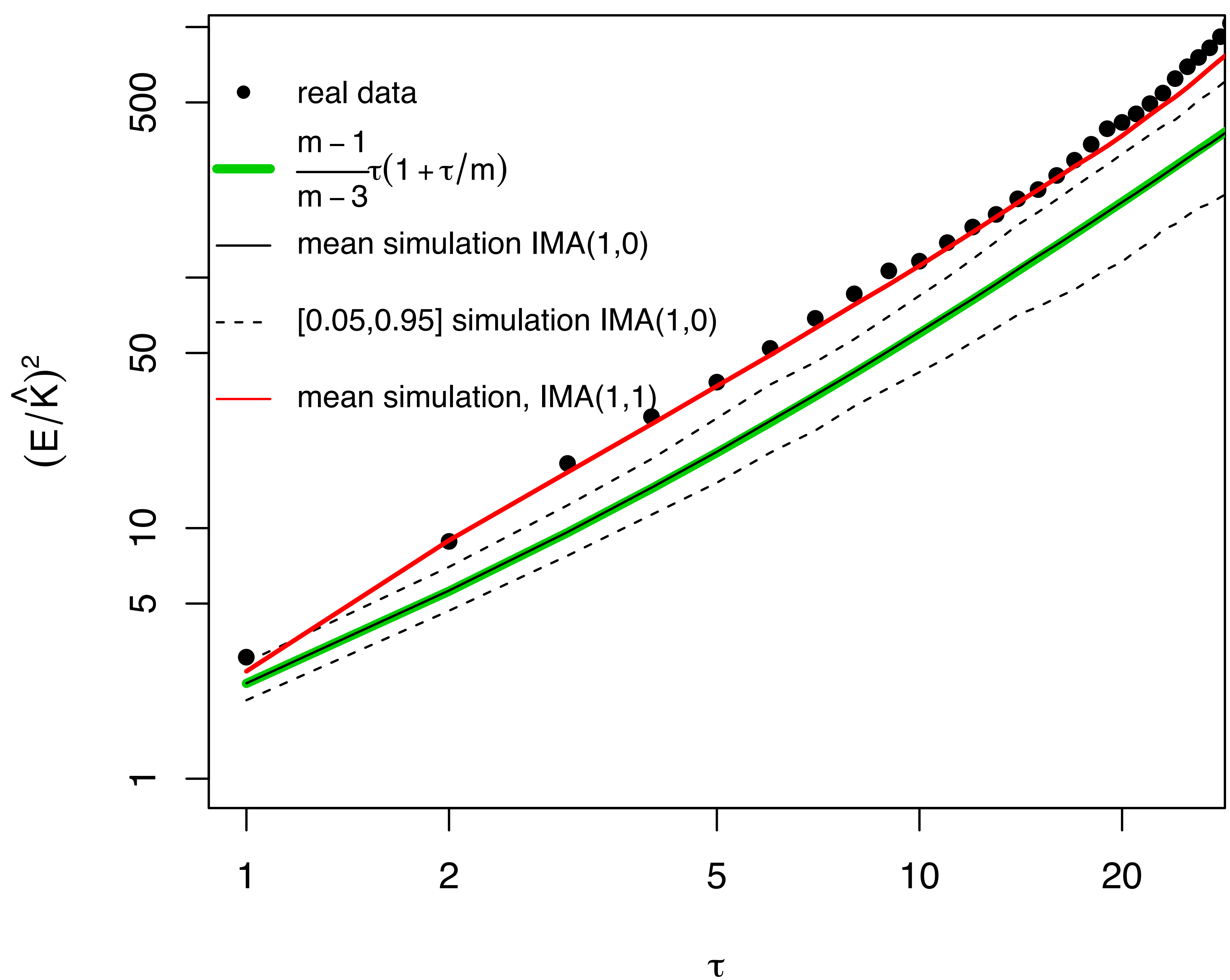
Comparison to empirical distribution for 48 technologies



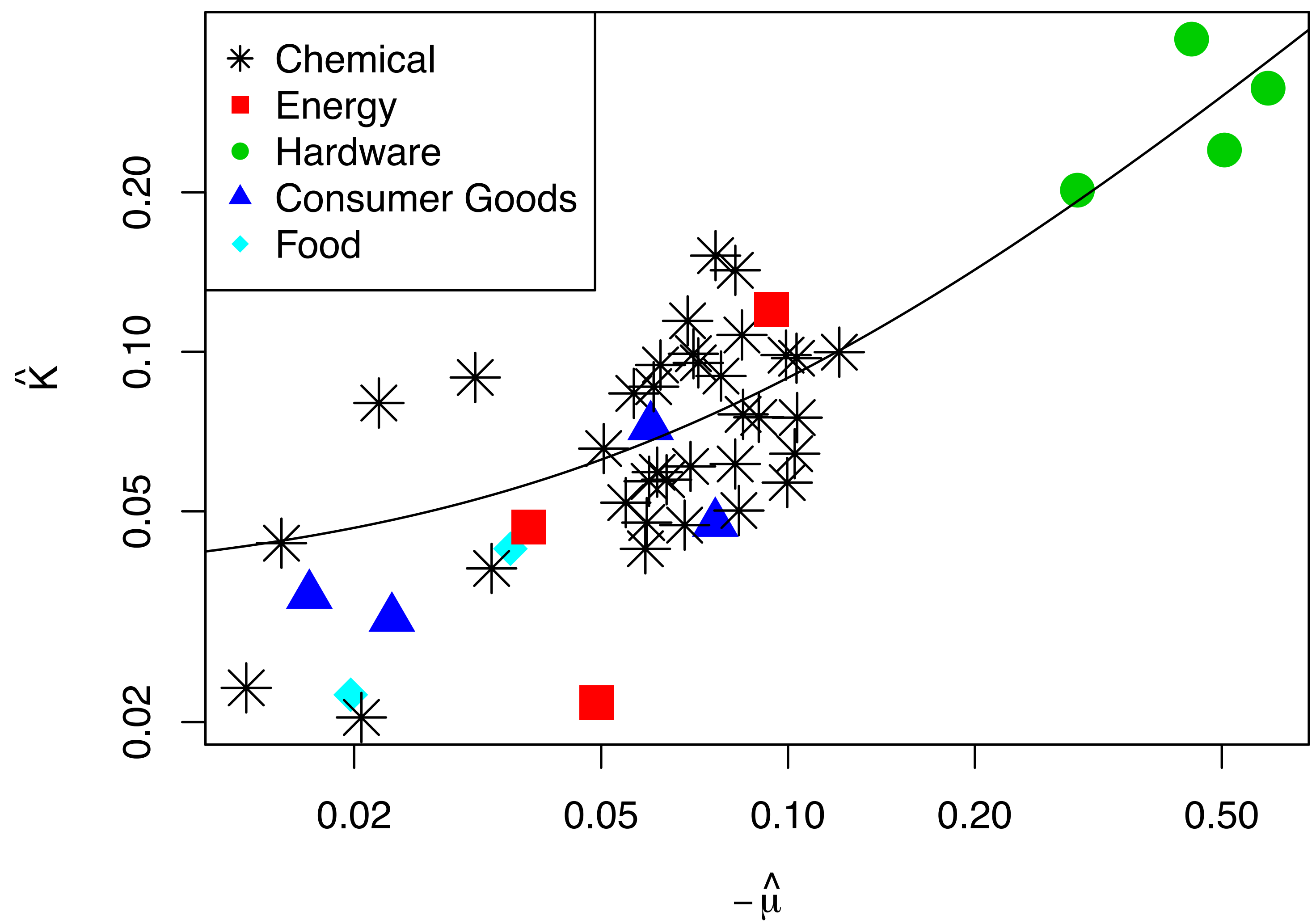
Errors vs. forecast horizon



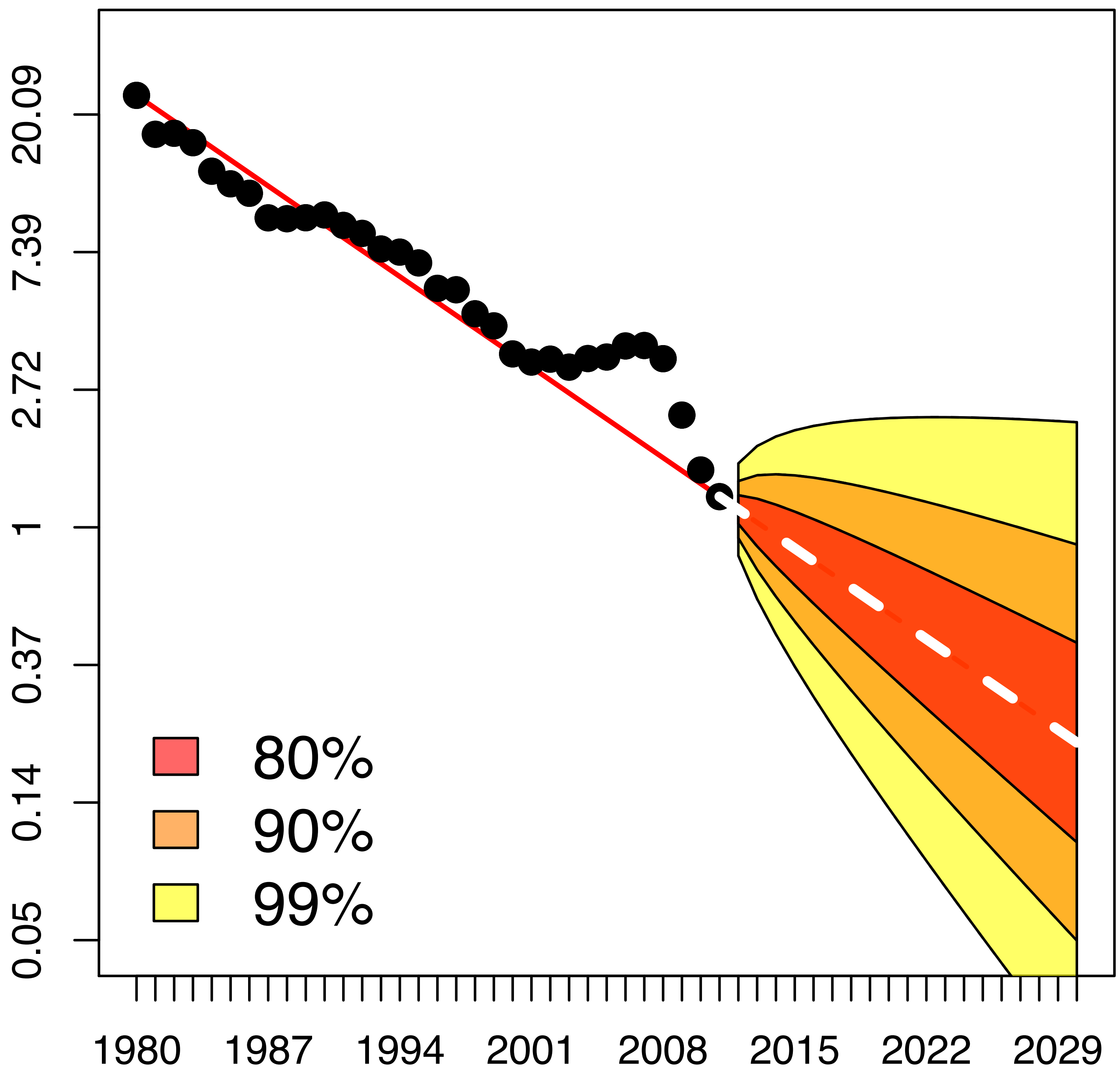
Comparison of errors vs forecast horizon



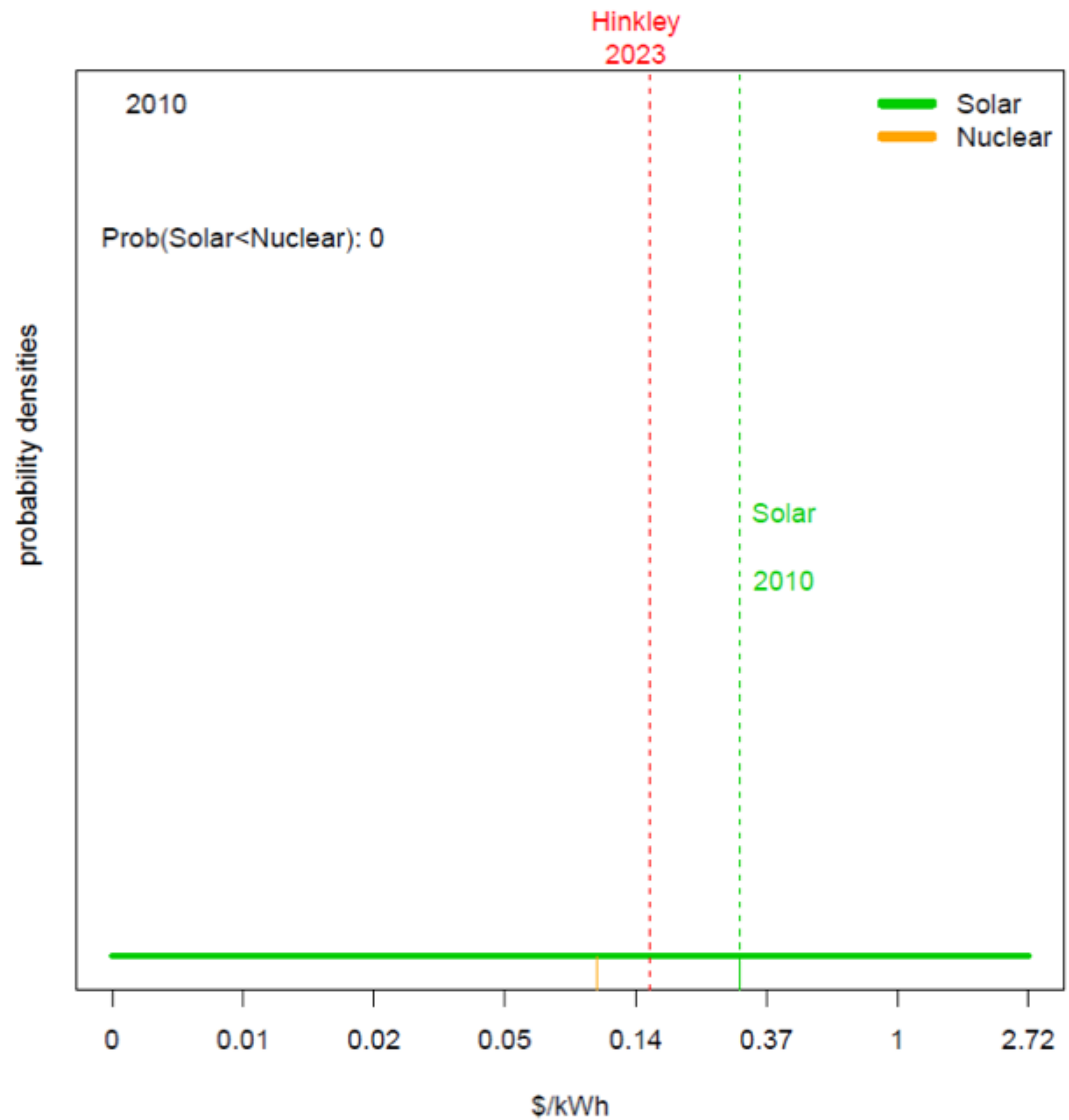
Innovation noise amplitude vs. improvement rate

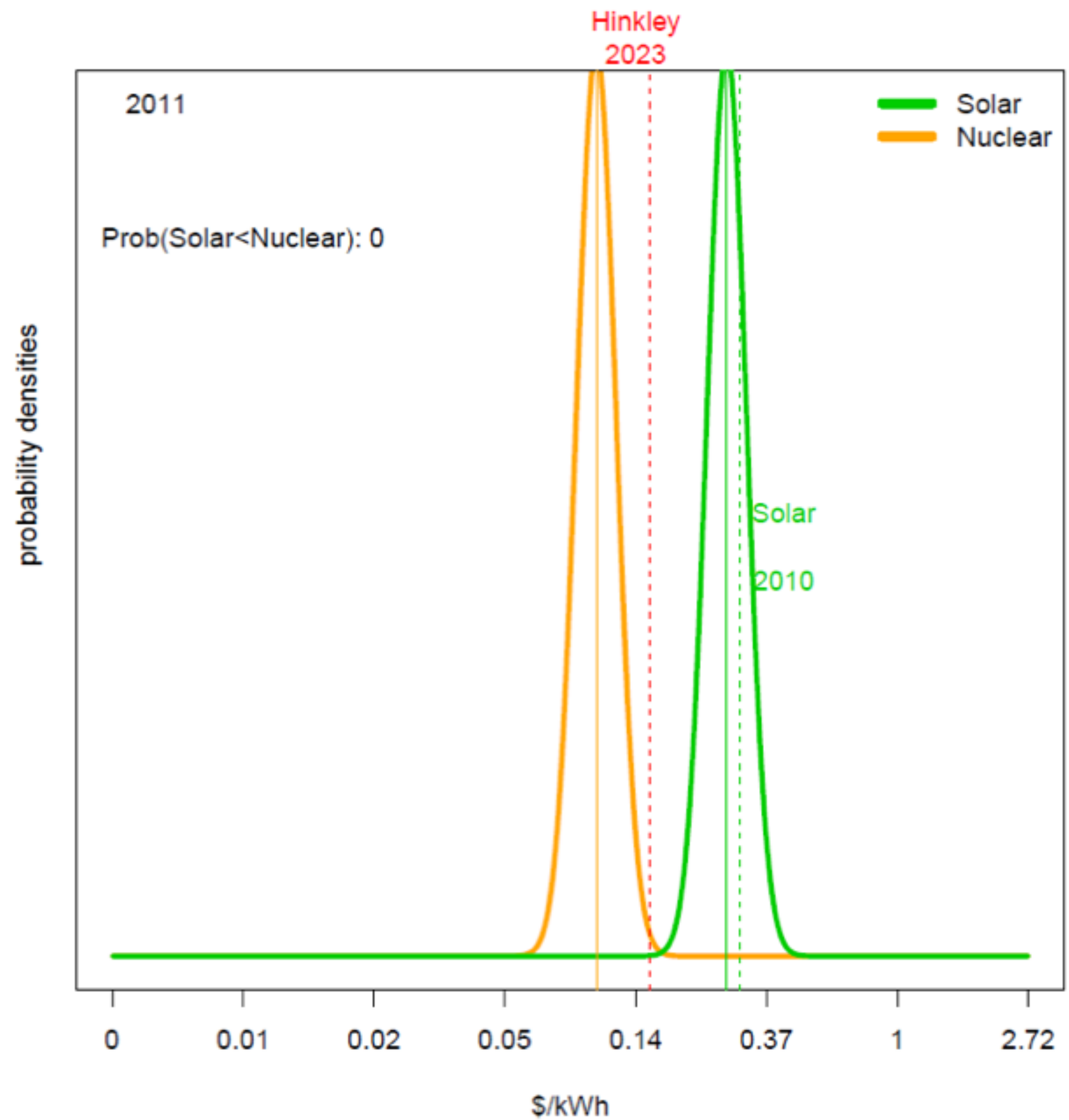


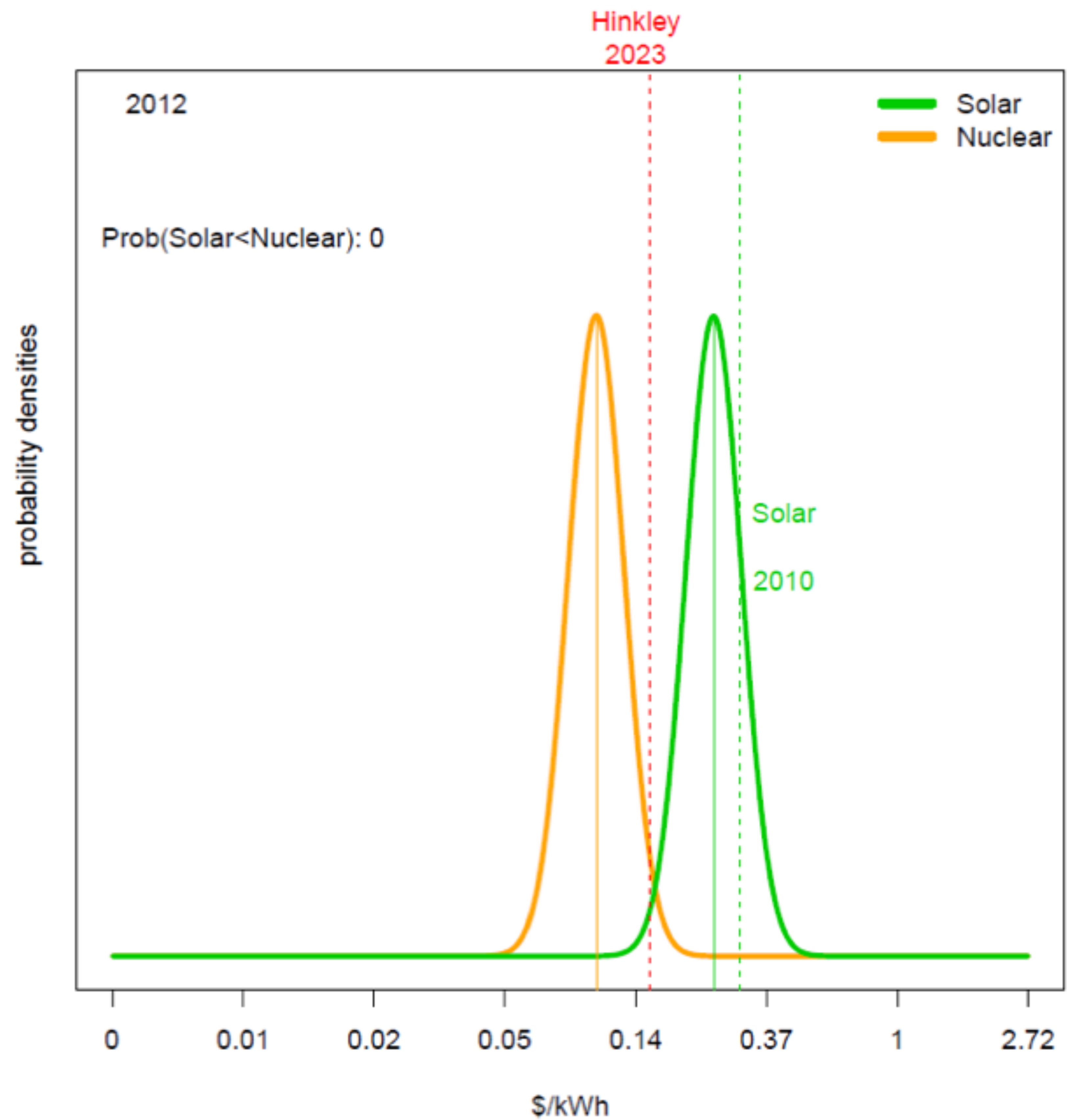
Distributional forecast of solar PV assuming business as usual

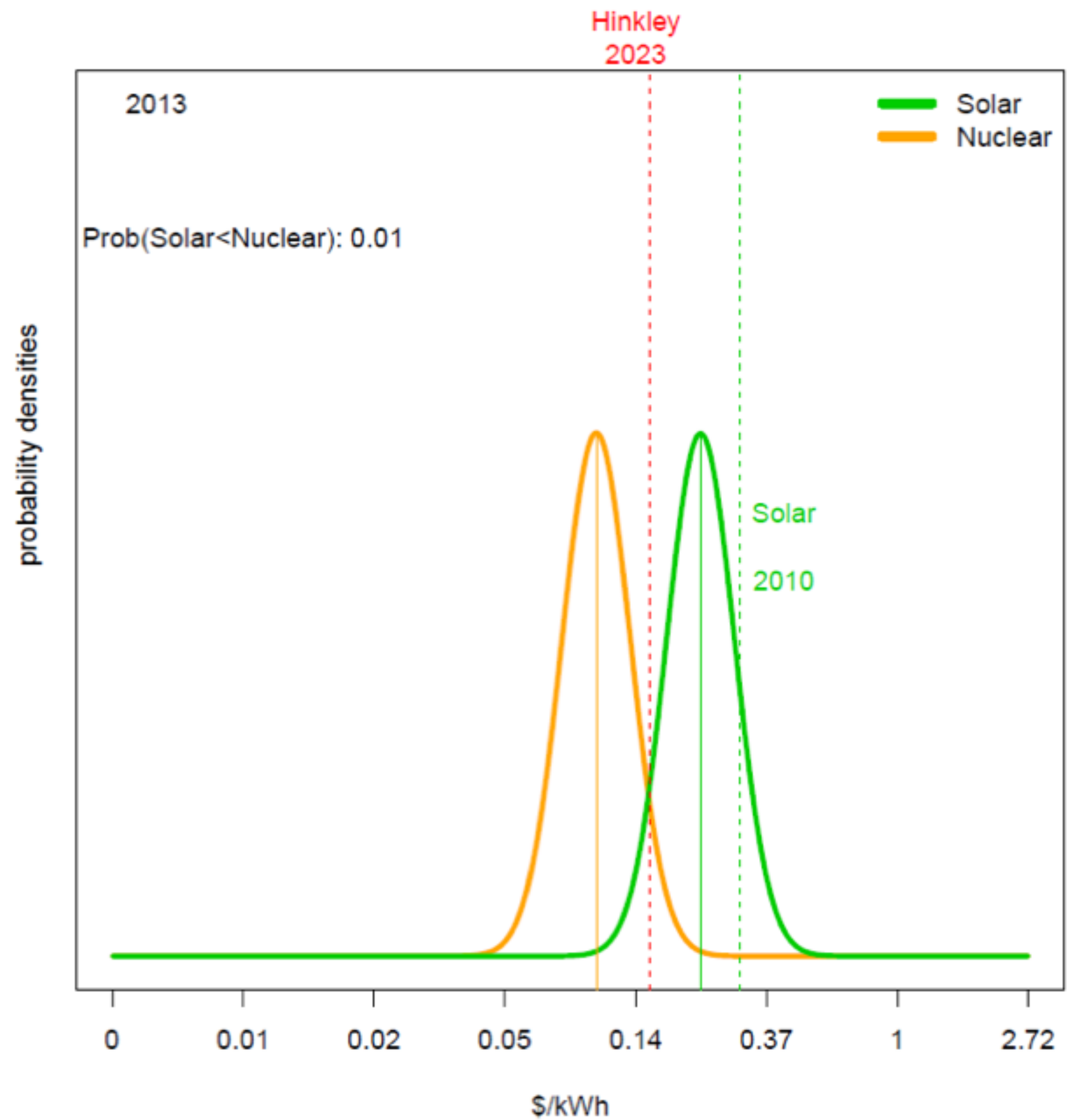


What is the probability that solar PV will be cheaper than nuclear power?

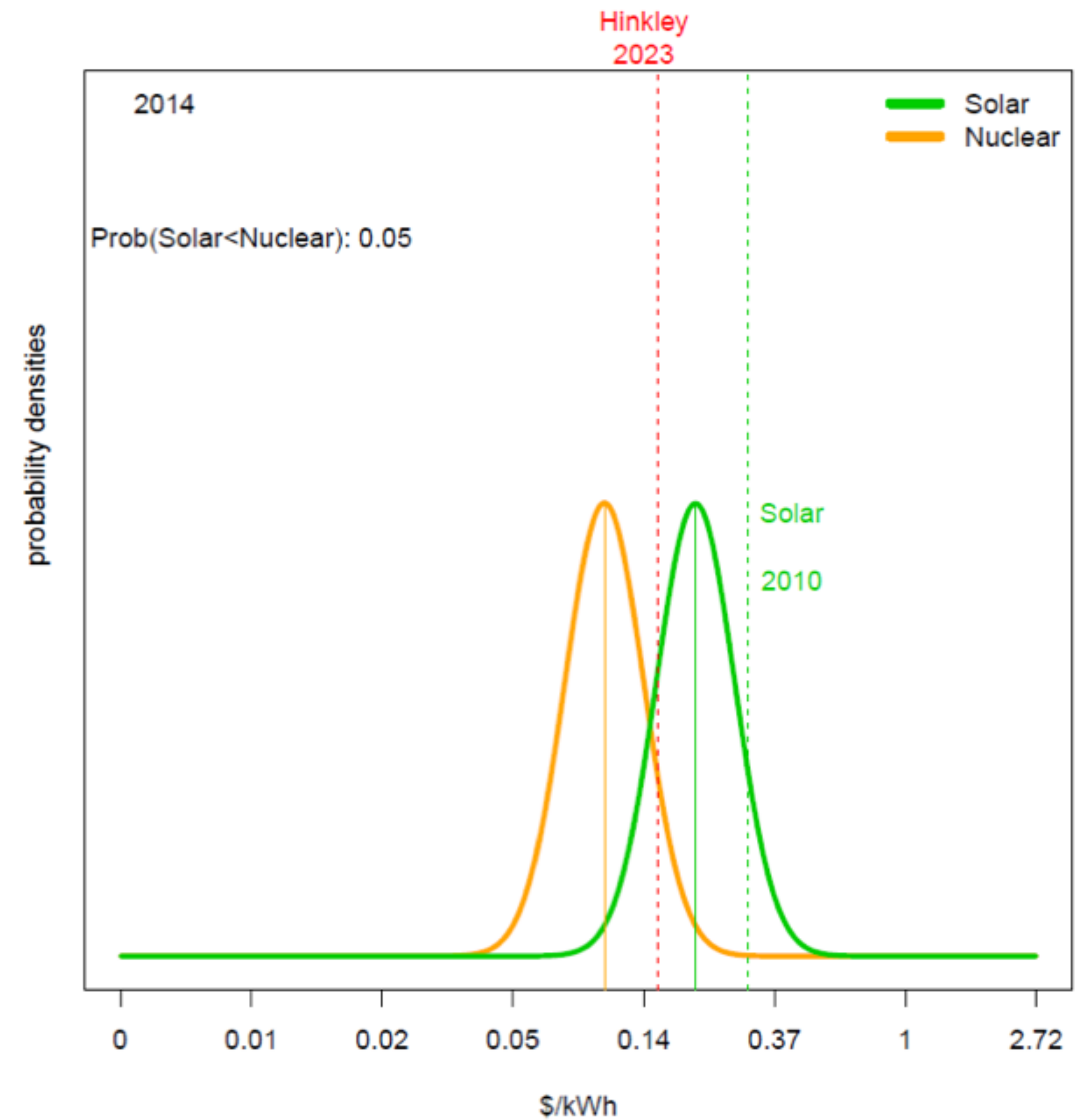

Hinkley
2023
2010
Solar
Nuclear
Prob(Solar<Nuclear): 0
Solar
2010
probability densities
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

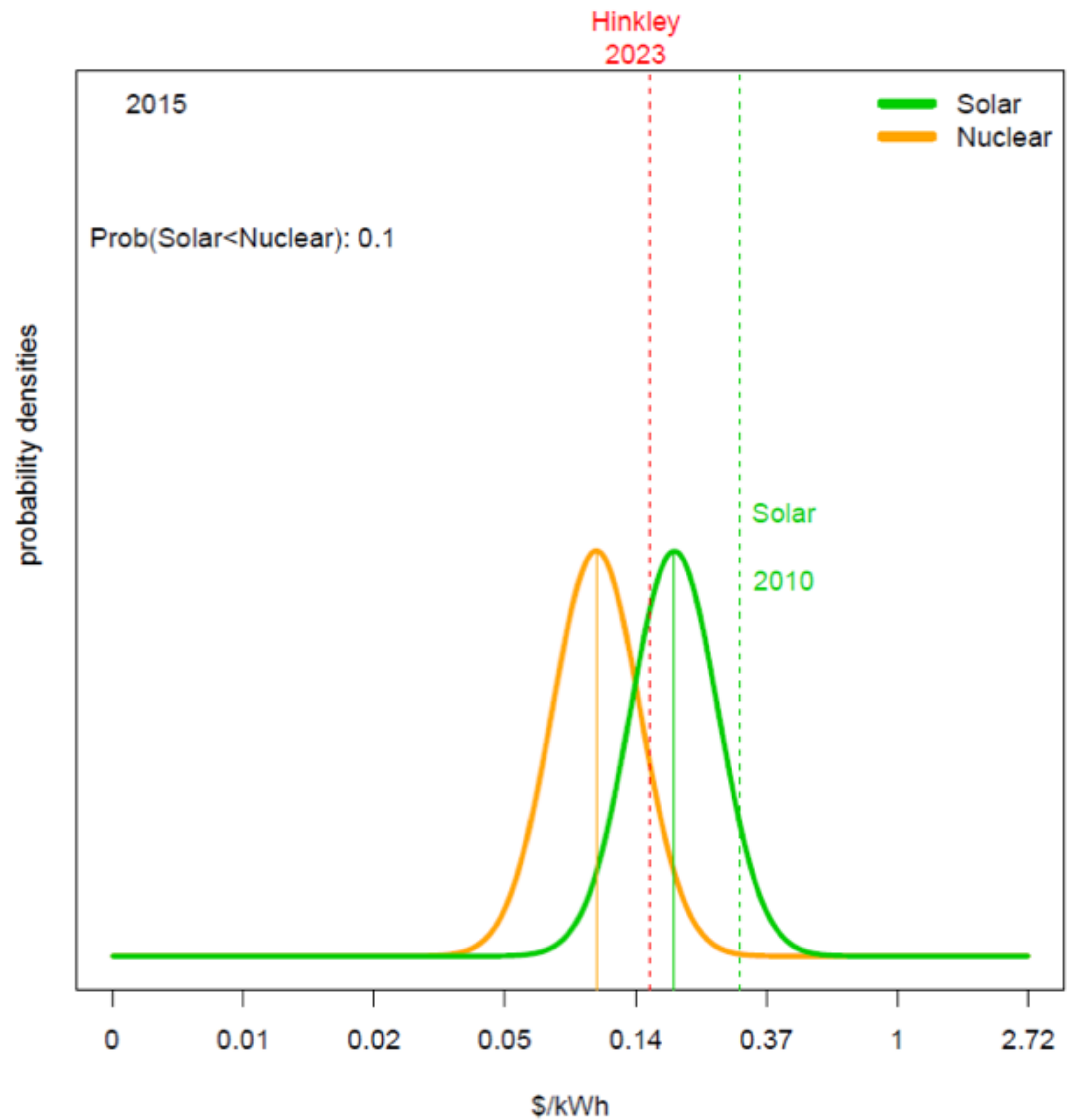

Hinkley
2023
2011
Solar
Nuclear
Prob(Solar<Nuclear): 0
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

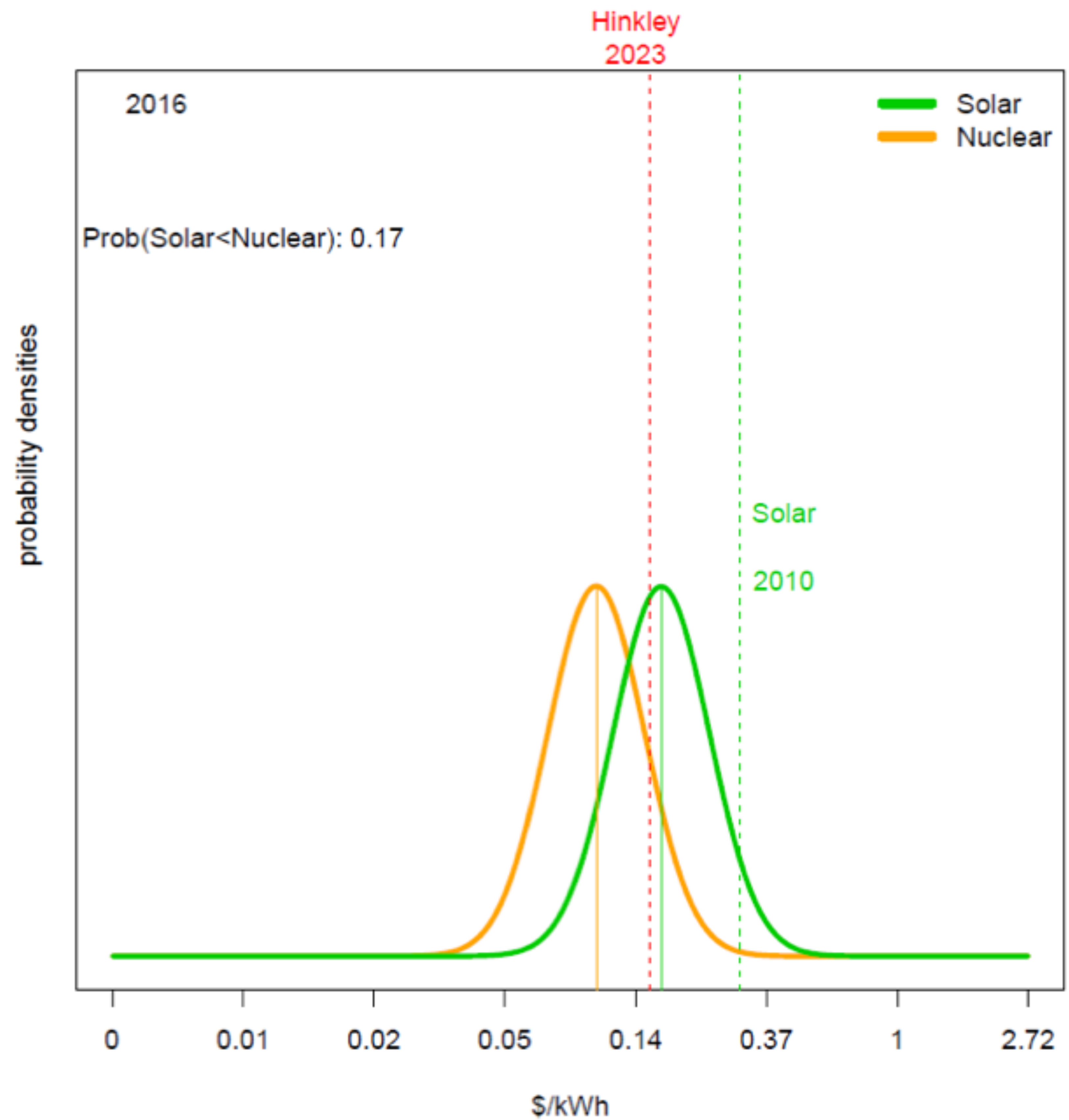

Hinkley
2023
2012
Solar
Nuclear
Prob(Solar<Nuclear): 0
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

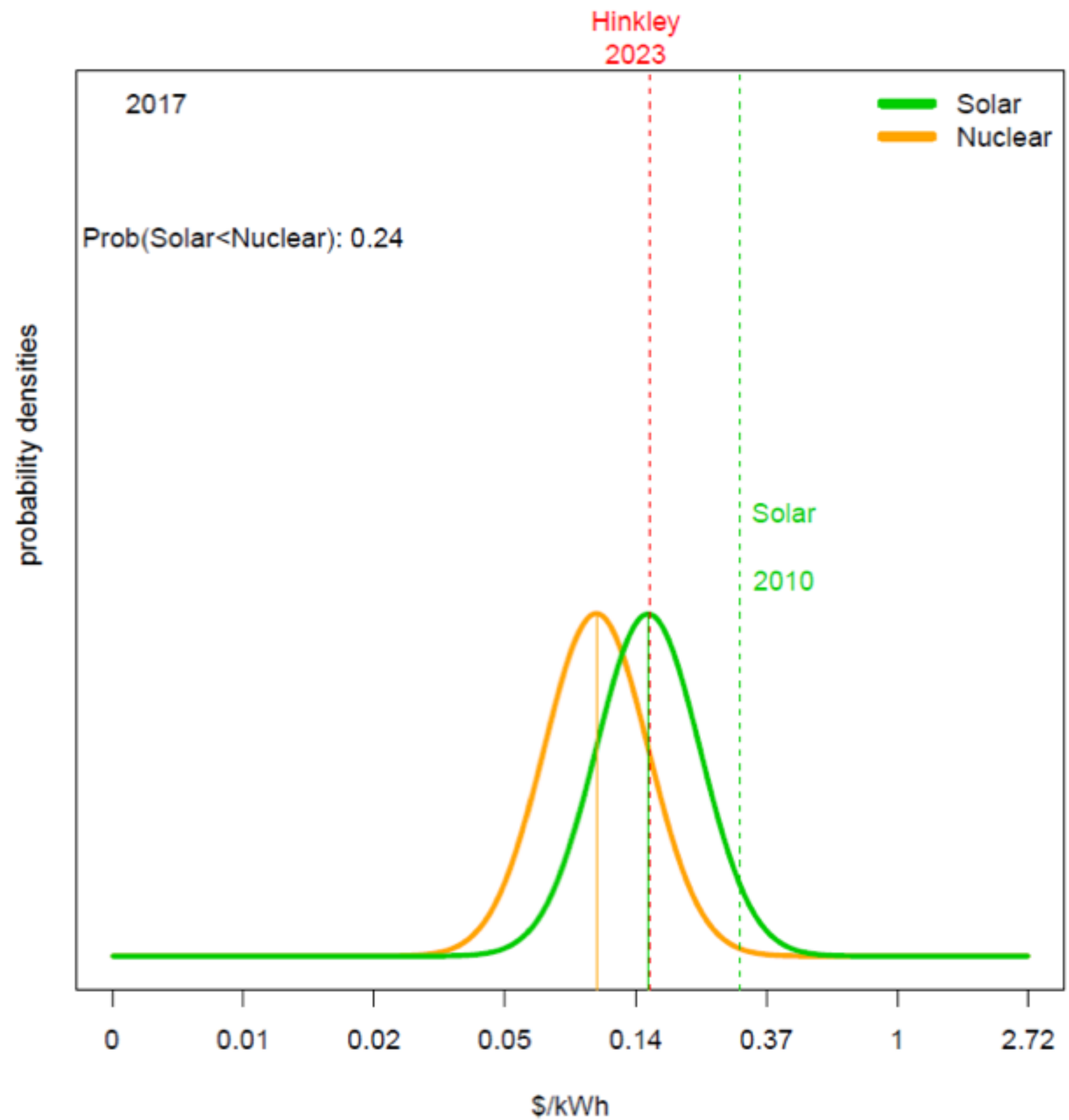


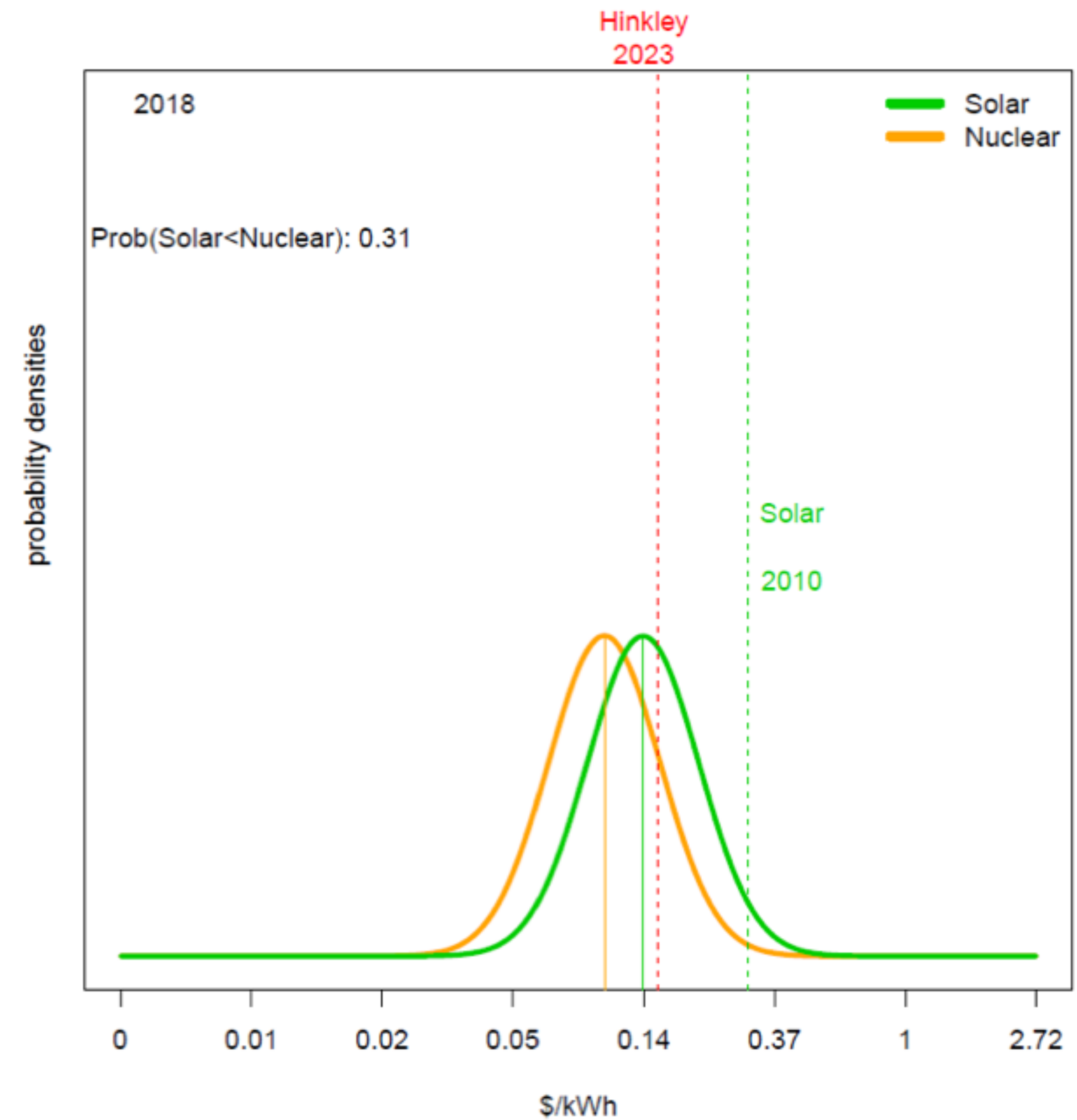
Hinkley
2023
2013
Solar
Nuclear
Prob(Solar<Nuclear): 0.01
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

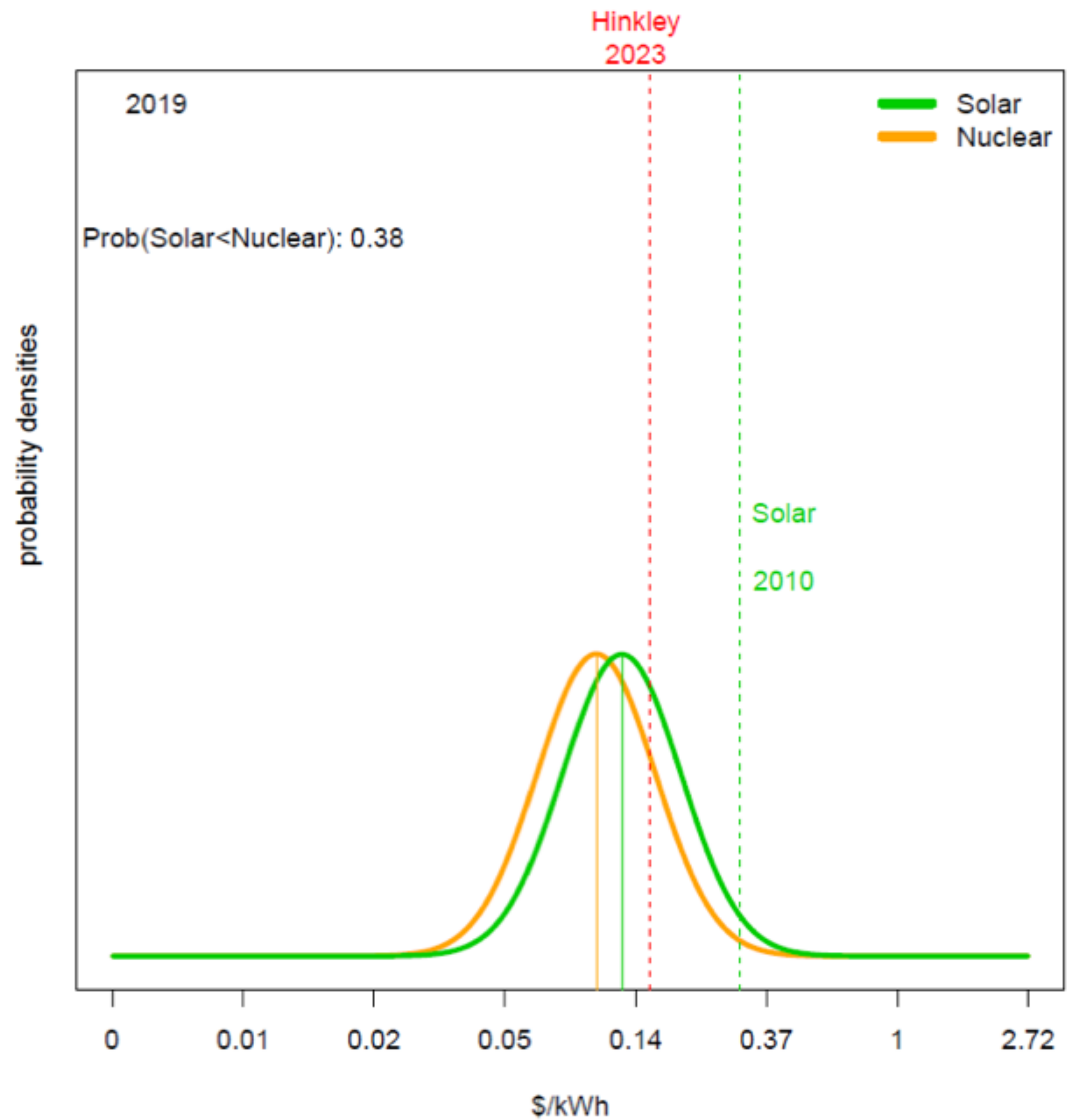

Hinkley
2023
2014
Solar
Nuclear
Prob(Solar<Nuclear): 0.05
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh


Hinkley
2023
2015
Solar
Nuclear
Prob(Solar<Nuclear): 0.1
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

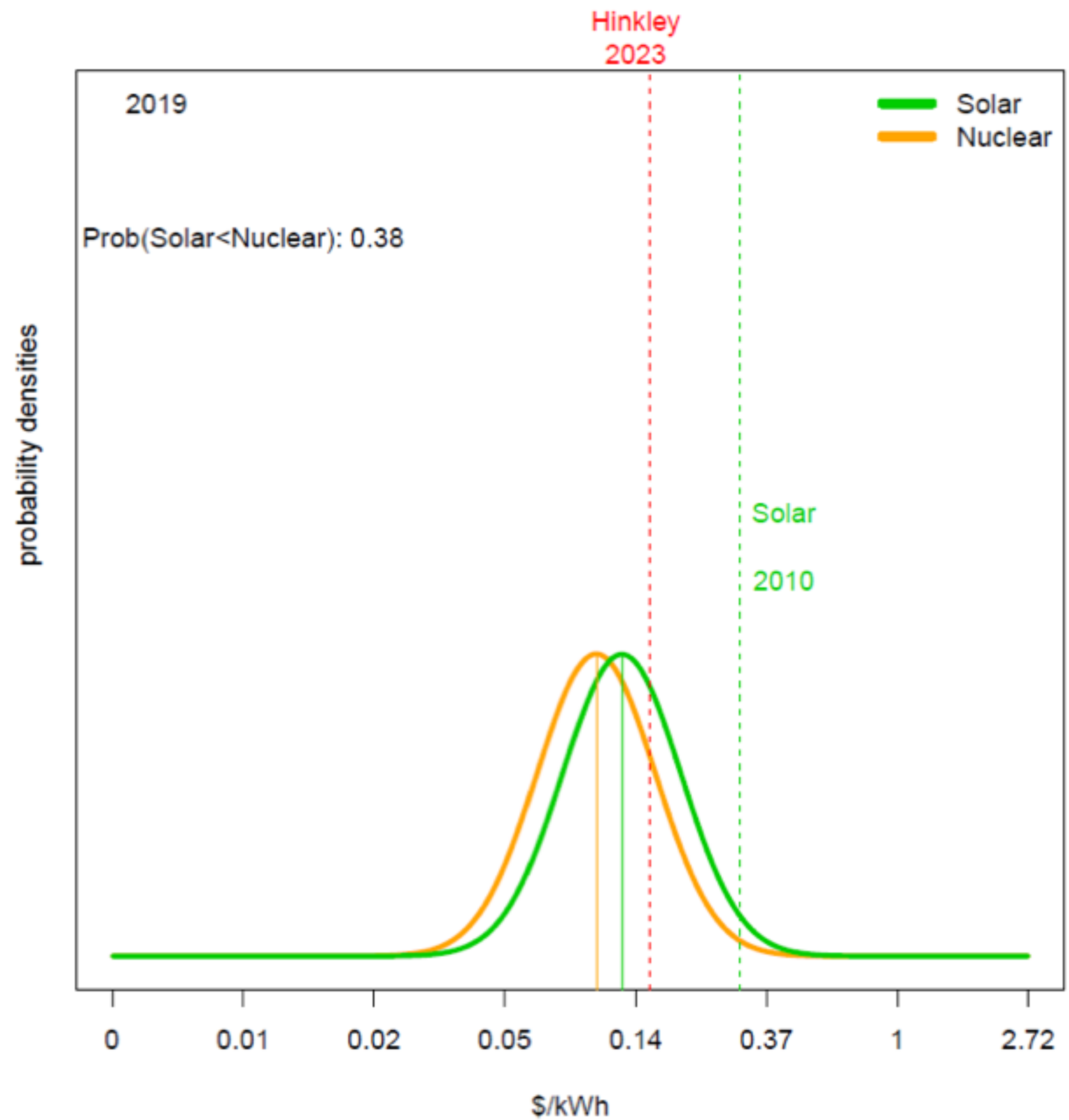

Hinkley
2023
2016
Solar
Nuclear
Prob(Solar<Nuclear): 0.17
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh


Hinkley
2023
2017
Solar
Nuclear
Prob(Solar<Nuclear): 0.24
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

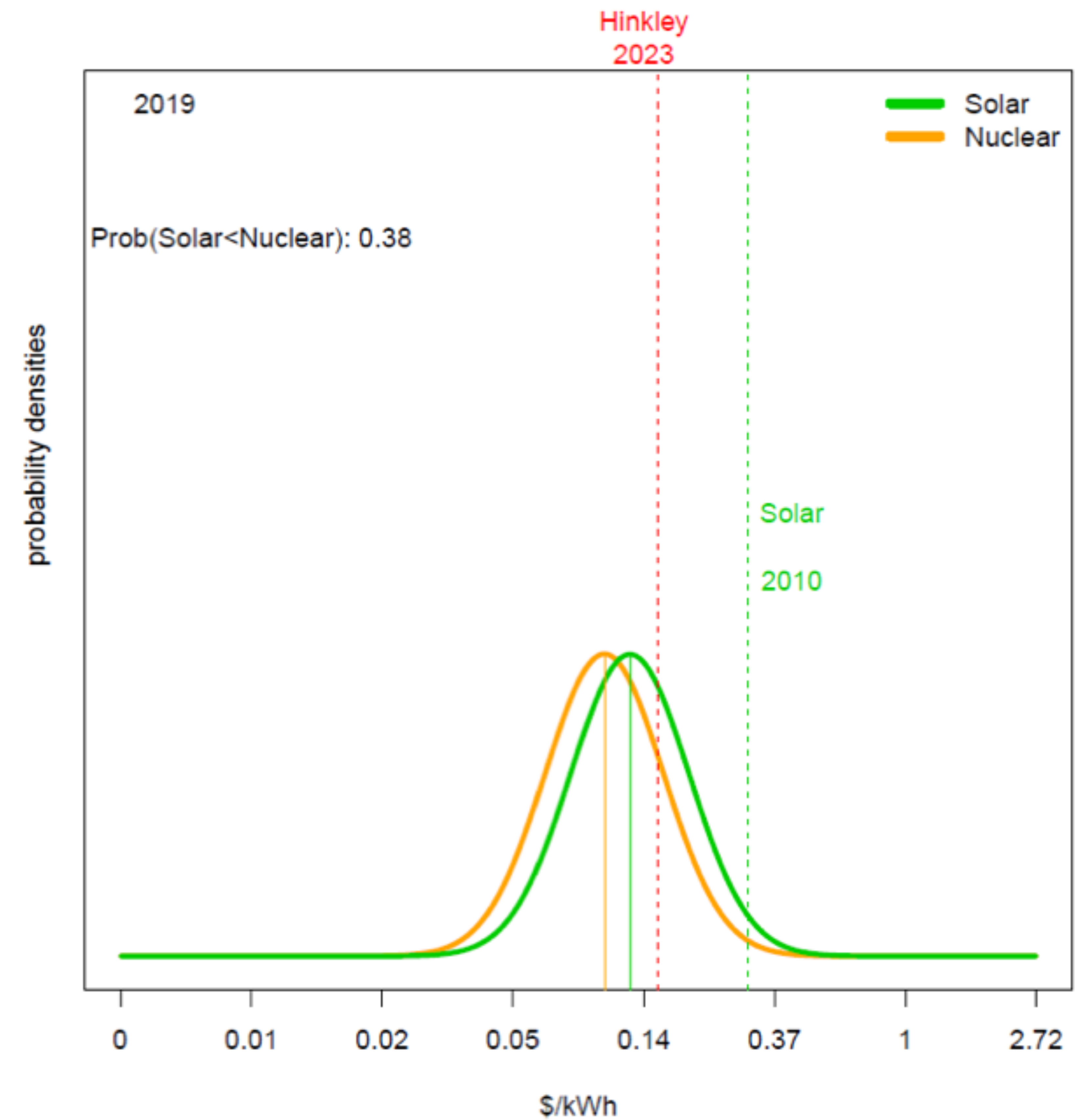

Hinkley
2023
2018
Solar
Nuclear
Prob(Solar<Nuclear): 0.31
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh



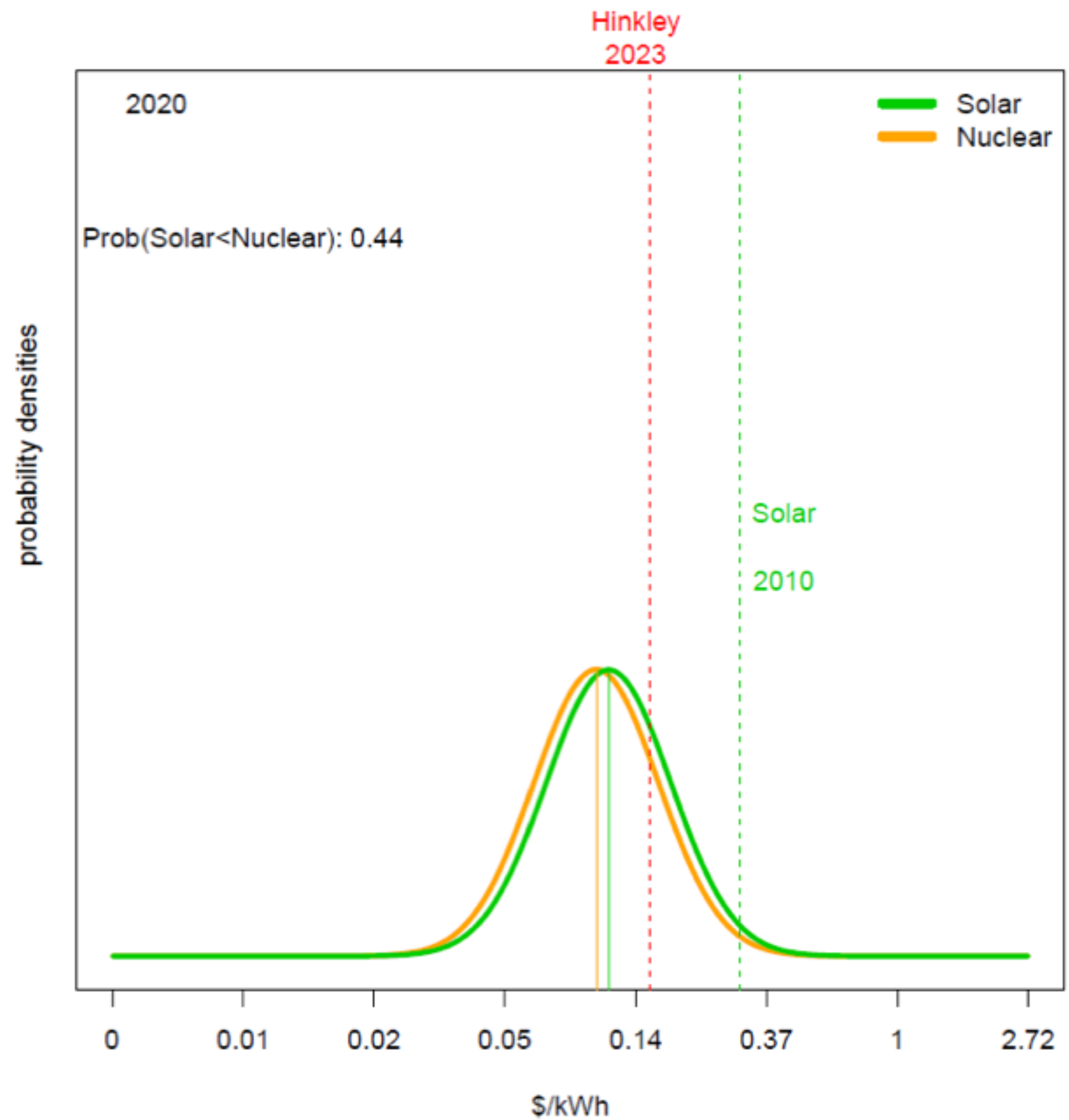
Hinkley
2023
2019
Solar
Nuclear
Prob(Solar<Nuclear): 0.38
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

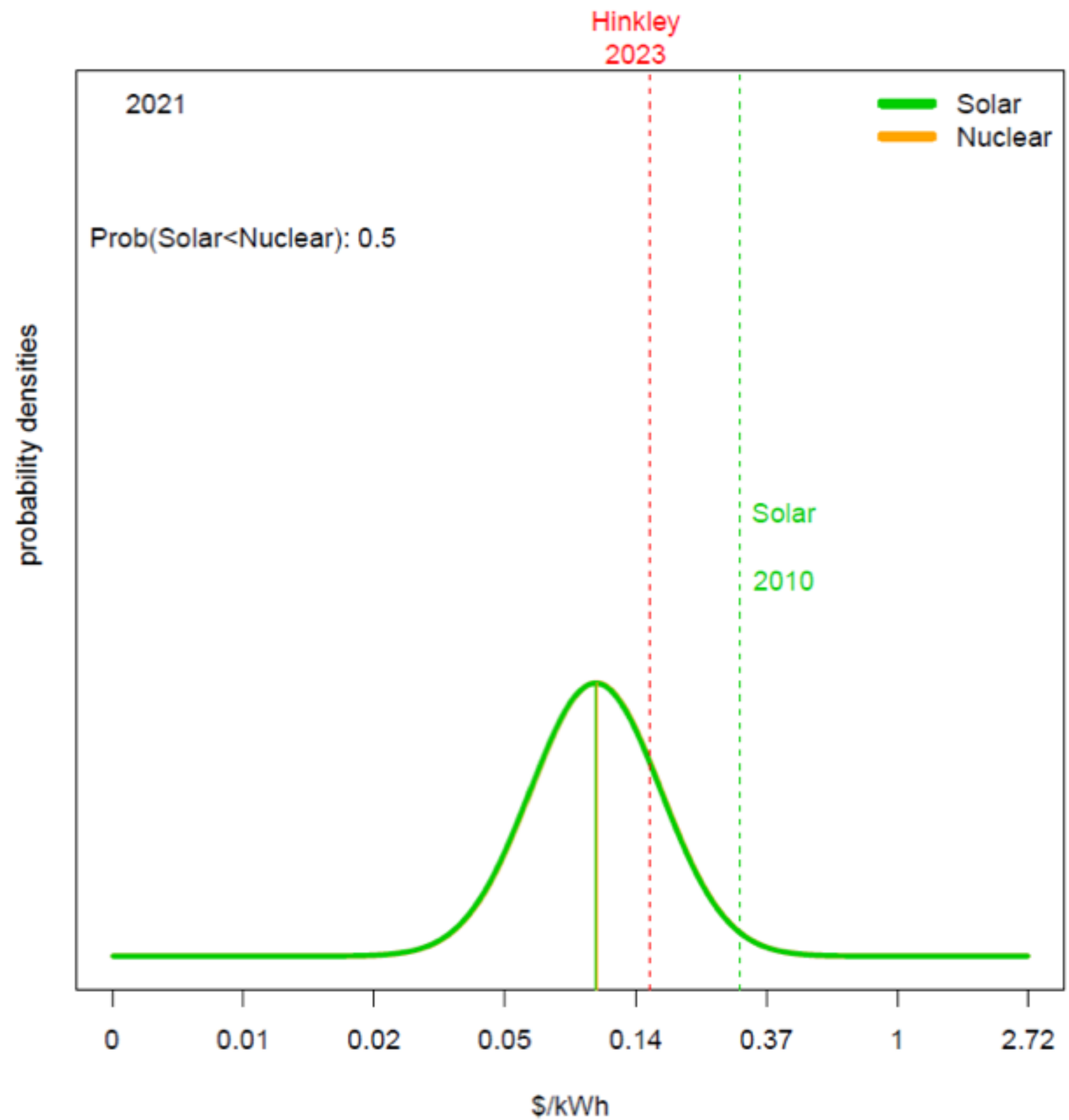


Hinkley
2023
2019
Solar
Nuclear
Prob(Solar<Nuclear): 0.38
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

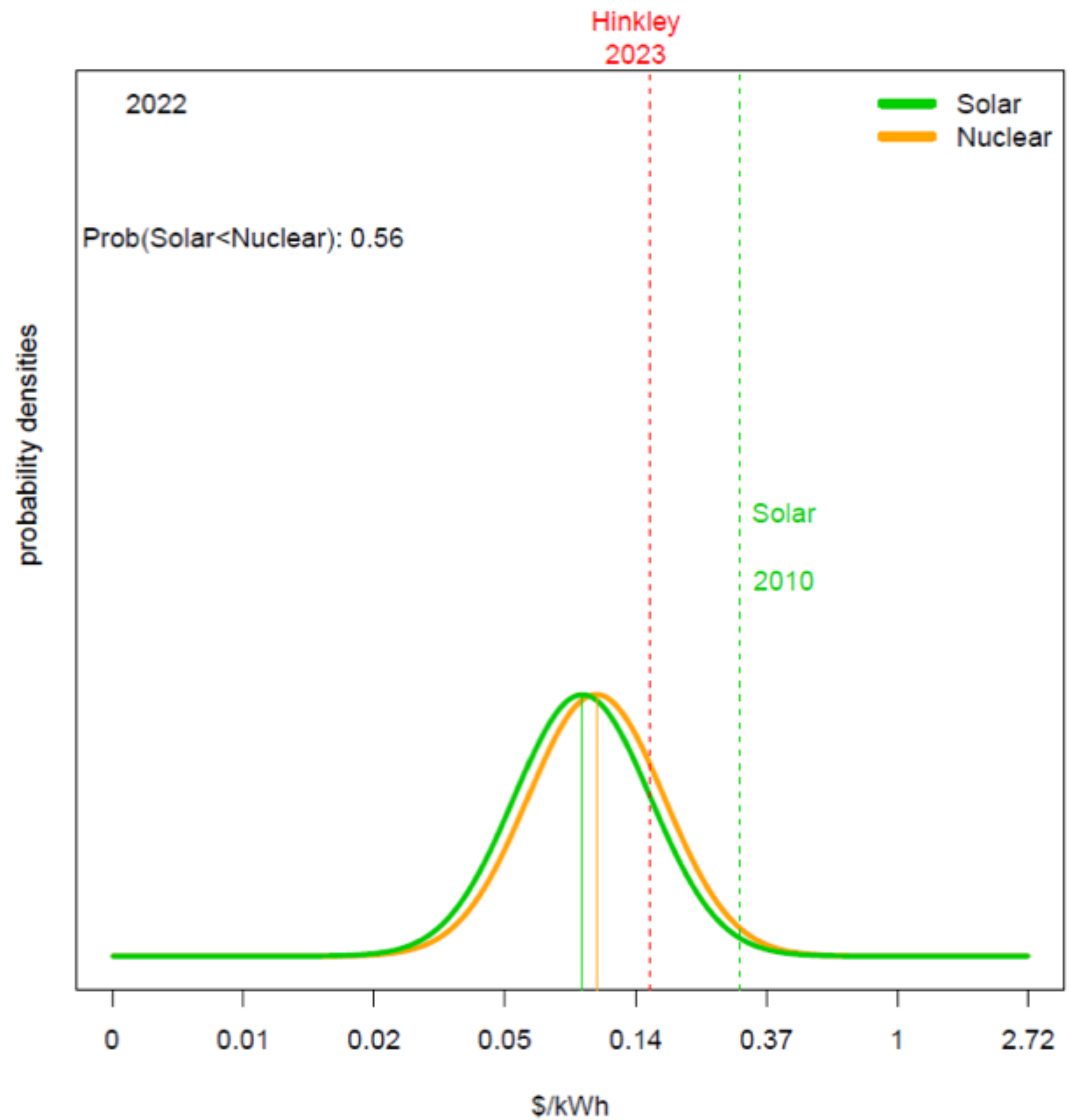


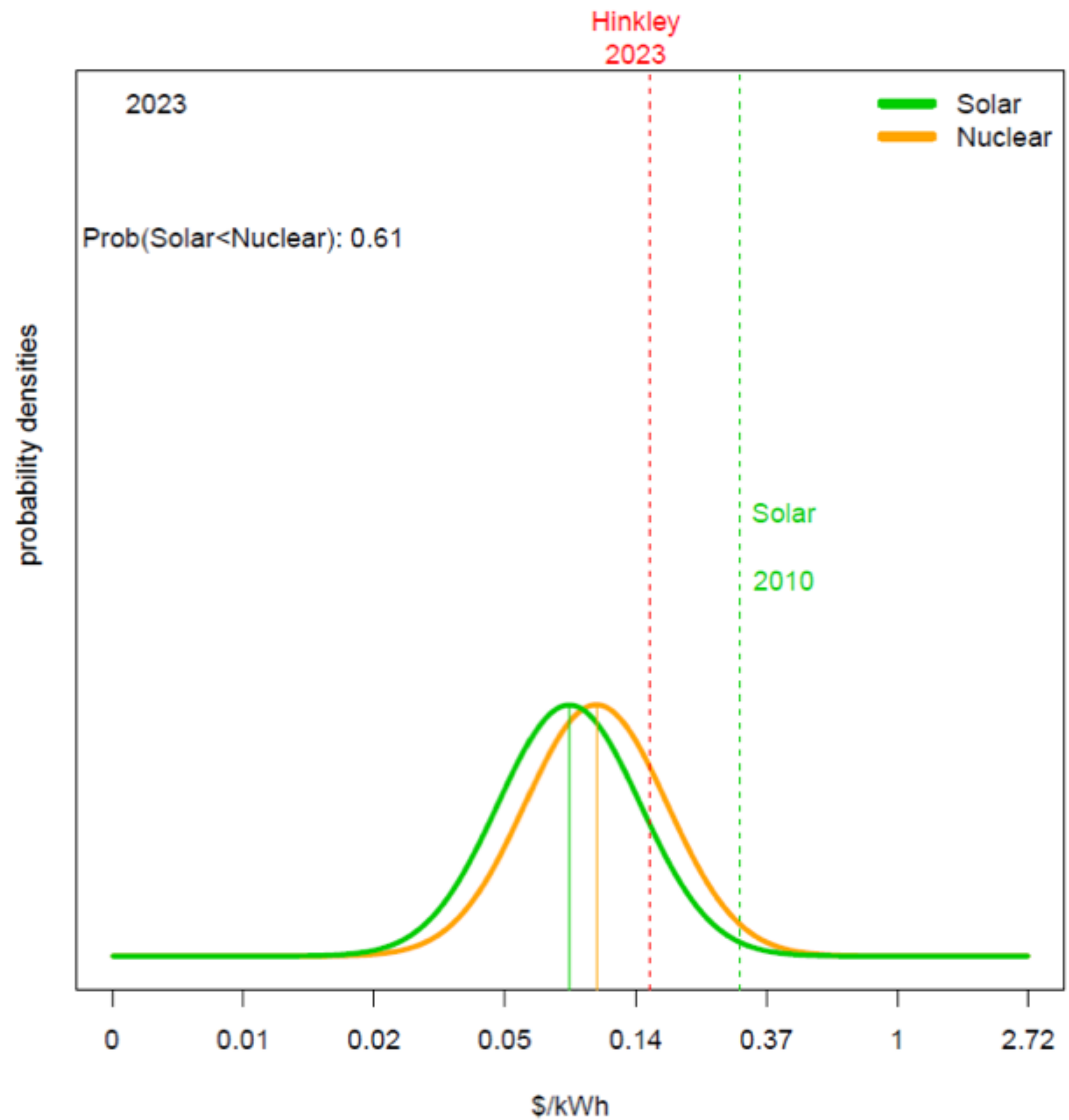
Hinkley
2023
2019
Solar
Nuclear
Prob(Solar<Nuclear): 0.38
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh


Hinkley
2023
2020
Solar
Nuclear
Prob(Solar<Nuclear): 0.44
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

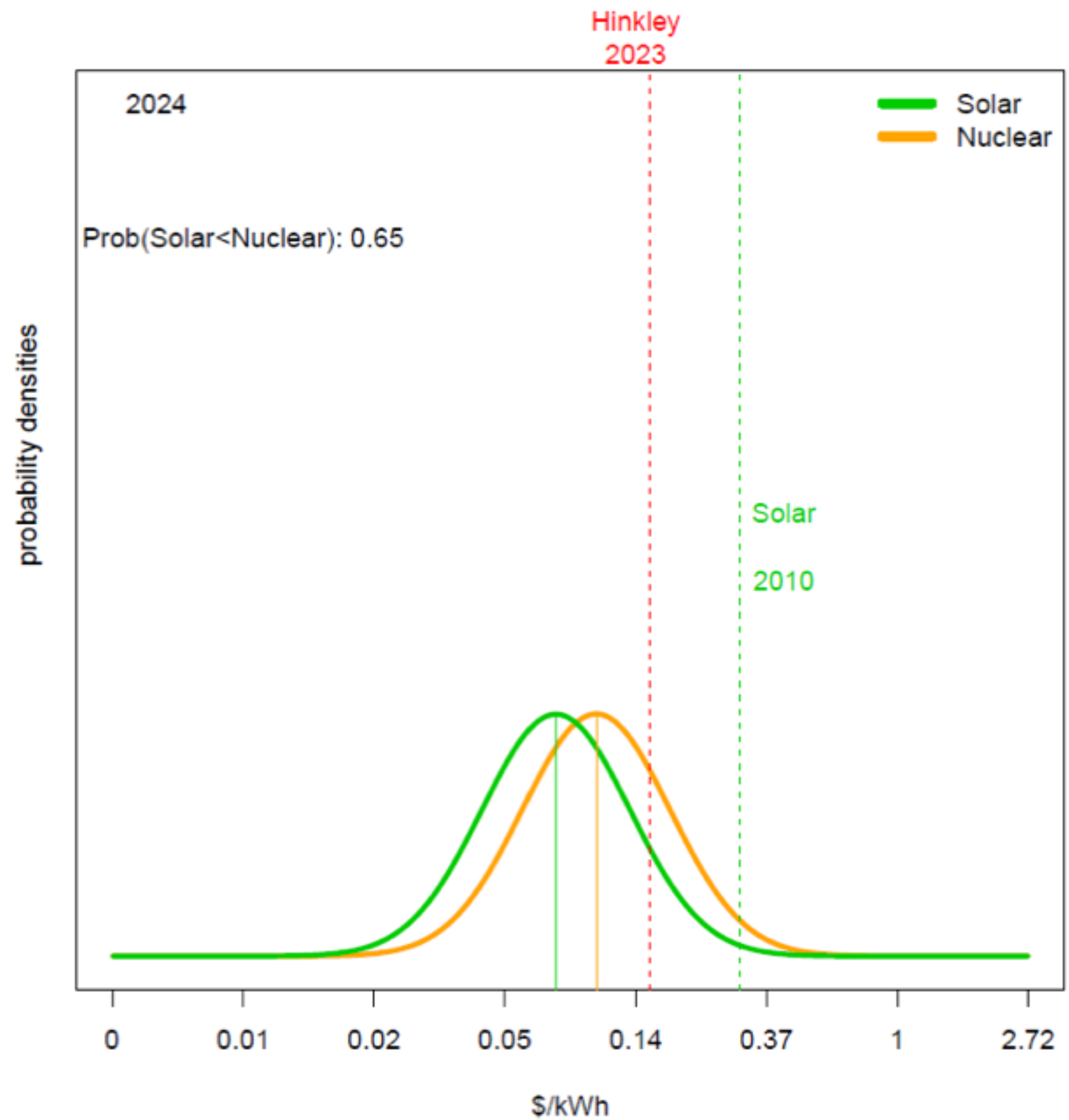


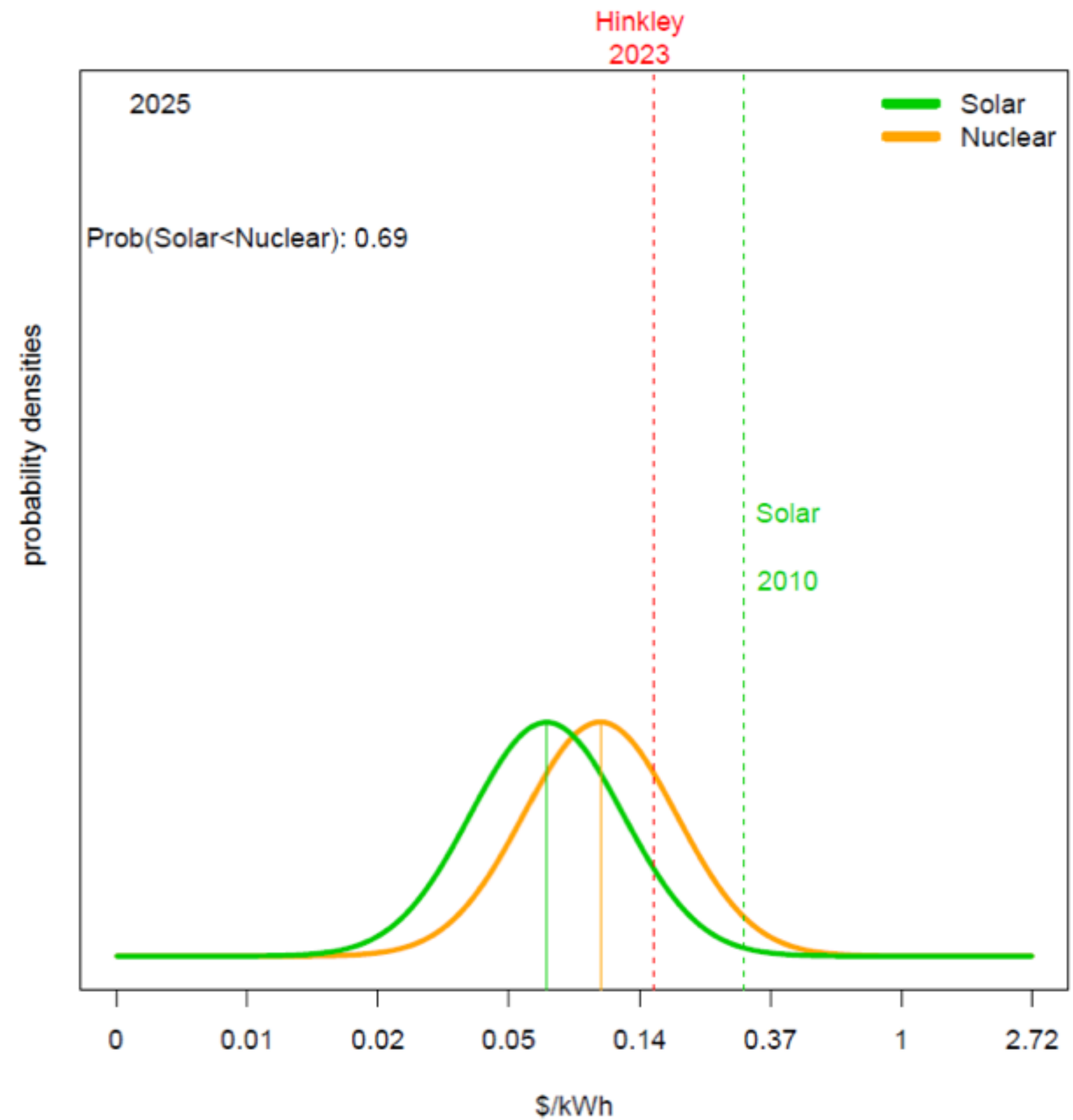
Hinkley
2023
2021
Solar
Nuclear
Prob(Solar<Nuclear): 0.5
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

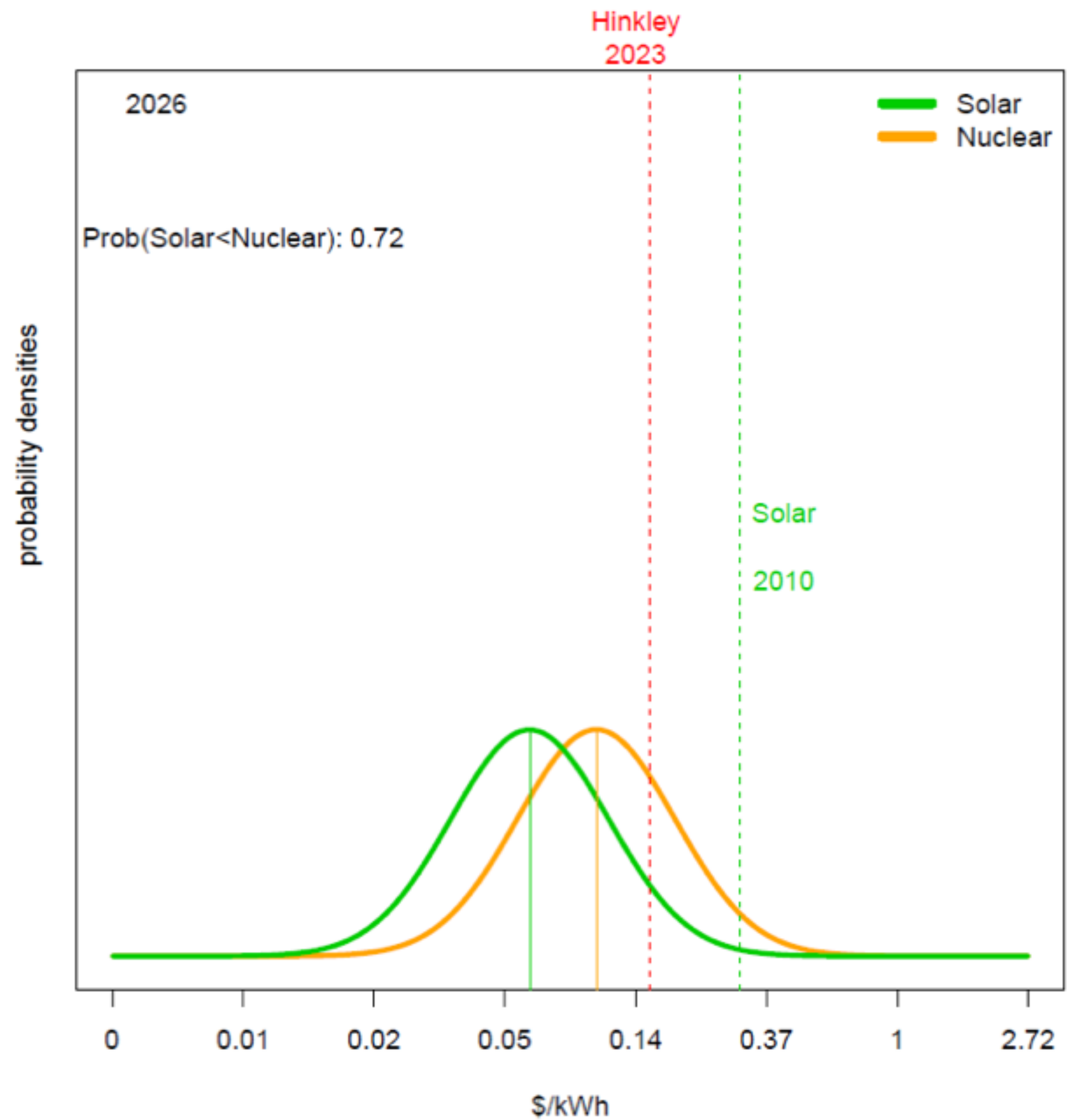

Hinkley
2023
2022
Solar
Nuclear
Prob(Solar<Nuclear): 0.56
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

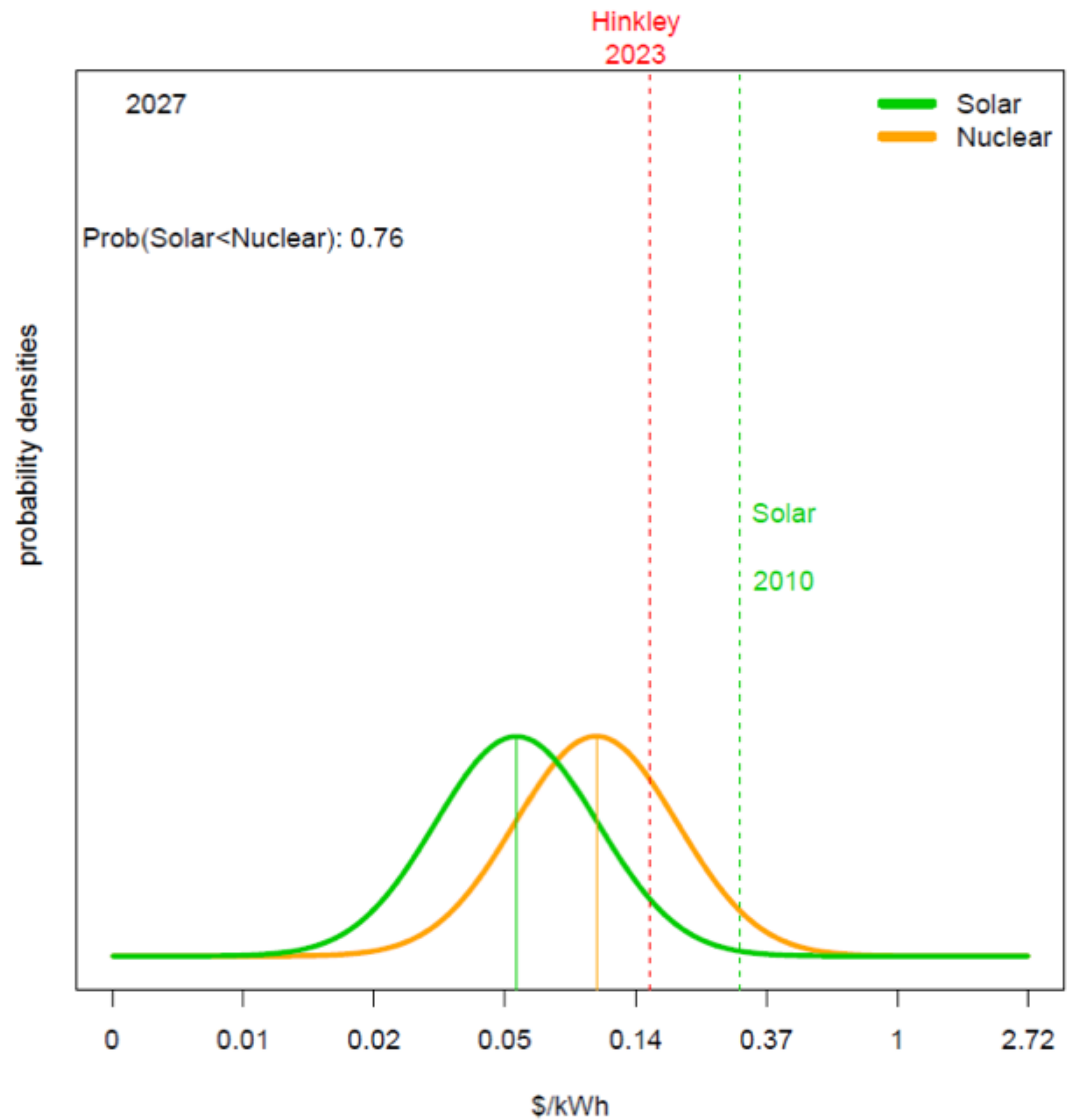


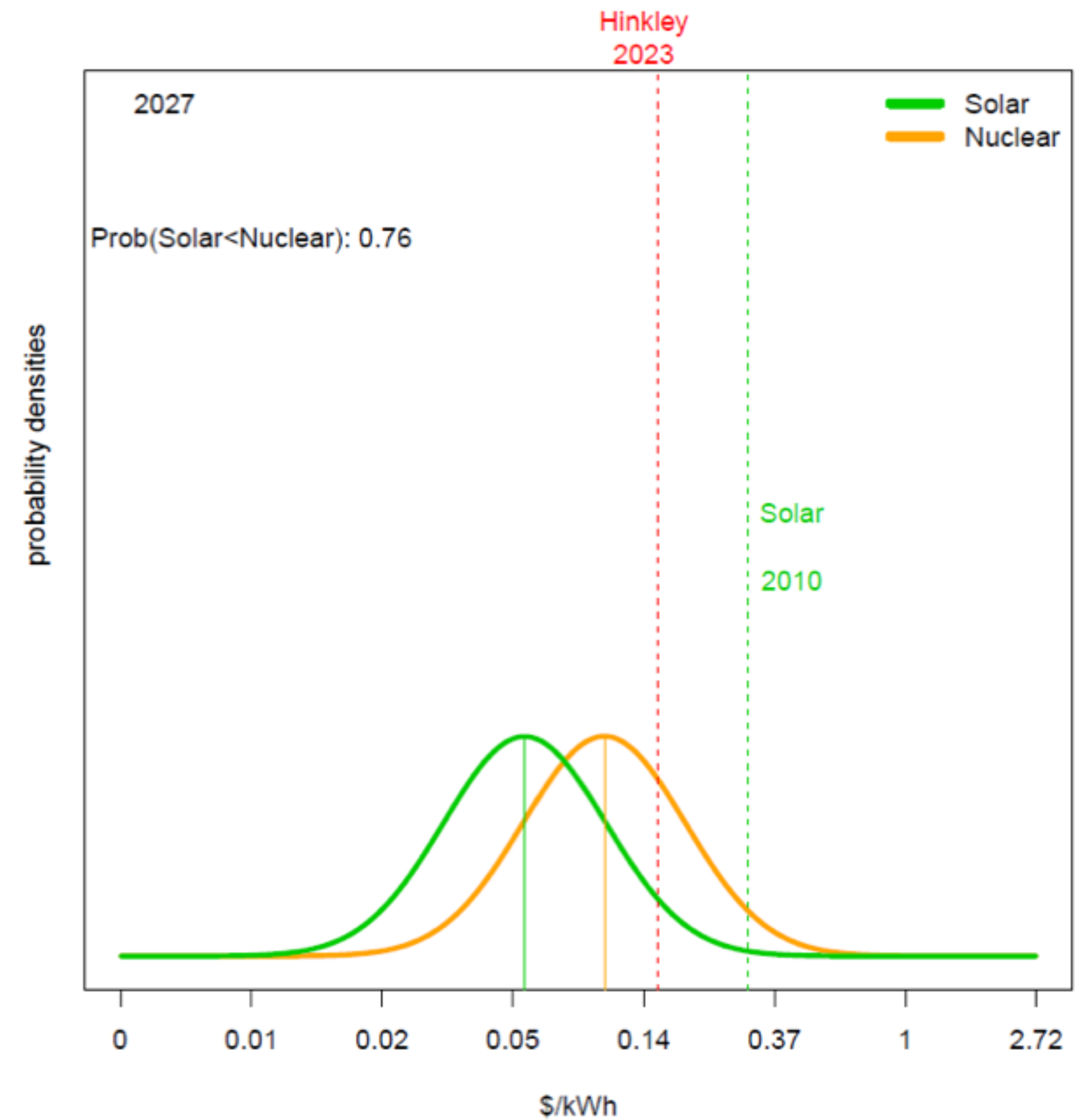
Hinkley
2023
2023
Solar
Nuclear
Prob(Solar<Nuclear): 0.61
Solar
2010
probability densities
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh


Hinkley
2023
2024
Solar
Nuclear
Prob(Solar<Nuclear): 0.65
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

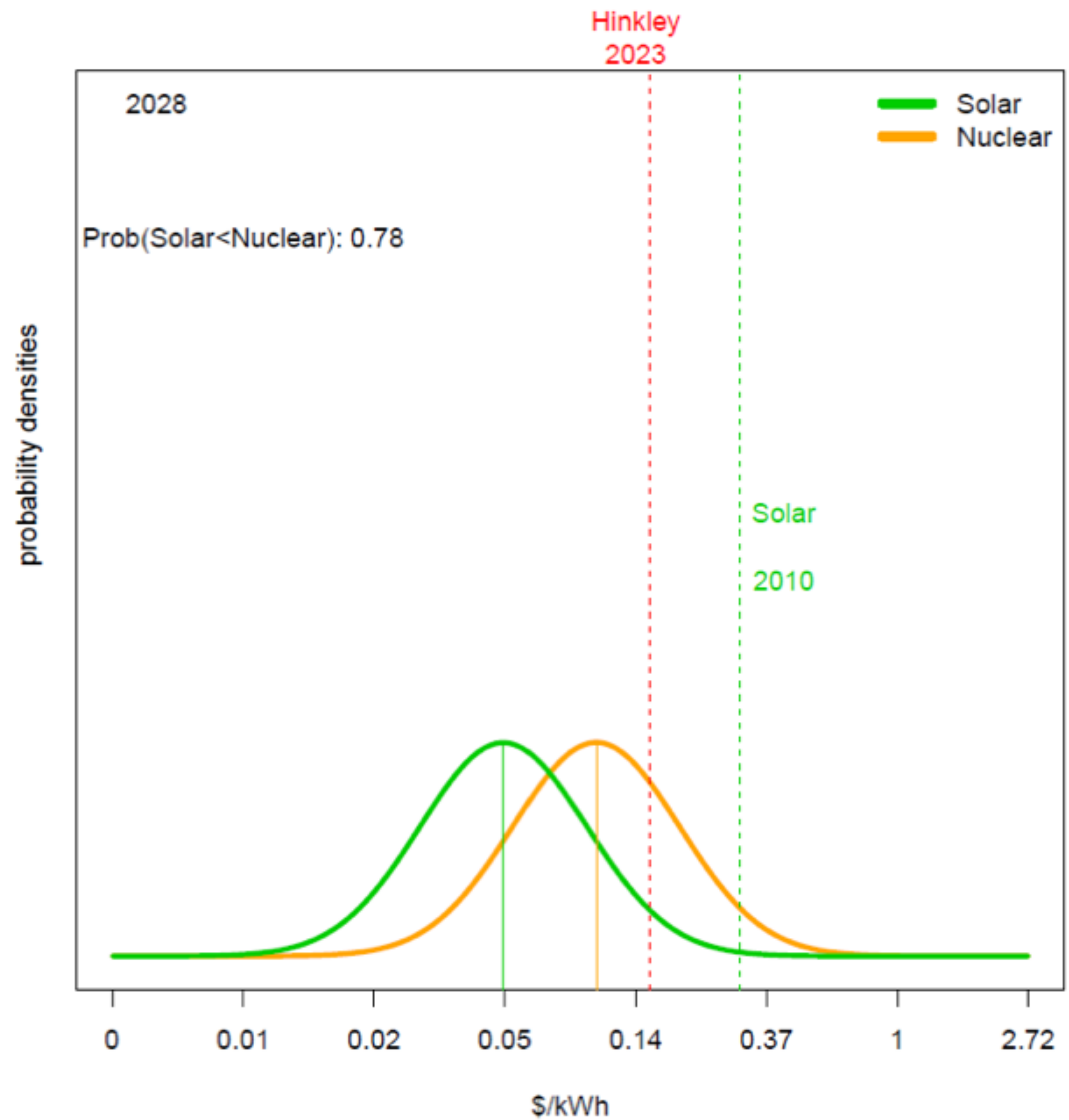

Hinkley
2023
2025
Solar
Nuclear
Prob(Solar<Nuclear): 0.69
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh


Hinkley
2023
2026
Solar
Nuclear
Prob(Solar<Nuclear): 0.72
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

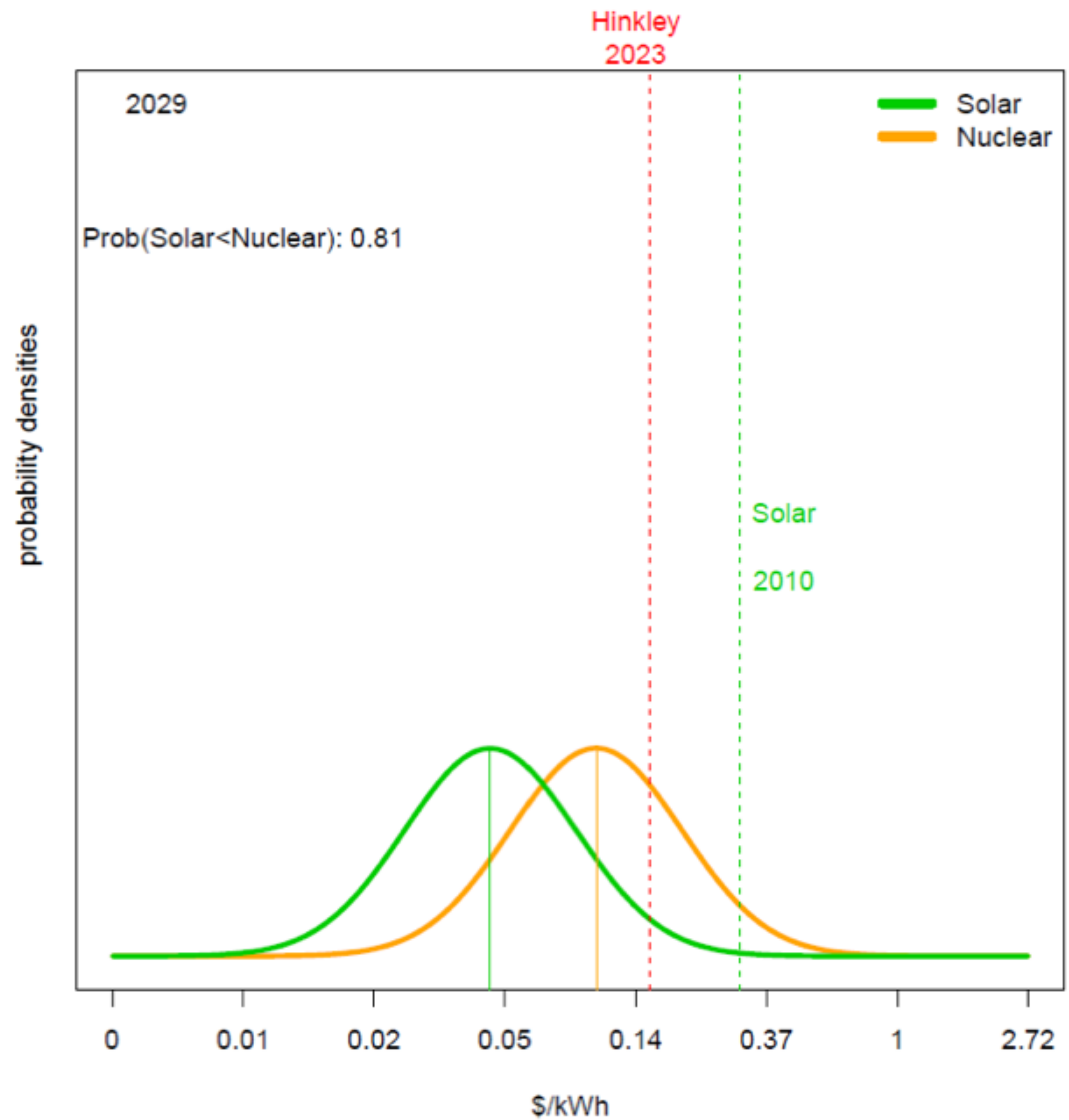

Hinkley
2023
2027
Solar
Nuclear
Prob(Solar<Nuclear): 0.76
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

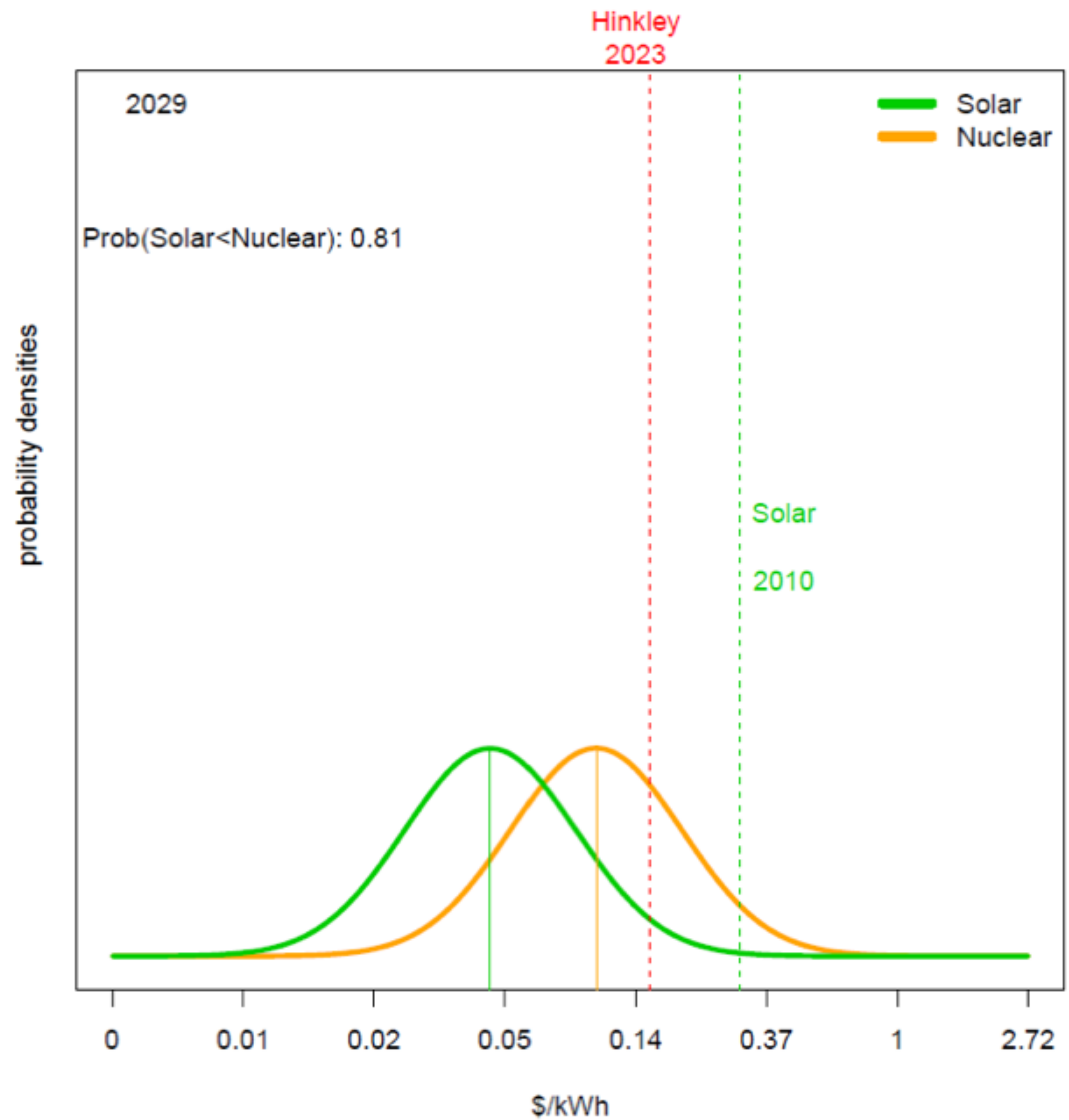


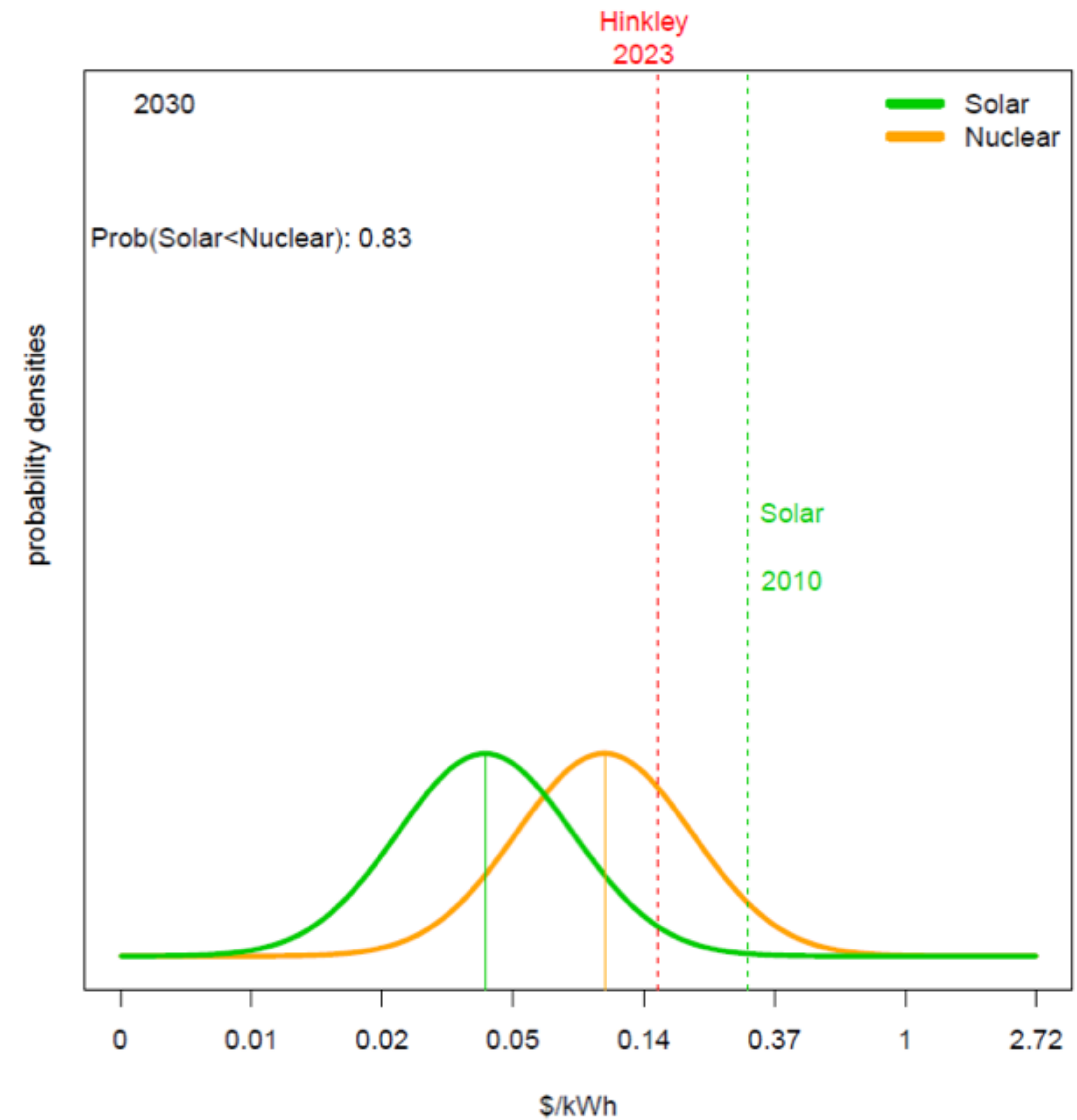
Hinkley
2023
2027
Solar
Nuclear
Prob(Solar<Nuclear): 0.76
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

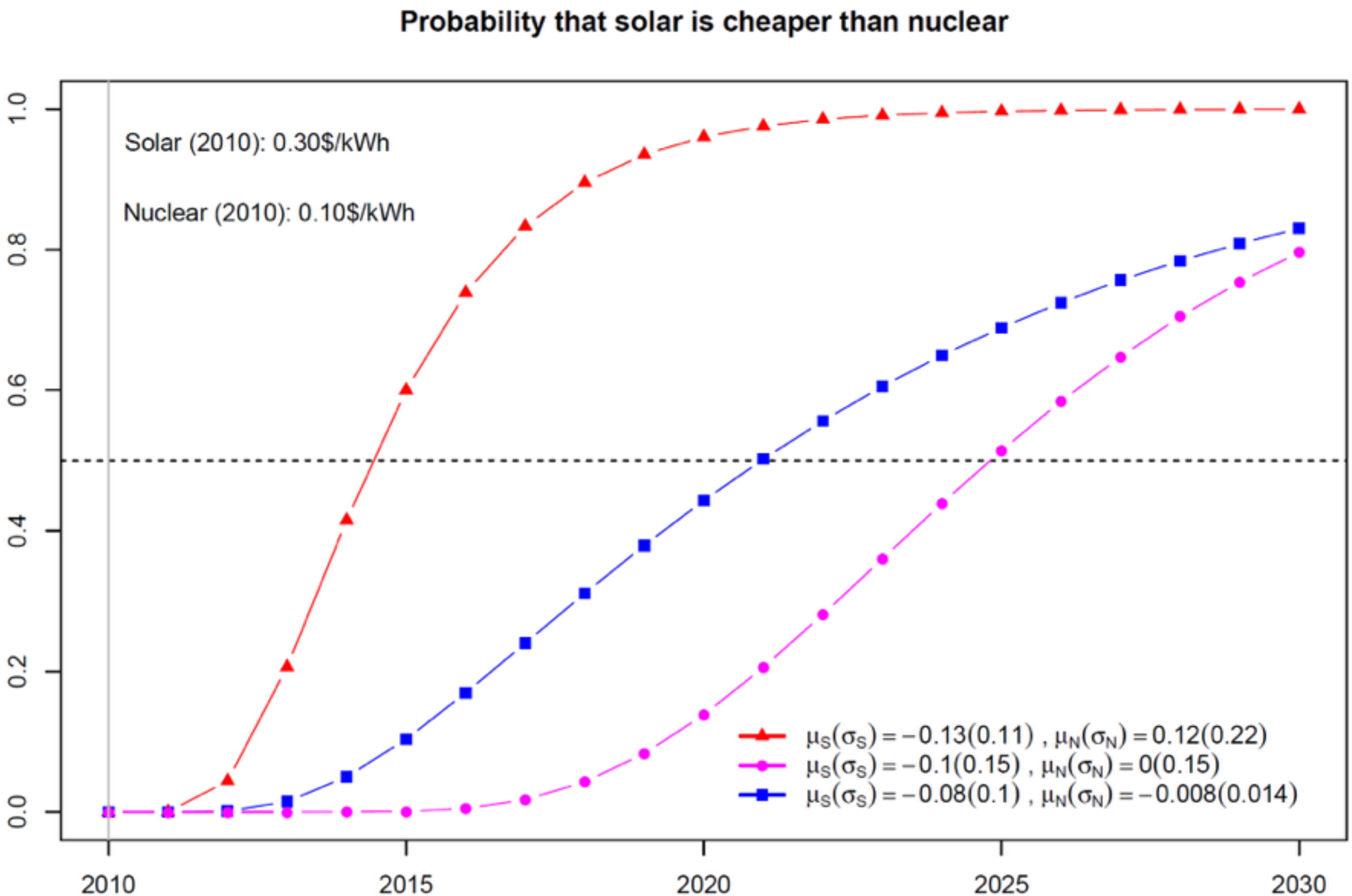


Hinkley
2023
2028
Solar
Nuclear
Prob(Solar<Nuclear): 0.78
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh


Hinkley
2023
2029
Solar
Nuclear
Prob(Solar<Nuclear): 0.81
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

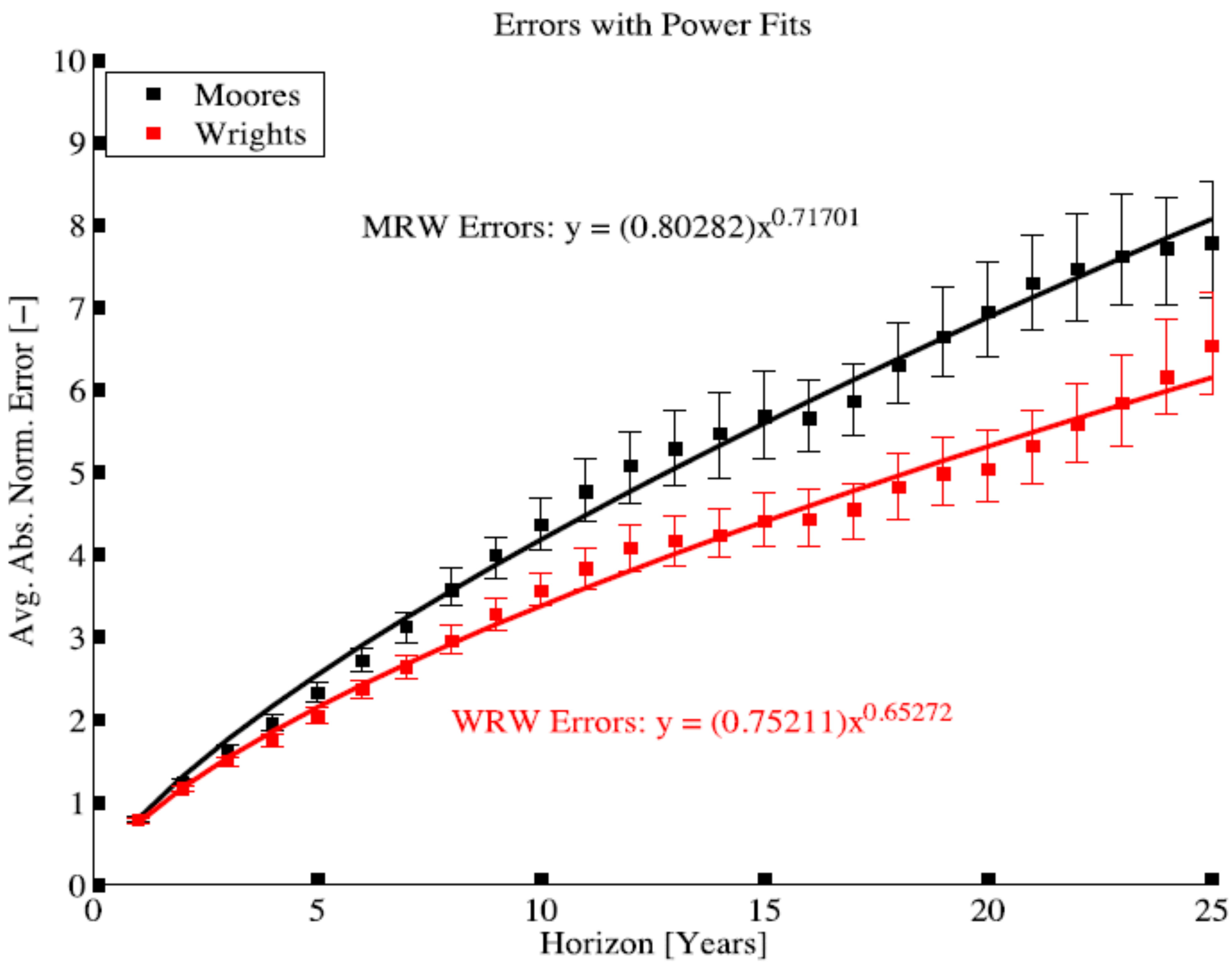

Hinkley
2023
2029
Solar
Nuclear
Prob(Solar<Nuclear): 0.81
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh

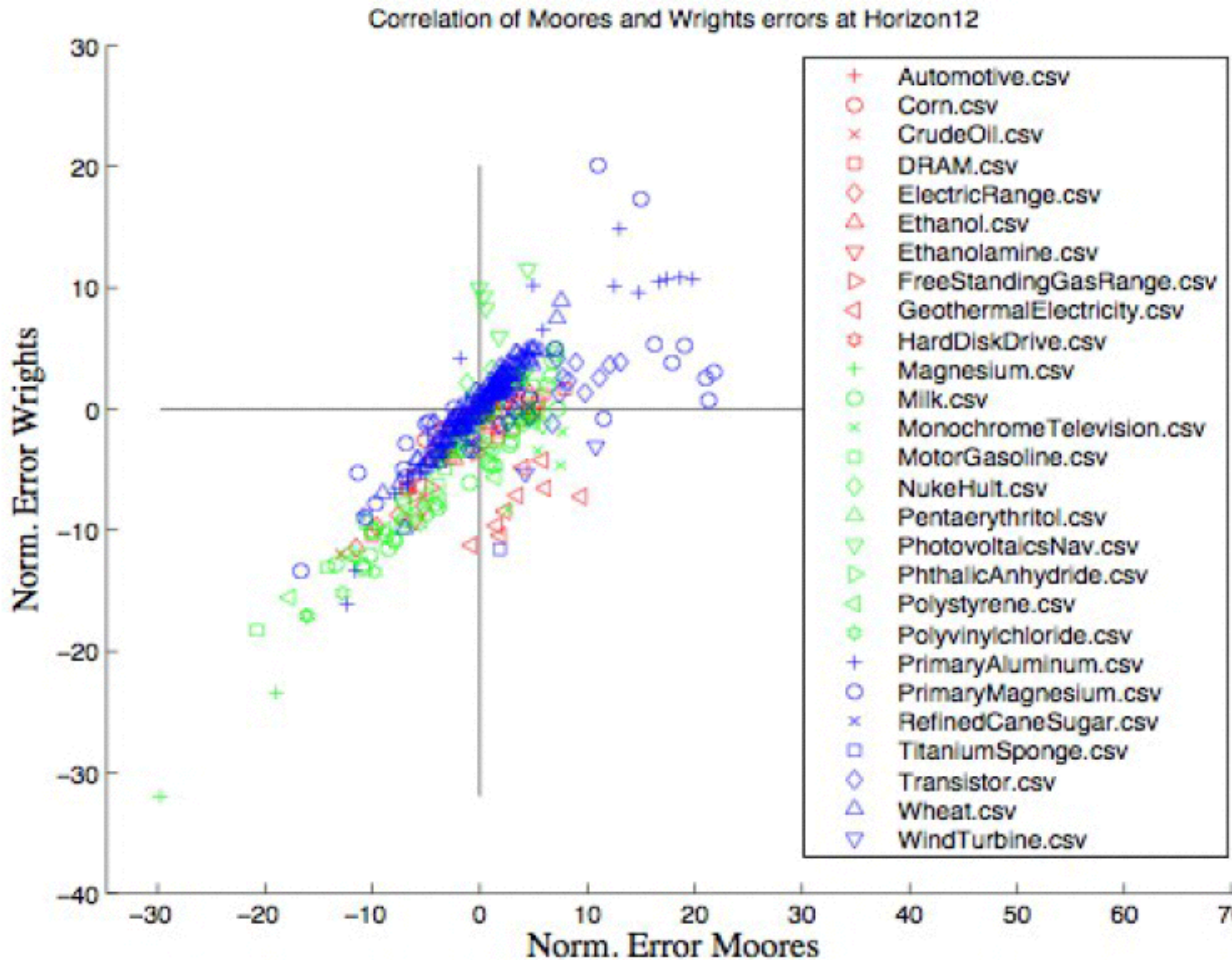

Hinkley
2023
2030
Solar
Nuclear
Prob(Solar<Nuclear): 0.83
probability densities
Solar
2010
0
0.01
0.02
0.05
0.14
0.37
1
2.72
$/kWh



Probability that solar is cheaper than nuclear
Solar (2010): 0.30$/kWh
Nuclear (2010): 0.10$/kWh
$\mu_S(\sigma_S) = -0.13(0.11)$, $\mu_N(\sigma_N) = 0.12(0.22)$
$\mu_S(\sigma_S) = -0.1(0.15)$, $\mu_N(\sigma_N) = 0(0.15)$
$\mu_S(\sigma_S) = -0.08(0.1)$, $\mu_N(\sigma_N) = -0.008(0.014)$
0.0
0.2
0.4
0.6
0.8
1.0
2010
2015
2020
2025
2030

Comparison of Wright's law and Moore's law



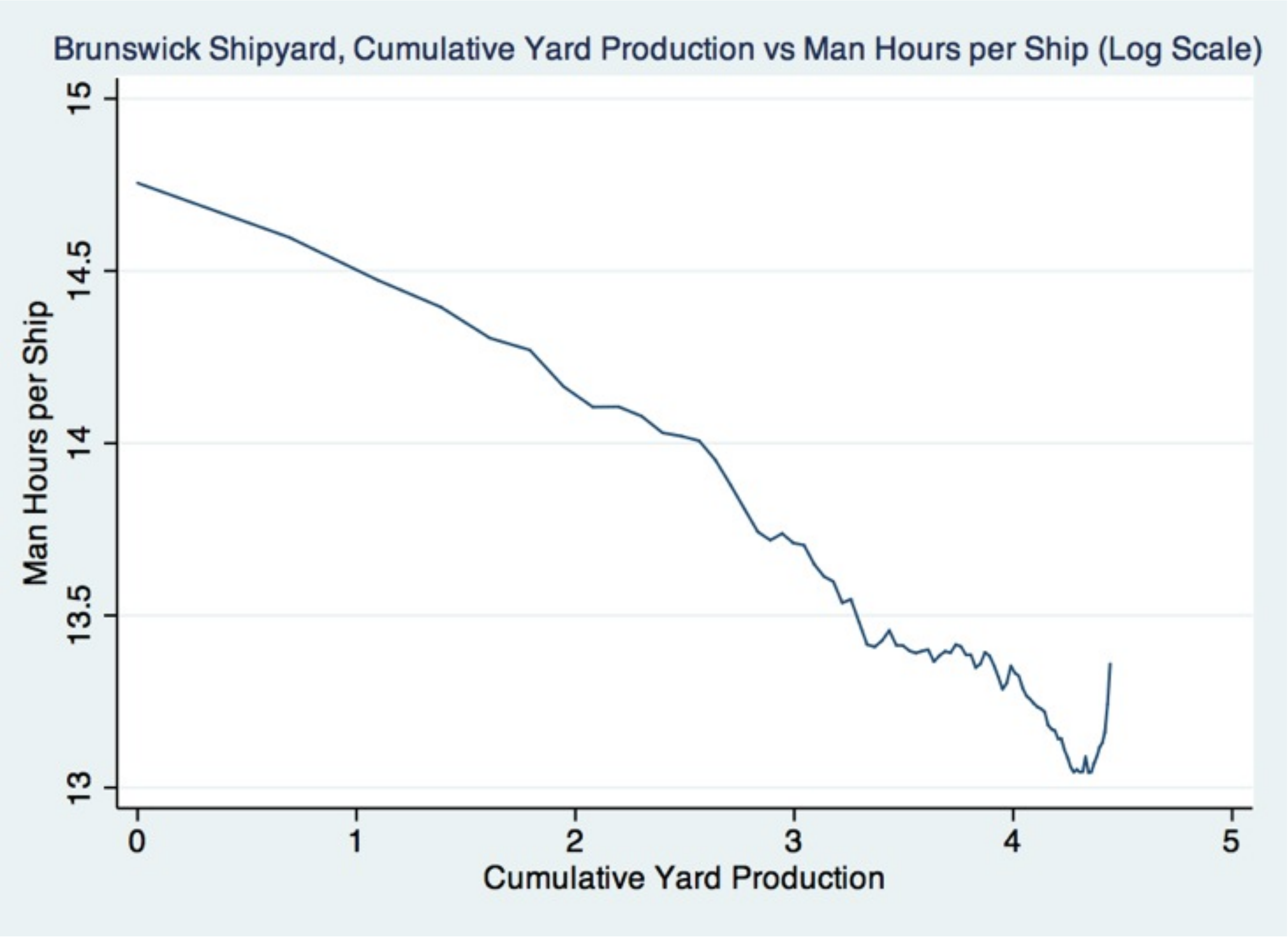


Correlation of Moores and Wrights errors at Horizon12
Norm. Error Wrights
Norm. Error Moores
30
20
10
0
−10
−20
−30
−40
−30
−20
−10
0
10
20
30
40
50
60
70
Automotive.csv
Corn.csv
CrudeOil.csv
DRAM.csv
ElectricRange.csv
Ethanol.csv
Ethanolamine.csv
FreeStandingGasRange.csv
GeothermalElectricity.csv
HardDiskDrive.csv
Magnesium.csv
Milk.csv
MonochromeTelevision.csv
MotorGasoline.csv
NukeHult.csv
Pentaerythritol.csv
PhotovoltaicsNav.csv
PhthalicAnhydride.csv
Polystyrene.csv
Polyvinylchloride.csv
PrimaryAluminum.csv
PrimaryMagnesium.csv
RefinedCaneSugar.csv
TitaniumSponge.csv
Transistor.csv
Wheat.csv
WindTurbine.csv

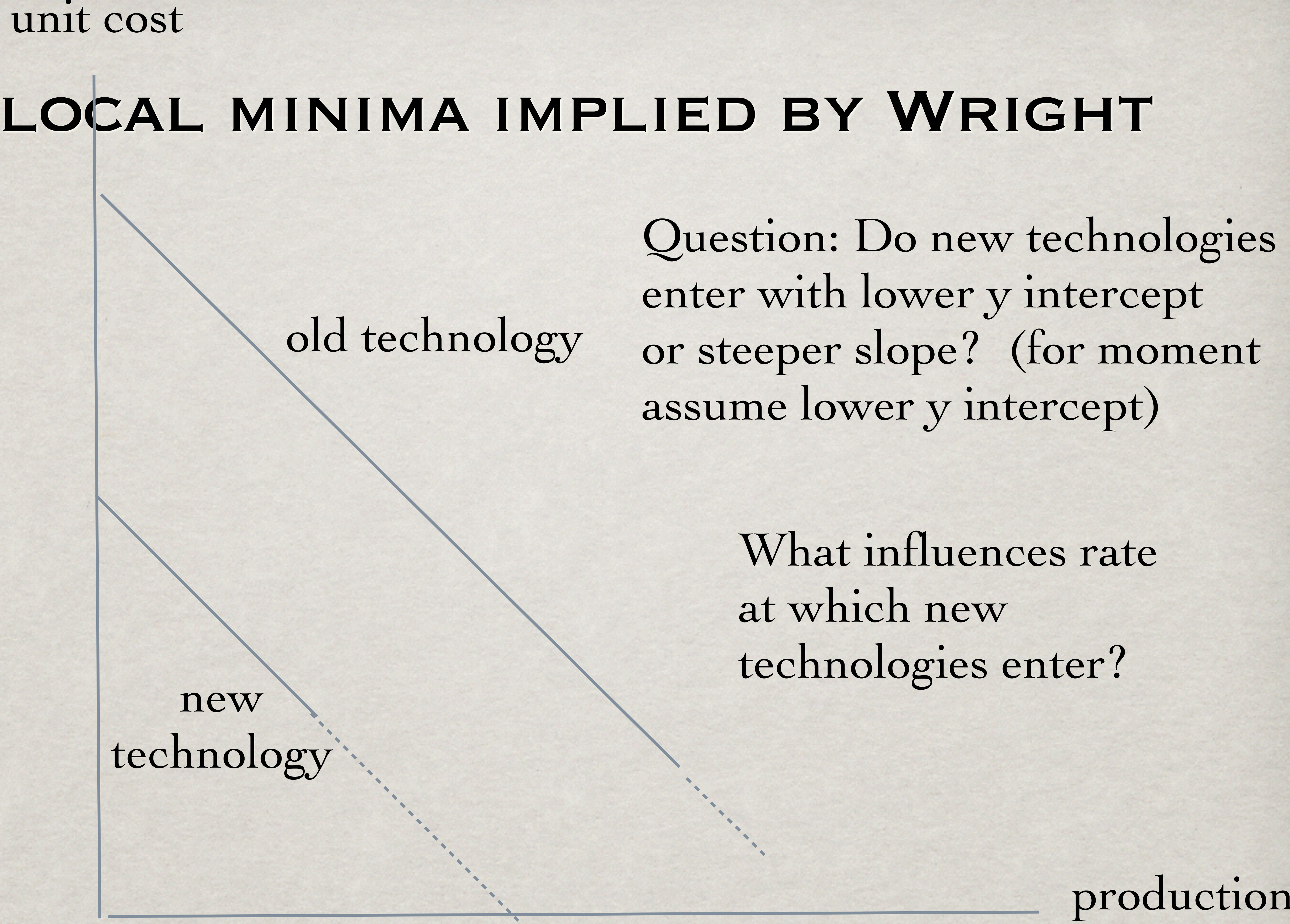
Summary of Results: Wright's law vs. Moore's law

- Wright's law forecasts based on production better than Moore's law based on time at long horizons
- Production history more useful than time.
- Suggestion: Costs can be driven down by stimulating production (feed-in tariffs).
- Need "artificial experiments", such as WWII, to test properly (correlation v.s causation).
  - Does production drive cost down, or does cost drive production up? Or both?

Liberty Ships



LOCAL MINIMA IMPLIED BY WRIGHT



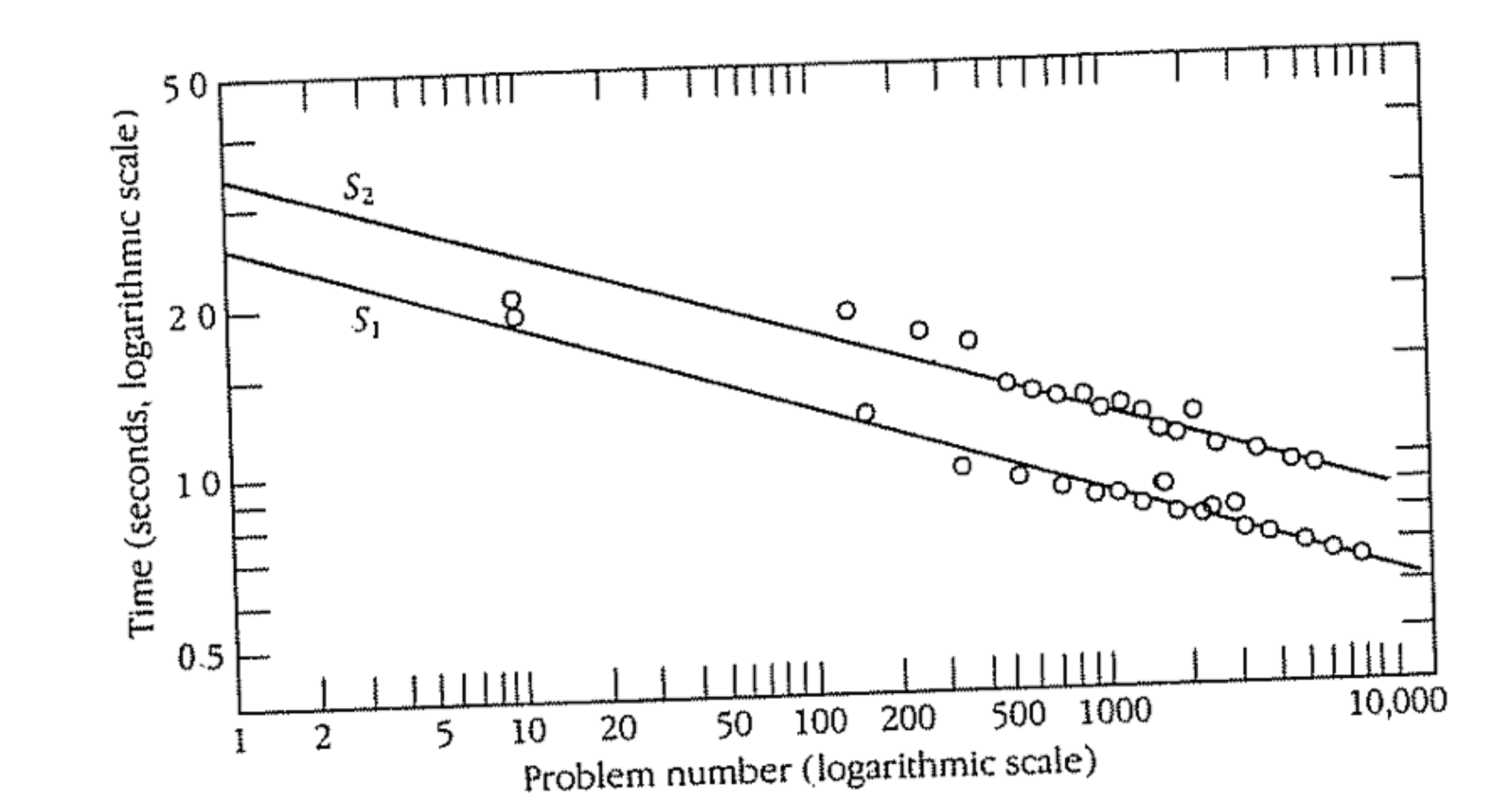
Question: Do new technologies enter with lower y intercept or steeper slope? (for moment assume lower y intercept)

What influences rate at which new technologies enter?

Generality of Wright's law

- Holds at the level of products, firms, industries, or best technology performing a given function.
- Explanation must be correspondingly general.

Power law of practice

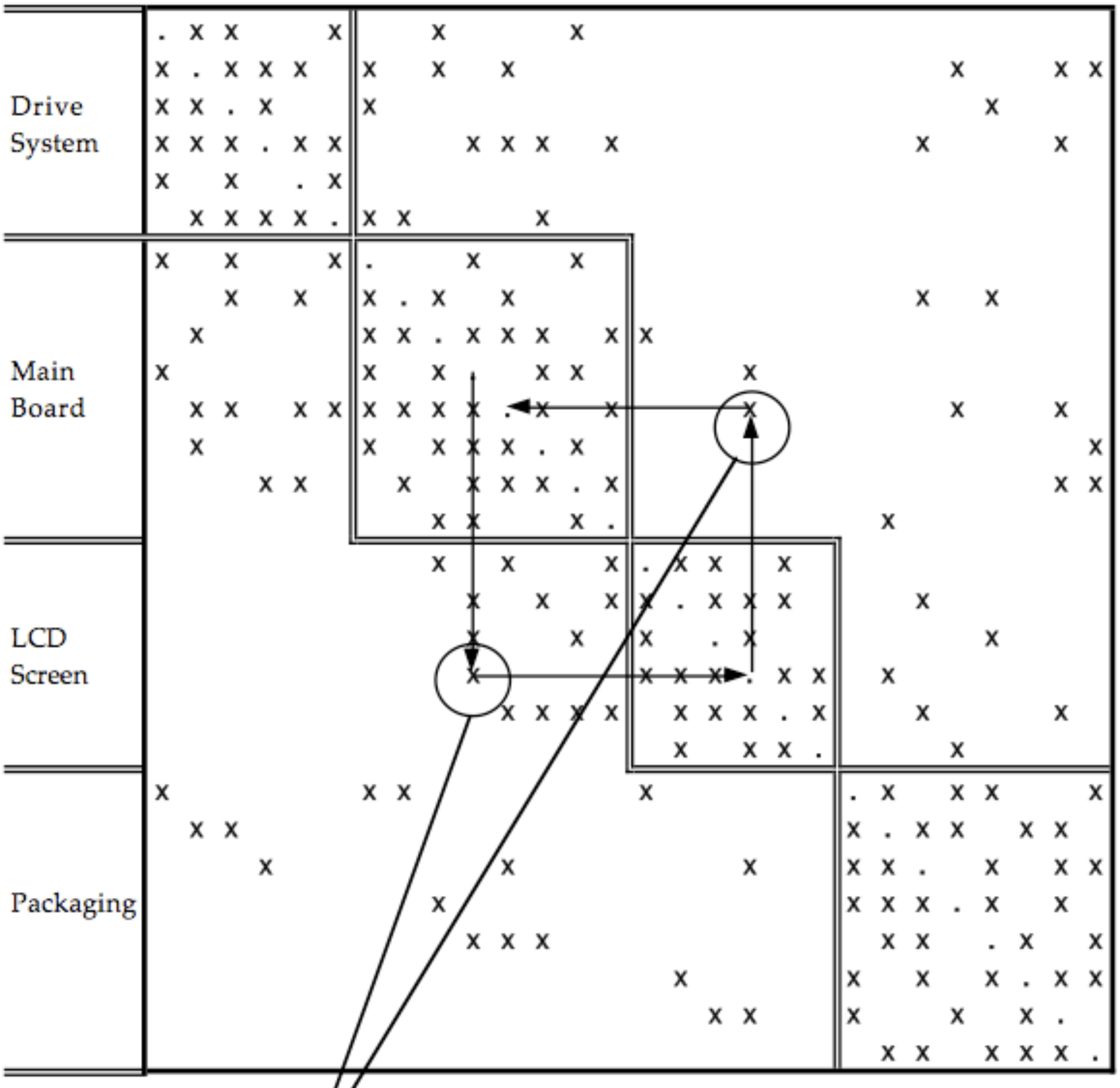


Improvement with practice in time to add two numbers (Blackburn, 1936)

Recipe model of technological improvement

- Muth (Management Science, 1987)
  - Engineers generate new solutions at random, accept them if they are better. Single component: Implies Wright's law with exponent = -1.
- Auerswald, Kauffman, Lobo and Shell (JEDC, 2000)
  - Multiple components that depend on each other. Accept improvements only if sum score improves.

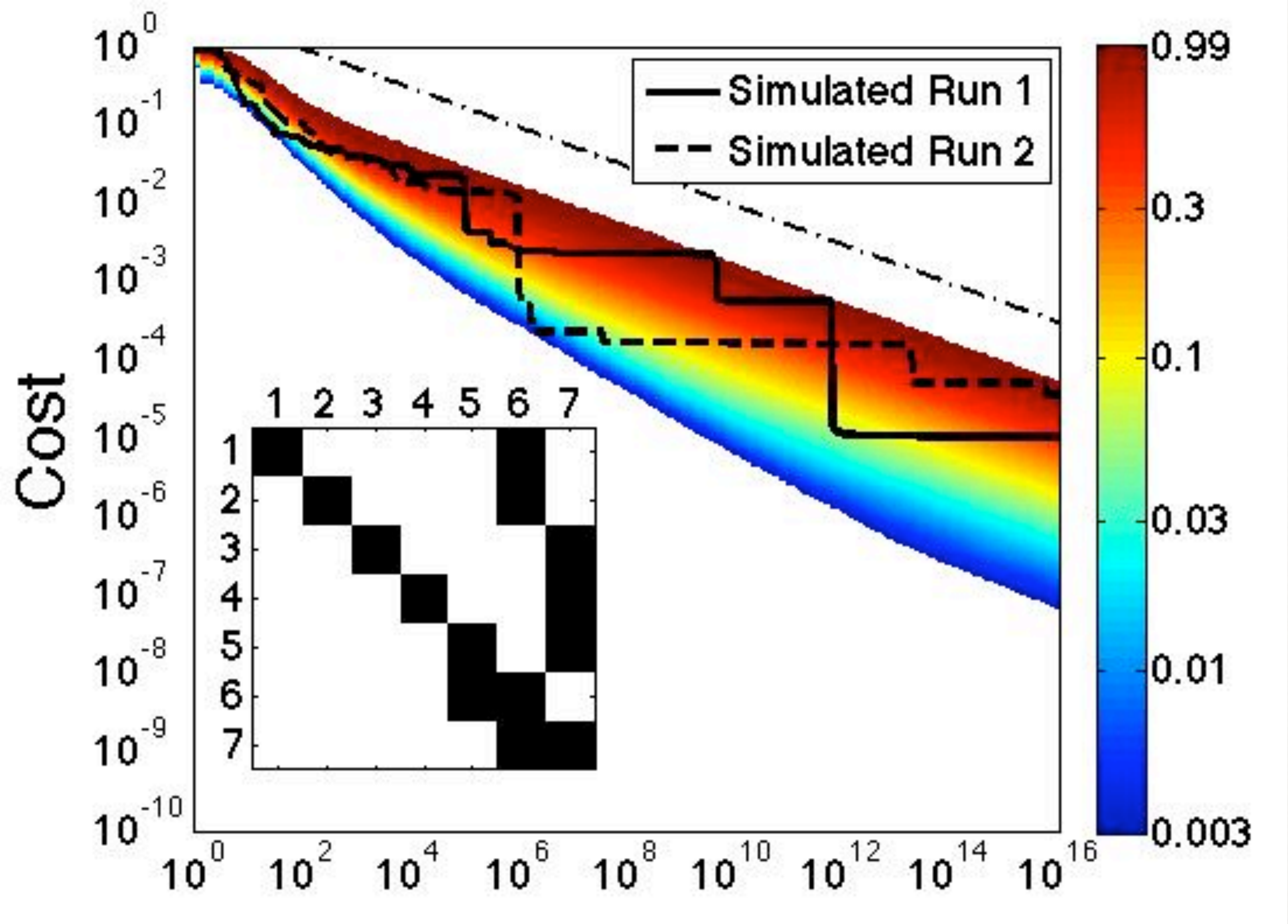
Design Structure Matrix Map of a Laptop Computer



Recipe model (continued)

- McNerney, Farmer, Redner, Trancik (PNAS, 2011)
  - simplified and solved recipe model
  - generates power law with exponent -(1/d), where d = "design complexity", which depends on DSM. For homogeneous networks d is in-degree of DSM.
  - for heterogeneous networks there are typically bottleneck components, d is more complicated to compute, and progress typically occurs via a sequence of punctuated equilibria

Cost vs. time for recipe model

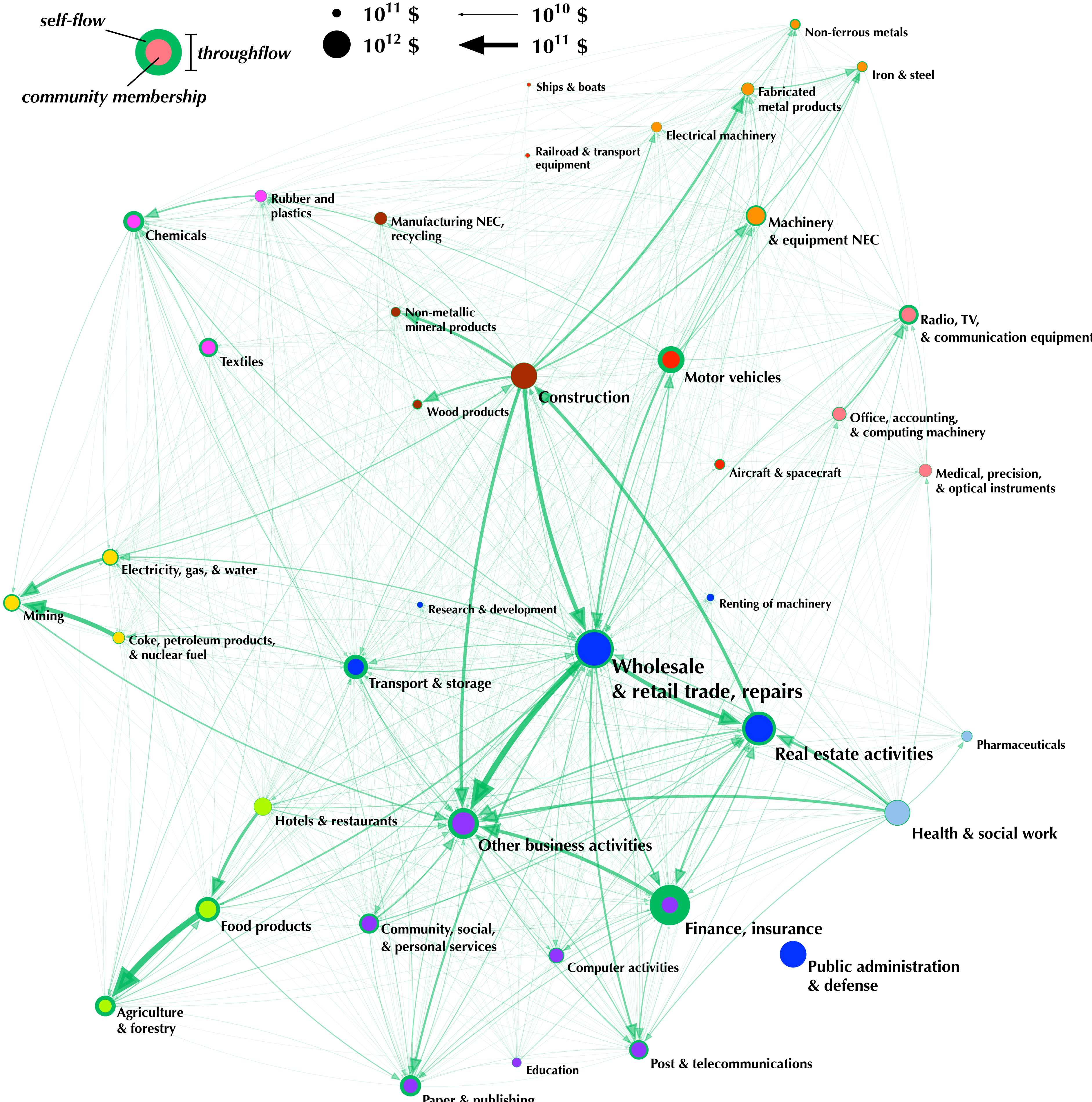


Need to go beyond recipe model

- Nice start, but only part of story
- Anecdotally: Innovations in one industry often drive innovations in others
  - solar PV, laser printers, digital cameras, ...
- Interactions between technologies are key
  - must model evolution of entire technological ecology to understand a single technology

LEONTIEF: INPUT-OUTPUT MODEL OF AN ECONOMY

- Nodes are industries, (weighted) directed links are inputs to each industry.
- Can be based on physical flows or on monetary flows.
- Precise analogy to equilibrium chemical kinetics (allowing non-integer stoichiometric parameters)
- Conservation laws lead to linear system of equations
- Used in national accounting, central planning.



U.S. industry network, 1997

McNerney, Fath, Silverberg (2013)

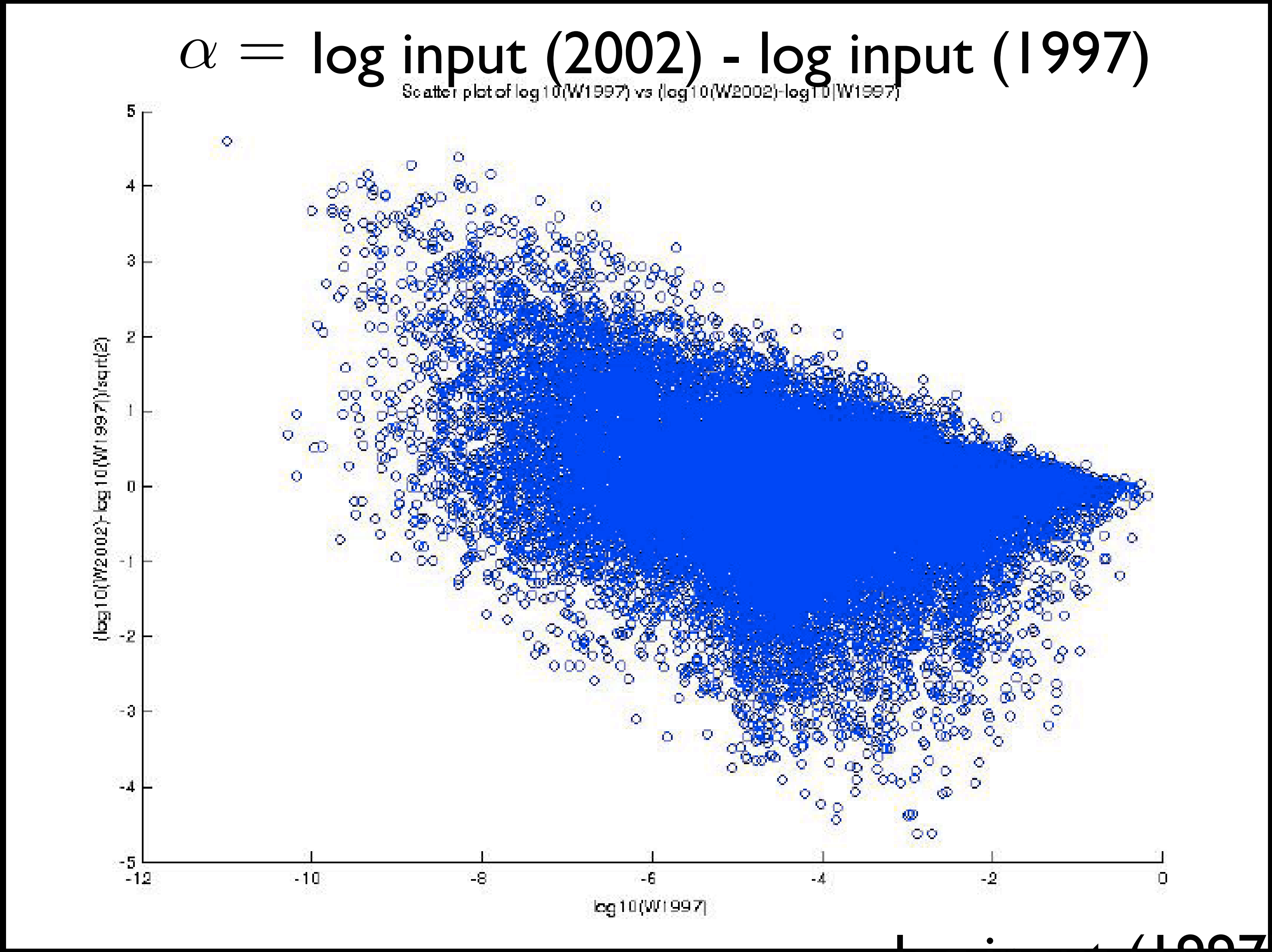
Our approach

Evolutionary extension of Leontief formalism

with James McNerney, Francesco Caravelli

- Design improvement happens through
  - Input tuning
  - Substitution of cheaper or better inputs
  - Creation of new goods: Network growth
  - Improved social technologies of production, distribution, ... invisible to Leontief network
- Increase in combinatorial possibilities -- palette gets larger and more powerful

Input fluctuations of I/O matrix for USA



"Deductive tinkering"

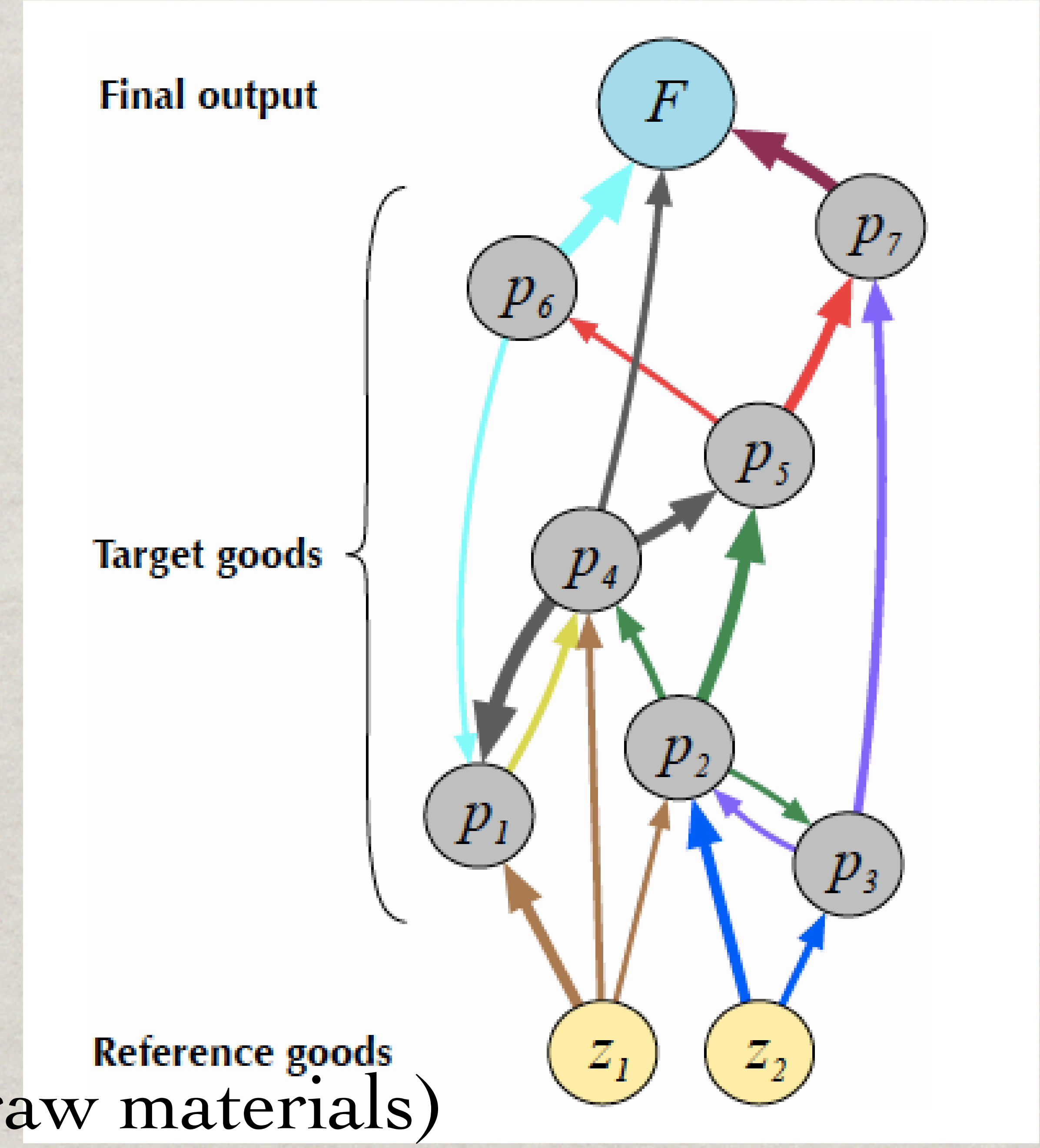
Simplest model: Efficiency improvements

- The net result of a design improvement is an overall decrease in material inputs to perform same function

$$\phi_{ij} \rightarrow \alpha\phi_{ij}$$

- Leads to conclusion that technologies have a trophic structure, like food webs

Technologies can be arranged in trophic levels

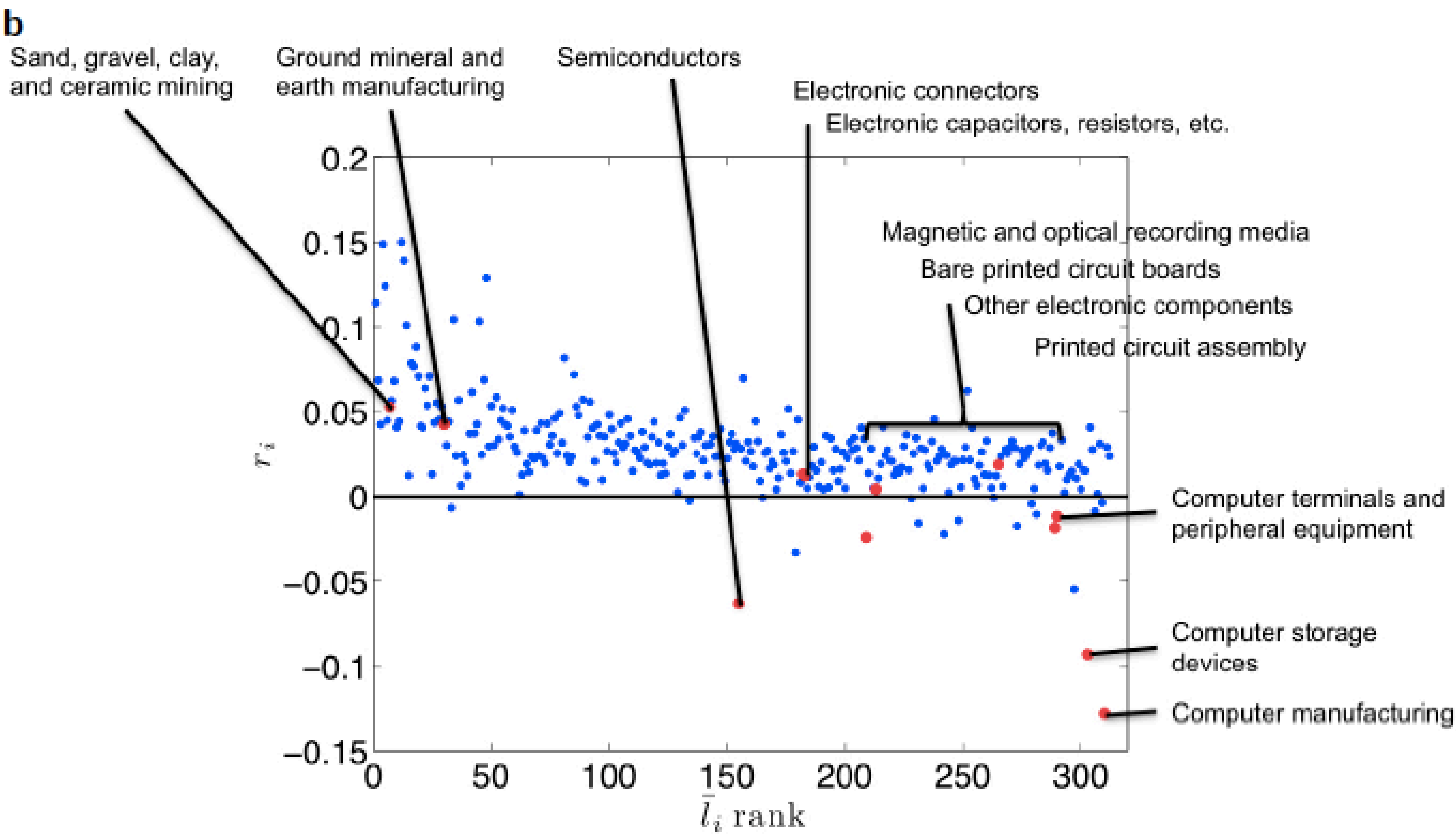


(raw materials)

with James McNerney and Francesco Caravelli

Hypothesis:
All else equal, technologies with high trophic level improve faster than technologies with low trophic level.

Reason: Improvements are amplified multiplicatively.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Sand, gravel, clay, and ceramic mining
Ground mineral and earth manufacturing
Semiconductors
Electronic connectors
Electronic capacitors, resistors, etc.
Magnetic and optical recording media
Bare printed circuit boards
Other electronic components
Printed circuit assembly
Computer terminals and peripheral equipment
Computer storage devices
Computer manufacturing
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0.15
0.1
0.05
0
−0.05
−0.1
−0.15
0
50
100
150
200
250
300
r_i
$\bar{l}_i$ rank

Provides alternate explanation for super-exponential population growth

- Paul Romer’s theory: population and technology co-evolved.
- Our theory: Trophic structure accellerates growth, graphic structure has grown.

Physics matters to economics

- Evolutionary search finds physical processes capable of rapid improvement
- Interaction between physics, which determines what is possible, and economics, which determines what is wanted
- Physics is key determinant of technological improvement (Funk and Magee)
- Migration toward "good physics" can result in dramatic improvements

Analogy: Evolution of autocatalytic networks

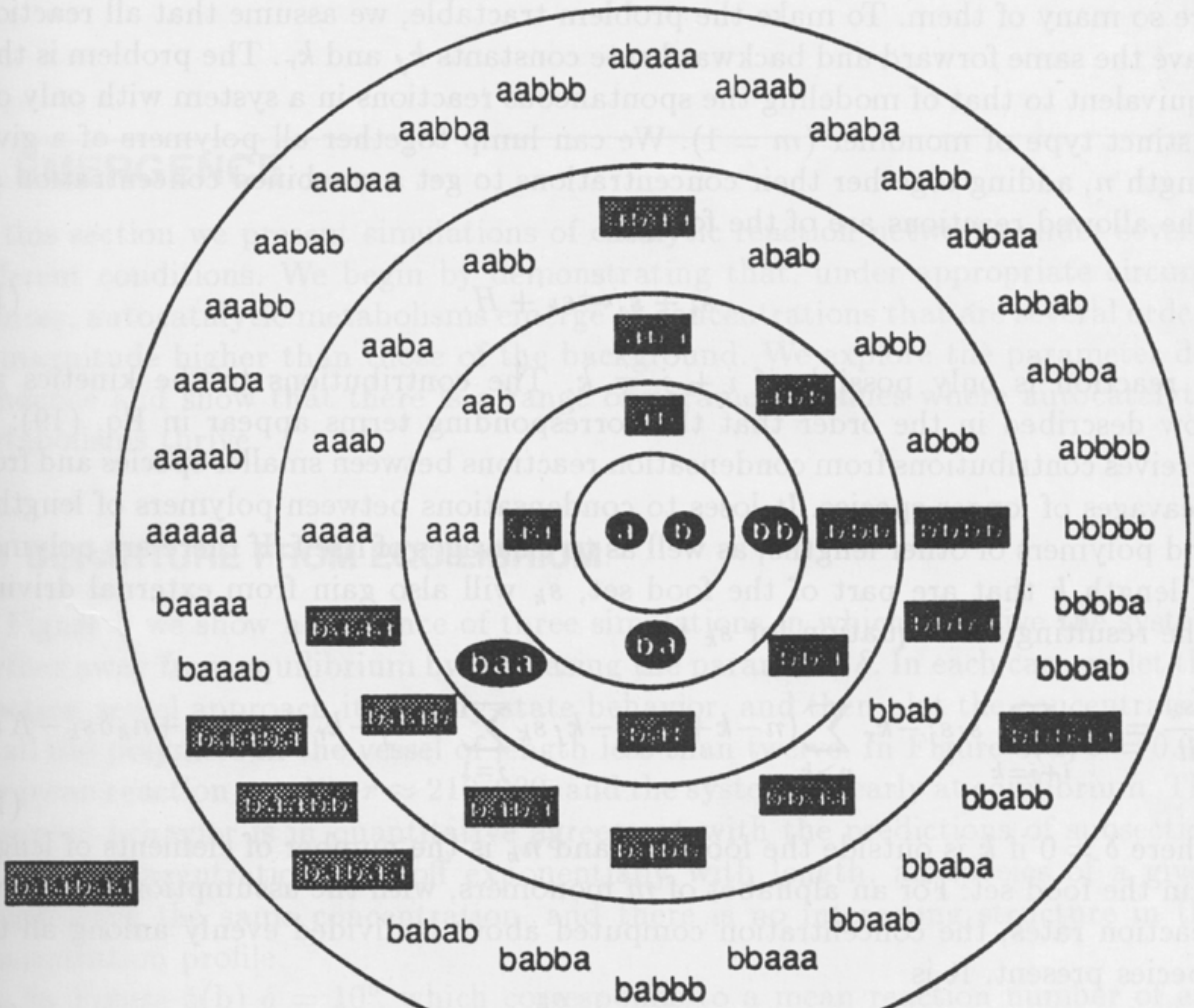
- Autocatalytic metabolism: Set of chemical species that jointly produce each other via catalyzed chemical reactions involving only other members of the set.

Metadynamics
(with Norman Packard)

- A *metadynamics* model is a dynamical systems model on a dynamic network. The dynamics induce changes in the network, which in turn induces changes in the dynamical system.
- For example, consider modeling a potentially infinite set of possible chemical reactions.
  - Chemical kinetics are solved on a network of dominant reactions. This network is defined by the set of existing chemical species, which can themselves change through time. As they change, they change the network.
- Key idea: Evolution toward the adjacent possible (Kauffman).

Metadynamics papers

- Farmer, J.D., S. Kauffman, N. Packard. "Autocatalytic Replication of Polymers." *Physica D* (1986).
- Farmer, J. D., N. H. Packard, A. Perelson. "The Immune System, Adaptation, and Machine Learning." *Physica D* (1986)
- Bagley, R. J., and J. D. Farmer. "Spontaneous Emergence of a Metabolism." In *Artificial Life II* (1991).
- Bagley, R. J., J. D. Farmer, and W. Fontana. "Evolution of a Metabolism." In *Artificial Life II* (1991).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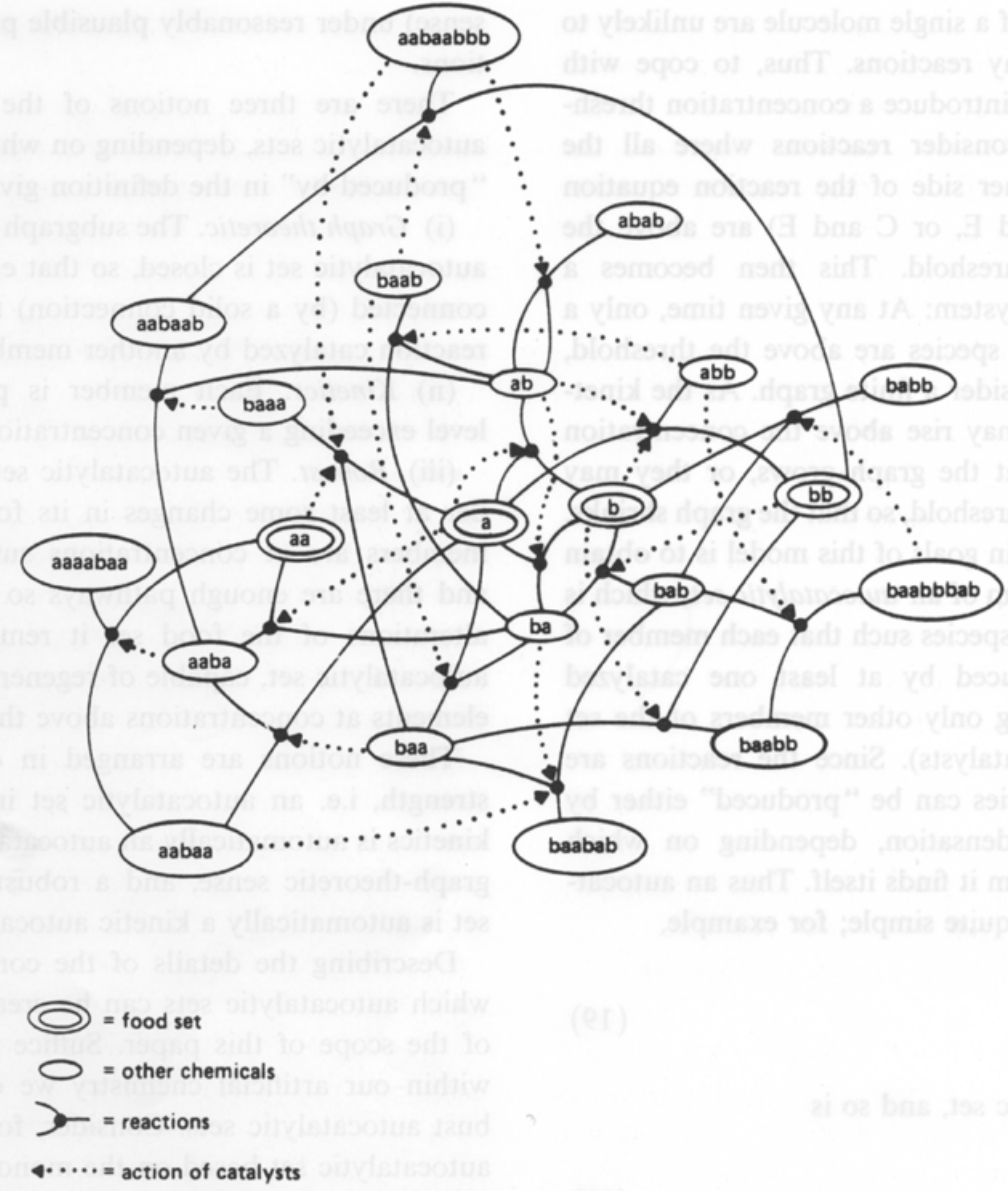
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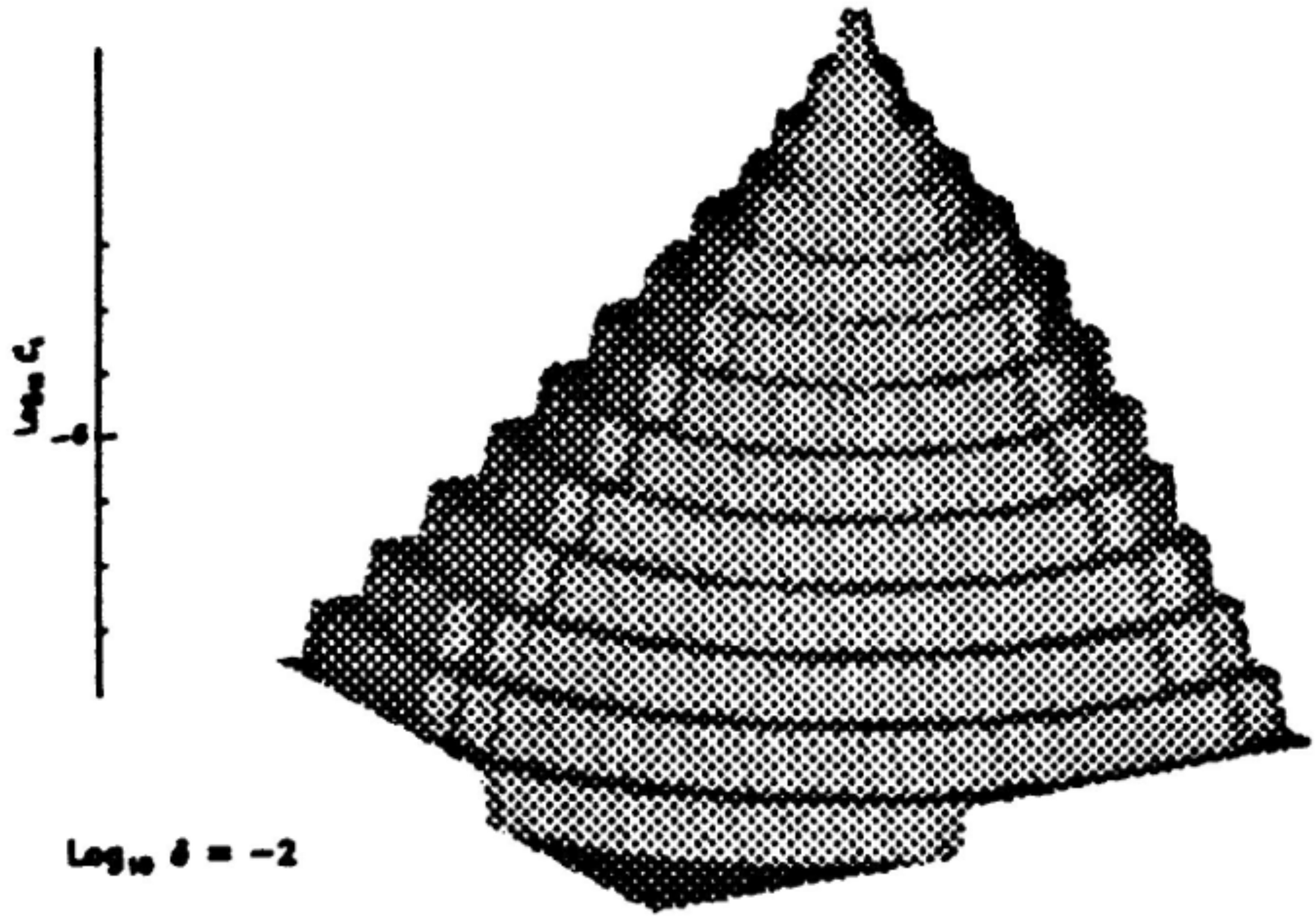
aaba
baa
baabb
aabaa
baabab
= food set
= other chemicals
= reactions
= action of catalysts

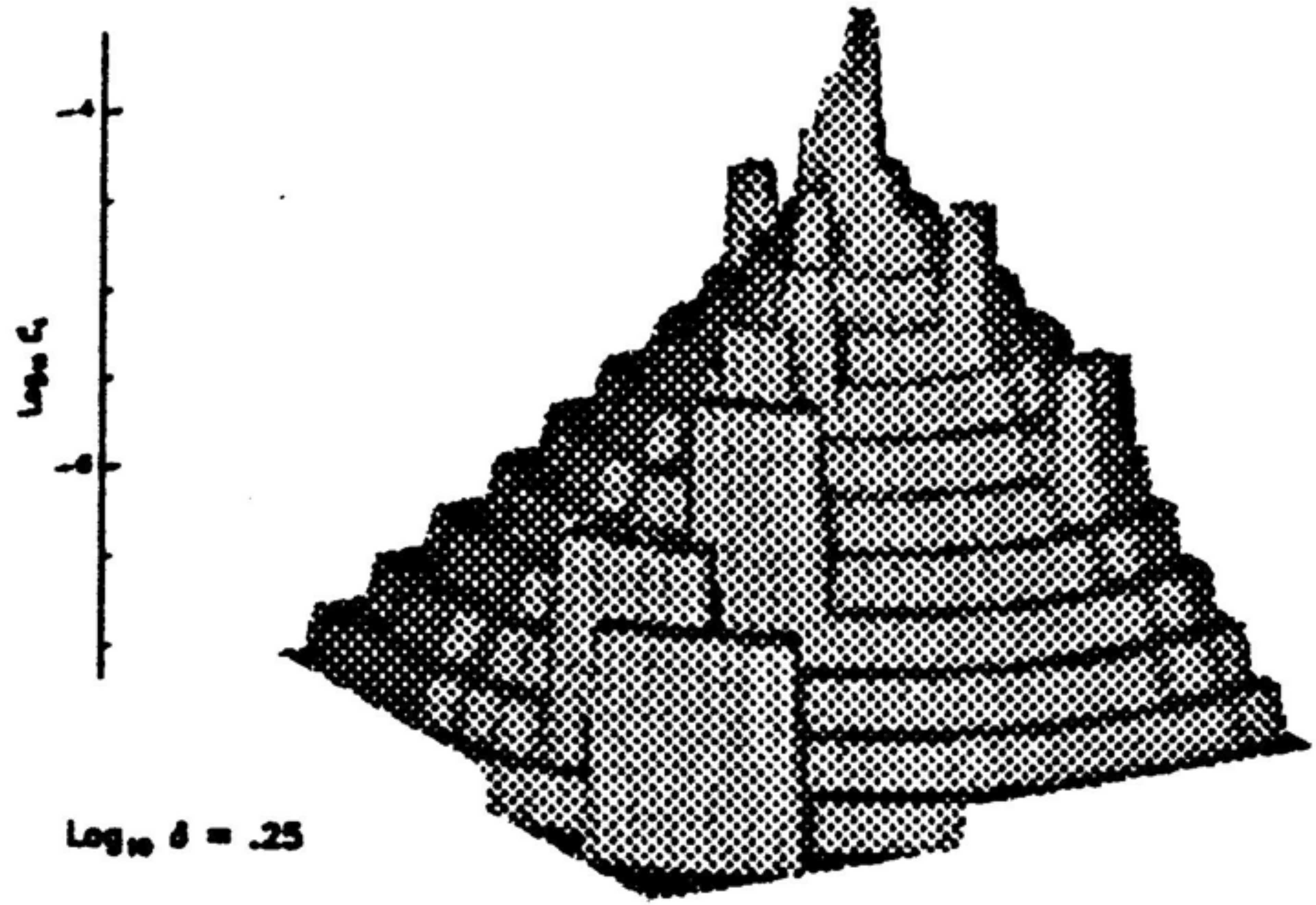
Simulation of an autocatalyic metabolism

- Start with simple food set (e.g. 5 species)
- Implement kinetics for catalyzed reactions among food set (which defines initial network).
- Define shadow set as species that can be reached by uncatalyzed reactions within network
- Create a new species from shadow set with probability depending on reaction rates.
- If this adds new catalyzed reaction, alter network of catalyzed reactions accordingly.
- Repeat.

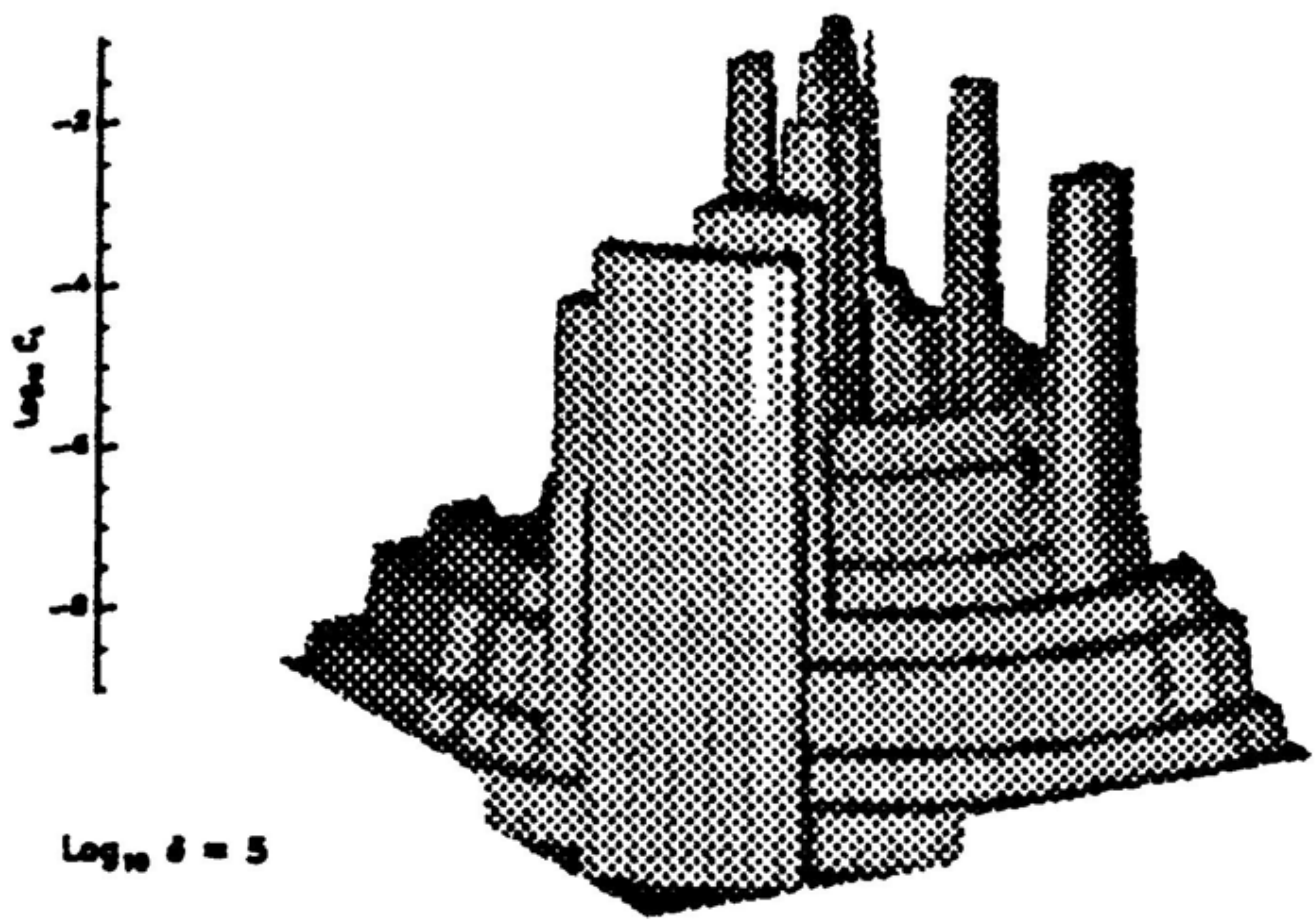
equilibrium concentration with only uncatalyzed reactions



from: The Functional Self-Organization of Autocatalytic Networks
In a Model of the Evolution of Biogenesis, Richard James Bagley, Ph.D. thesis (1991)



from: <u>The Functional Self-Organization of Autocatalytic Networks In a Model of the Evolution of Biogenesis</u>, Richard James Bagley, Ph.D. thesis (1991)



from: The Functional Self-Organization of Autocatalytic Networks
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Spontaneous emergence of an evolving metabolism (with R. Bagley, W. Fontana)

- Set of specific chemical species
- Capable of "digesting" many possible food sets
- Composition of of species evolves through time under random variation and selection.
- Metadynamic model generates network through dynamics of components of network.

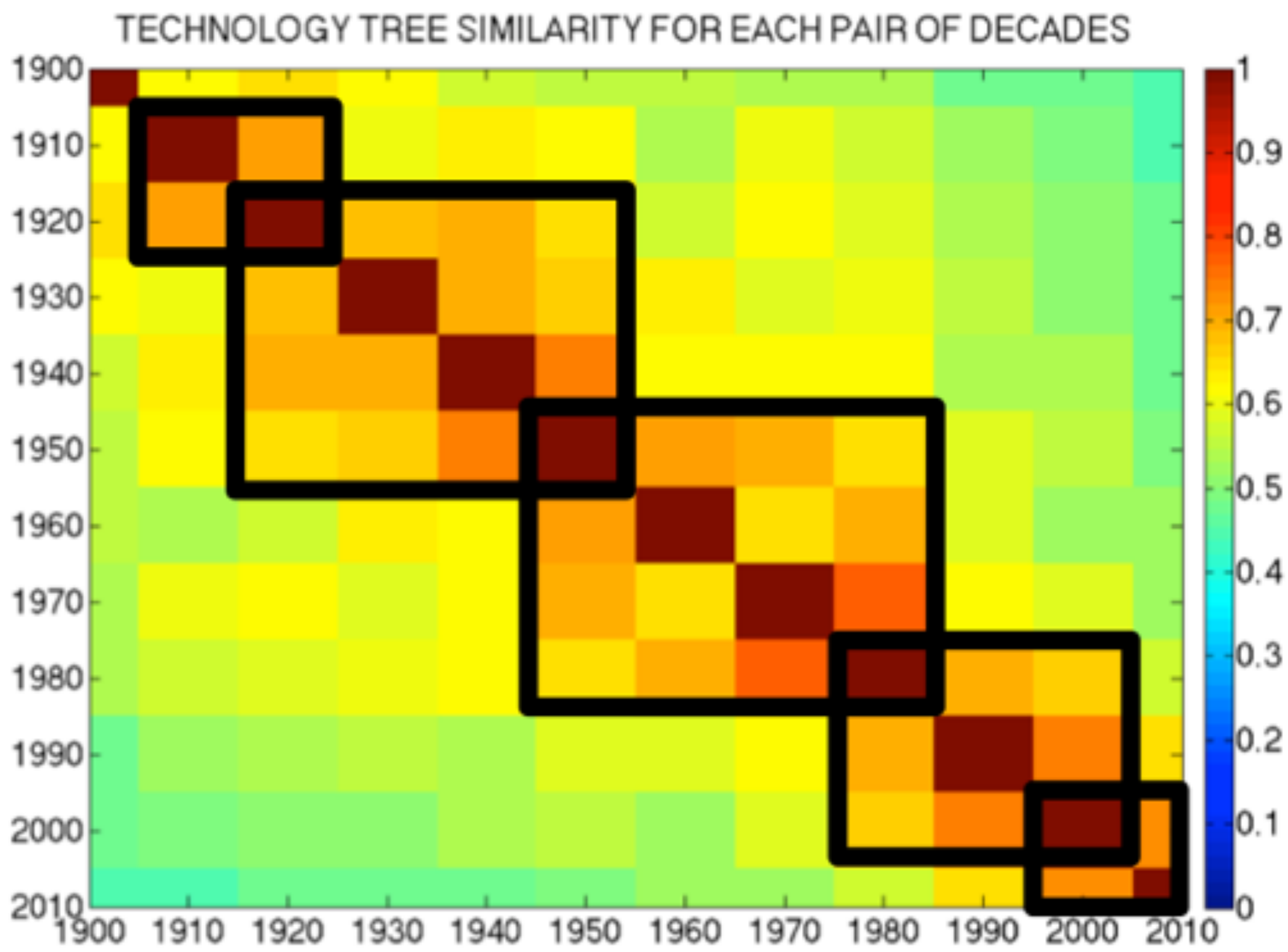
Investigating technological evolution via US patents

- 9M patents
- 1790 to present:
  - 10,000 tech. codes -> 150,000 tech. codes
- Closest thing to a fossil record of tech. change

Co-occurence network

- Can define co-occurence network as the frequency with which two technology codes appear together.
- Defines network with technology codes as nodes and co-occurence frequency as weighted links.
- Provides a way to understand how technologies interact with each other and how this evolves through time.

Evidence for technological epochs

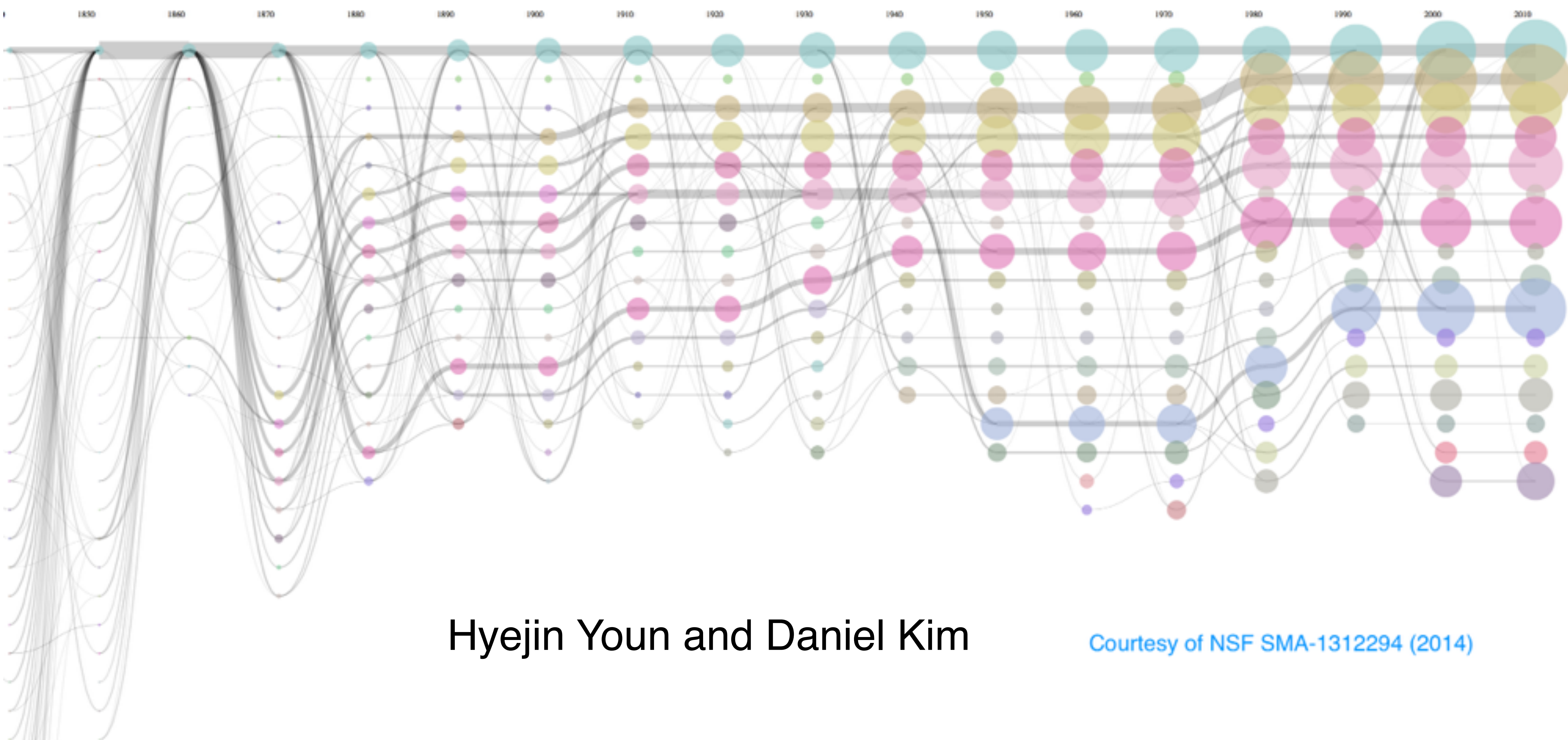


with Ioannis Psorakis

- Inventing activity changes, based on technological, economic, social, even geopolitical trends.
- We investigate the self-organization patterns of technologies across time, given our combination-based communities at each decade.
- Our analysis reveals clusters of self-similarity across time, corresponding to various historical eras (WWI, WWII, Cold War, modern era).
- Cluster boundaries correspond to *technological shifts,* that allow us to "sandbox" different models at different time periods.

Community dynamics

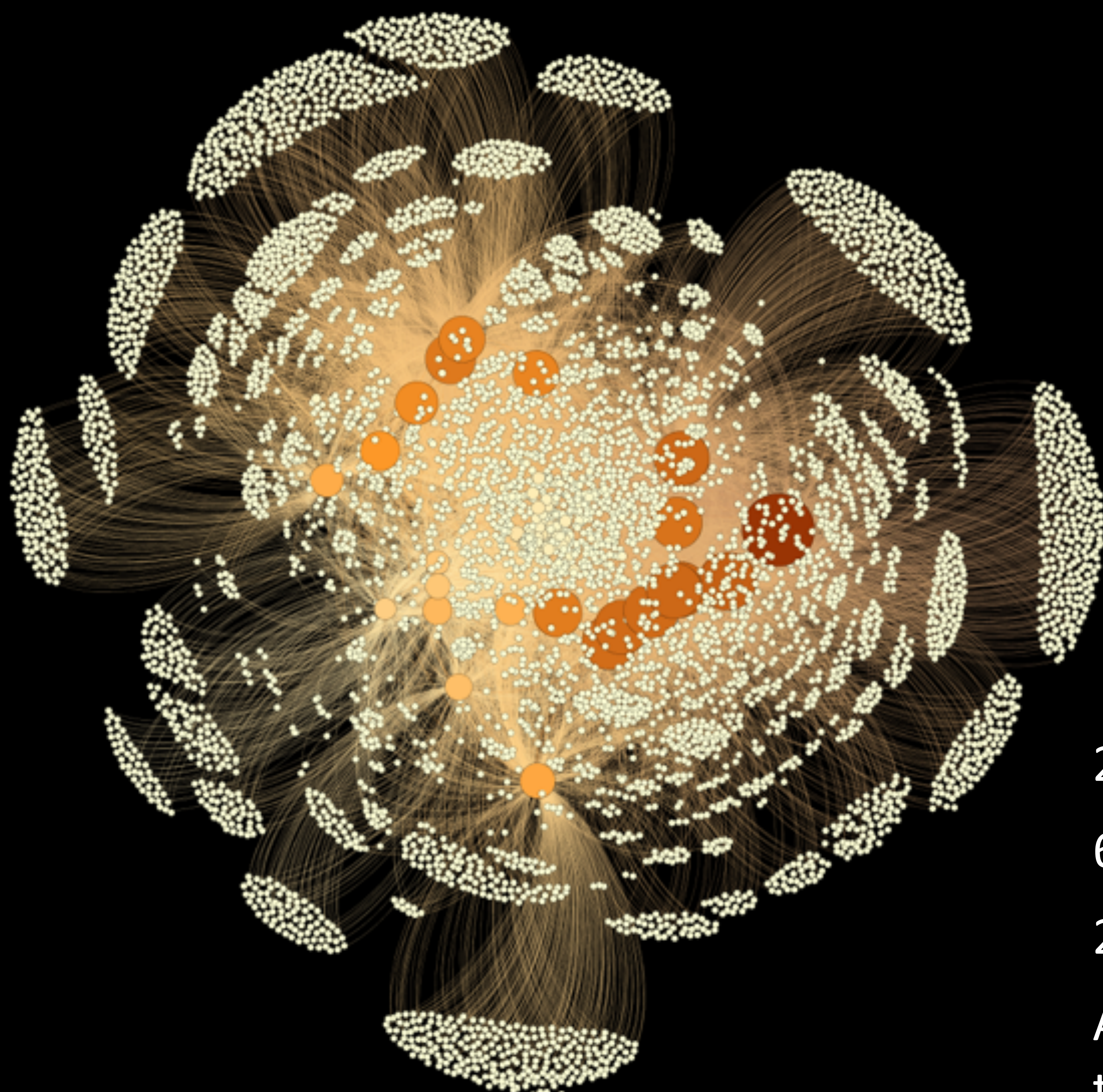
Fuzzy early communities, taxonomy stabilizes over time



Hyejin Youn and Daniel Kim

Courtesy of NSF SMA-1312294 (2014)

The PV technology ecosystem



22 PV-specific technologies

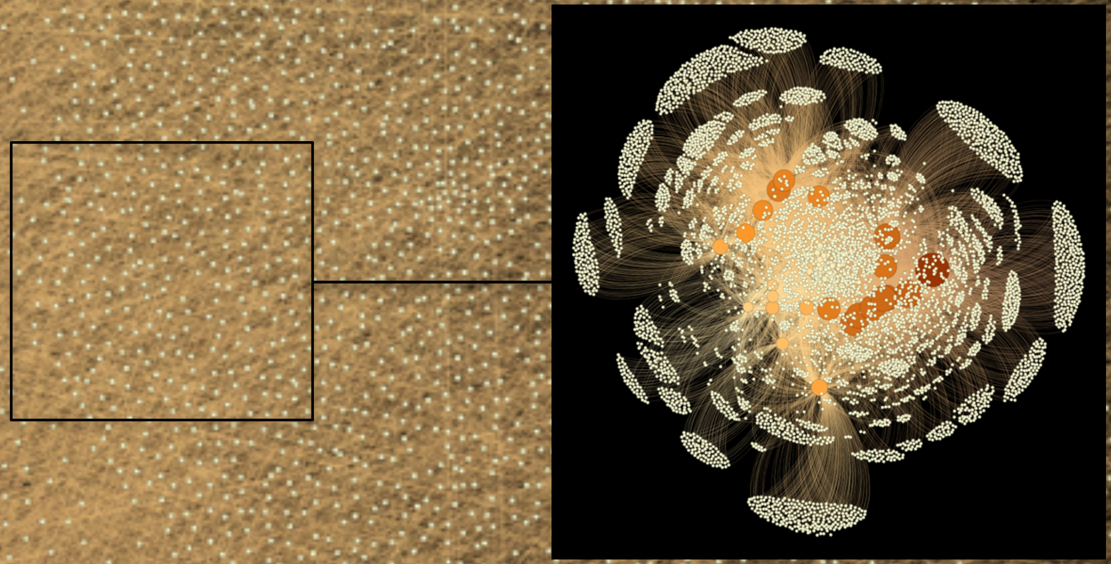
6198 PV-related technologies

20,697 combinations

Aggregated across entire time history

The technological ecosystem is vast

- ~150,000 technologies
- Connected via ~10m patents
- Dynamic and changing through time – 1790 to now.
- Temporal changes (through patenting activity) reflect:
  - Creation of new technological capabilities
  - Refinement of existing technologies



Rebooting the economy?

- Suppose all technology were destroyed
  - Library with all explicit knowledge remains
  - All tacit knowledge remains (100M technicians?)
  - Century supply of freeze dried food
- Could we reboot the economy?
- How would we do it?

Economy is strongly autopoetic

Last Sander question

Did being a scientist change your view of the world in general, and in what sense?

Optimal technology investment portfolios

- How should a decision maker invest in substitutable technologies (e.g. green energy)?
  - Depends: Is Wright or Moore correct?
- If Moore: Don't bother -- investments don't matter
- If Wright: Investment can play key role
  - cost decrease depends on investment
  - tradeoff between concentration and diversification
  - critical to have error estimates for forecasts.
  - compromise between risk and performance
- Expert forecasts vs. time series forecasts?
- R&D vs. production stimulus? Patenting activity?