The Economics of Science

Part Deux: Returns, Spillovers, & Adjustments

Kyle R. Myers

Innovation Research Boot Camp, Summer 2023

The Economics of Science
Part Un: Open Science

- **Aghion, Dewatripont, & Stein**. "Academic Freedom, Private Sector Focus, and the Process of Innovation."
- **Azoulay, Fons-Rosen, & Graff Zivin**. "Does Science Advance One Funeral at a Time?"
- **Azoulay, Graff Zivin, & Manso**. "Incentives and Creativity: Evidence from the Academic Life Sciences"
- **Furman & Stern**. "Climbing Atop the Shoulders of Giants: The Impact of Institutions on Cumulative Research"
- **Hill & Stein**. "Race to the Bottom: Competition and Quality in Science."

Marginal Returns and Spillovers of Science

and the basic—applied spectrum

- **Azoulay, Li, Graff Zivin, & Sampat**. "Public R&D Investment and Private Sector Patenting: Evidence from NIH Funding Rules."

  The Review of Economic Studies 86, no. 1 (2019): 117-152.

- **Myers & Lanahan**. "Estimating Spillovers from Publicly-Funded R&D: Evidence from the US Department of Energy."

  American Economic Review 112, no. 7 (2022): 2393-2423.

- **Bloom, Schankerman, & Van Reenen**. "Identifying Technology Spillovers and Product Market Rivalry."

  Econometrica 81, no. 4 (2013): 1347-1393.

Identifying Technology Spillovers and Product Market Rivalry

Bloom, Schankerman, & Van Reenan

Econometrica 81, no. 4 (2013): 1347-1393

Summary

Bloom, Schankerman, Van Reenan (2013)

- Approach:
  - Construct technology- and product-market spillover matrices
  - Construct own R&D stocks based on lagged data
  - Instrument R&D spending with state-specific R&D tax credits
  - Construct "spillover" R&D stocks by interacting matrices and other-firms' stocks
- Findings:
  - Over-investment in R&D when looking at product markets
  - Under-investment in R&D when looking at technology markets
  - The latter is much larger than the former $\Rightarrow$ we are underinvesting in R&D!

Now, what about…

- … the econometrics of working with spillover matrices
- … absorptive capacity
- … the (relatively) high private returns to R&D
- … state-specific tax credits and R&D reallocations
- … markets for technologies and “spillovers” versus “externalities”
- … other sources of distortions in R&D

Now, what about:

Working with spillover matrices

Stay up to date on “Bartik” or “Shift-share” variables

- **Borusyak, Hull, & Jaravel**. *"Quasi-experimental shift-share research designs." The Review of Economic Studies (2022).*
- **Goldsmith-Pinkham, Sorkin, & Swift**. *"Bartik instruments: What, when, why, and how." American Economic Review (2020).*
- **de Chaisemartin & Lei**. *“More Robust Estimators for Panel Bartik Designs, With An Application to the Effect of Chinese Imports on US Employment.” Working Paper (2023)*

Now, what about:
Absorptive capacity

Def'n: Doing more R&D now helps you benefit from others' R&D in the future

- **Cohen & Levinthal**. *"Innovation and learning: the two faces of R&D." The Economic Journal (1989).*
- **Aghion & Jaravel**. *"Knowledge spillovers, innovation and growth." The Economic Journal (2015).*

Now, what about:
the relatively high returns to R&D

Stay in contact with the finance and accounting literature

- **Brown, Fazzari, & Petersen**. *"Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom." The Journal of Finance (2009).*
- **Cheng**. *"R&D expenditures and CEO compensation." The Accounting Review (2004).*

Now, what about:
state-specific R&D tax credits

Don't forget the aggregate!

- **Wilson**. *"Beggar thy neighbor? The in-state, out-of-state, and aggregate effects of R&D tax credits." The Review of Economics and Statistics (2009).*

"I estimate that the long-run elasticity of in-state R&D with respect to the in-state user cost is about -2.5, while its elasticity with respect to out-of-state user costs is a bout+2.5, suggesting a zero-sum game among states."

Now, what about:
the market for technology

“Spillovers” are not necessarily “externalities”

- **Arqué-Castells & Spulber**. *"Measuring the private and social returns to R&D: Unintended spillovers versus technology markets." Journal of Political Economy (2022).*

“This finding cautions against the common practice of assuming that spillover pools contribute purely to the social returns … the wedge between the social and private returns to R&D is smaller than estimated in earlier studies. Finally, back-of-the-envelope estimates suggest that the gains from trade in the market for technology are larger than $1 trillion per year”

.

Now, what about:
other distortions in R&D

Jones & Williams. *"Too much of a good thing?" Journal of Economic Growth (2000).*

- **Over-** or **under-**investment in R&D due to:
  - Imperfect price discrimination of consumers ("surplus approp. problem")
  - Imperfect price discrimination of suppliers ("knowledge spillovers")
  - R&D effort duplication ("simultaneous discovery")
  - Creative destruction ("business stealing")
- Only three of these are captured in Bloom, Schankerman, Van Reenan (2013)

Jones & Williams (2000)

change in aggregate R&D per friction

- Internalize duplications: R&D would decline by ~35%
- Internalize creative destruction: R&D would decline by ~25%
- Internalize knowledge spillovers: R&D would rise by ~25%
- **Internalize consumer surplus: R&D would rise by ~140%**

- Remember, based on a calibration, but still…

Estimating Spillovers from Publicly-Funded R&D: Evidence from the US Department of Energy

Myers & Lanahan

American Economic Review 112, no. 7 (2022): 2393-2423

Outline

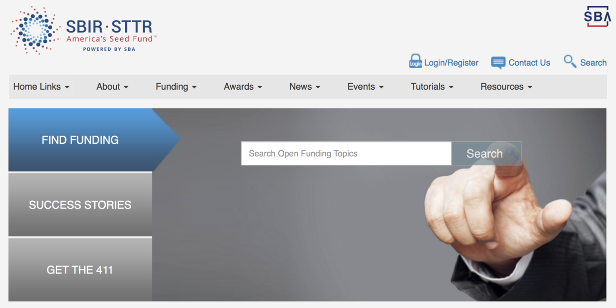
1. Motivation & Setting
2. Research Design & Data
3. Main Results
4. Additional Results & Takeaways

e.g., you'd miss $\sim$50% of spillovers

if you used citation paper trails

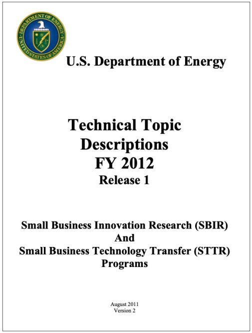
R&D Spillovers,
Small Business R&D Grants,
and the US Department of Energy

Small Business Innovation Research (SBIR) at the U.S. Department of Energy (DOE)



- SBIR: \$150K – \$1M research grants to small firms ($\leq$500 emp.)

Small Business Innovation Research (SBIR) at the U.S. Department of Energy (DOE)



U.S. Department of Energy

Technical Topic
Descriptions
FY 2012
Release 1

Small Business Innovation Research (SBIR)
And
Small Business Technology Transfer (STTR)
Programs

August 2011
Version 2

- SBIR: \$150K – \$1M research grants to small firms ($\leq$500 emp.)
- at DOE: Large reliance on targeted funding, "please invent ____ "

Small Business Innovation Research (SBIR) at the U.S. Department of Energy (DOE)

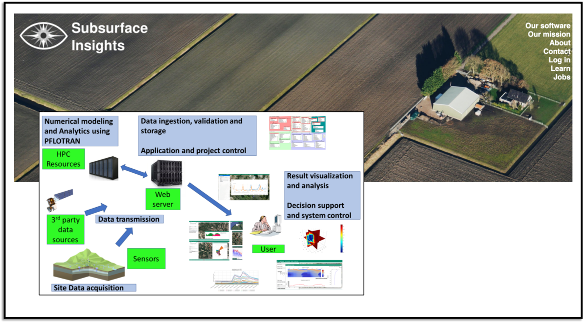
20. TECHNOLOGIES FOR SUBSURFACE CHARACTERIZATION AND MONITORING (PHASE I, $150,000/PHASE II, $1,000,000)

In support of the Department of Energy's (DOE's) secure and sustainable energy mission the Office of Biological and Environmental Research seeks to advance fundamental understanding of coupled biogeochemical processes in complex subsurface environments to enable systems-level prediction and decision support. This basic scientific understanding is applicable to a wide range of DOE relevant energy and environmental challenges including:

- Cleanup of contaminants and stewardship of former weapons production sites
- Underground storage of spent nuclear fuel
- Carbon cycling and sequestration in the environment
- Nutrient cycling in the environment in support of sustainable biofuel development
- Fossil fuel processing and recovery from the deep subsurface.

- SBIR: $150K – $1M research grants to small firms ($\leq$500 emp.)
- at DOE: Large reliance on targeted funding, "please invent ____ "

A Case Study: Subsurface Insights, Inc.



- Based in New Hampshire → projects across U.S. & Europe
- Initial funding to monitor contamination zones → now supplying aquifer thermal energy storage companies

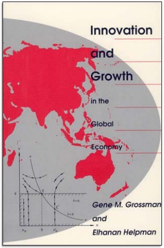
When are R&D Subsidies Successful?


THE HILL

Energy isn't a horse race, and the government doesn't pick winners

BY DREW BOND, OPINION CONTRIBUTOR — 02/06/18 01:30 PM EST
THE VIEWS EXPRESSED BY CONTRIBUTORS ARE THEIR OWN AND NOT THE VIEW OF THE HILL

36 COMMENTS

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Energy Innovation in the FY 2021 Budget: Congress Should Lead

By Colin Cunliff | March 30, 2020

Lawmakers should make energy innovation a national imperative, and at least double U.S. investment in clean energy RD&D by 2025.


CNBC MARKETS BUSINESS INVESTING TECH POLITICS CNBC TV

POLITICS

The government as venture capitalist

PUBLISHED TUE, JUN 24 2014•6:10 PM EDT

Laura Tyson, former chair of the US President's Council of Economic Advisers

SHARE

We already know it works! (Howell 2017)

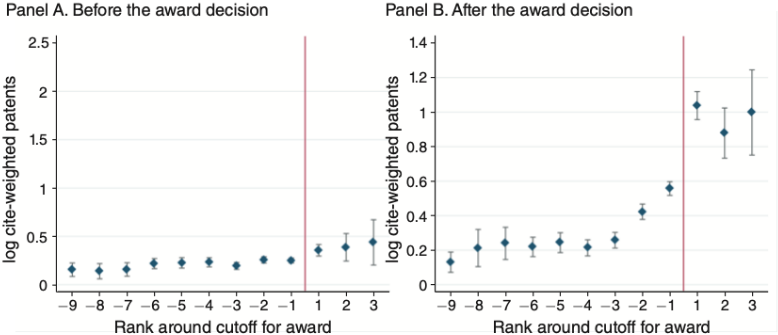


FIGURE 2. CITE-WEIGHTED PATENTS BEFORE AND AFTER PHASE 1 GRANT BY RANK

Possible approaches to catching spillovers?

- a la Bloom et al. (2013)
- a la Azoulay et al. (2018)

Data Sources & Research Design

Empirical Model

For each area of technology-space j in year t:

$$\mathbb{E}[Y_{jt} \mid K_{jt}] = \exp\left(\log(K_{jt})\beta + \tau_t + \omega_{jt}\right) \tag{1}$$

- Y_{jt}: Flow of patents
- K_{jt}: Stock of DOE SBIR investments
- τ_t: Aggregate trends
- ω_{jt}: Unobservable supply/demand shocks

Empirical Model

For each area of technology-space j in year t:

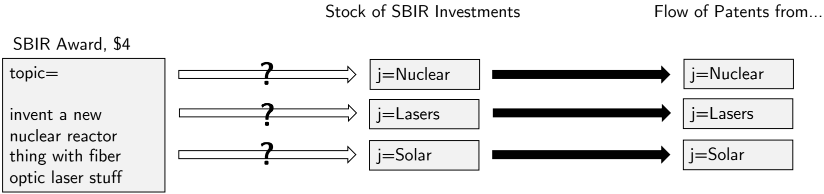
(1)

What are j?

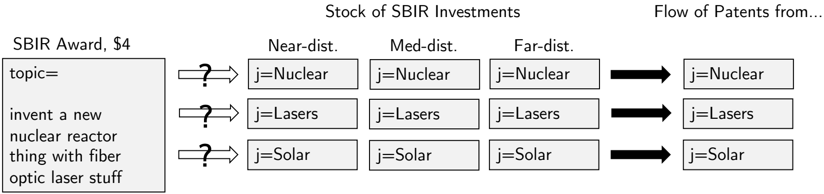
- 10,000 levels of the Cooperative Patent Classification (CPC)
- 1 or more assigned to all patents
- "zip codes" of technology space
- Designed to help examiners (not researchers!)

- Y_{jt}:
- K_{jt}:
- τ_t: Aggregate trends
- ω_{jt}: Unobservable supply/demand shocks

Dataset Construction



Dataset Construction



Dataset Construction

SBIR

topic=

invent
nuclea
thing
optic l

How to measure match between award topic and j?

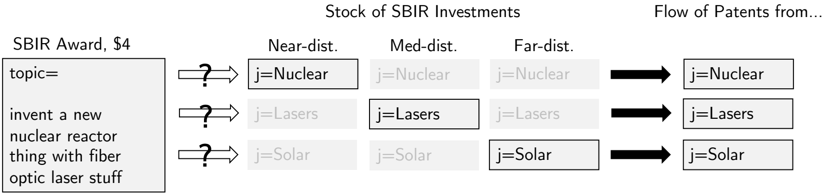
- If DOE asks for a "giant blue laser"...

...and all patents that mention a "giant blue laser" are class j=1

...then we assume DOE is most interested in j=1

- 3-gram tf-idf cosine similarity
- Use similarity scores to group into "near, med., far" tech. distances
- No assumptions based on CPC hierarchy or citations

Dataset Construction



Dataset Construction

How to allocate \$ from topic to j?

- Determine how "far out" in tech. space spillovers occur
- Cross-validation (Clarke '17)

SB

topi

inve
nuc
thin
opti

Dataset Construction

SB
topi
inve
nuc
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How to allocate $ from topic to j?

- Determine how "far out" in tech. space spillovers occur
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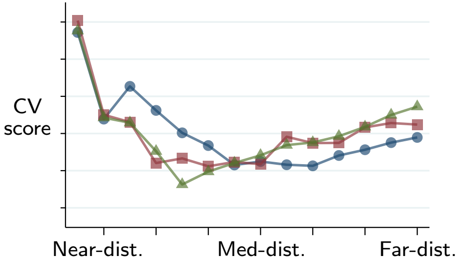
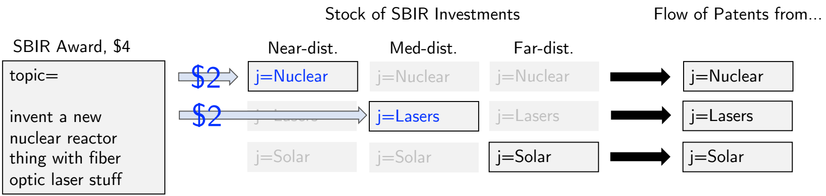


Dataset Construction



Technological Areas with Largest DOE SBIR Investments

Funding Rank	CPC 3-digit Title
1	G01: measuring; testing
2	H01: basic electric elements
3	H02: generation; conversion or distribution of electric power
4	H03: basic electronic circuitry
5	H04: electric communication technique
6	G06: computing; calculating; counting
7	C10: petroleum, gas or coke industries; technical gases ...
8	F16: engineering elements and units...
9	C12: biochemistry; microbiology; enzymology...
10	B60: vehicles in general
11	F02: combustion engines; hot-gas engine plants
12	B01: physical or chemical processes or apparatus

Estimating spillovers across geographic and technological space

For each area of technology-space j in year t:
(a simplified representation)

$$\begin{aligned}\text{Grant recipients' patents}_{jt} = \alpha_1 &+ (\text{\$ invested in topics with Near distance to } j)_{jt} \times \beta_1^N \\ &+ (\text{\$ invested in topics with Medium distance to } j)_{jt} \times \beta_1^M + \epsilon_{1jt}\end{aligned}$$

- Technological spillovers
    - Compare \$-per-patent implied by β^N versus β^M
    - *within regression comparison of different coefficients*

Estimating spillovers across geographic and technological space

For each area of technology-space j in year t:
(a simplified representation)

$$\begin{aligned}\text{Grant recipients' patents}_{jt} = \alpha_1 &+ (\$\text{ invested in topics with Near distance to } j)_{jt} \times \beta_1^N \\ &+ (\$\text{ invested in topics with Medium distance to } j)_{jt} \times \beta_1^M + \epsilon_{1jt}\end{aligned}$$

$$\begin{aligned}\text{All patents}_{jt} = \alpha_2 &+ (\$\text{ invested in topics with Near distance to } j)_{jt} \times \beta_2^N \\ &+ (\$\text{ invested in topics with Medium distance to } j)_{jt} \times \beta_2^M + \epsilon_{2jt}\end{aligned}$$

- Geographic spillovers
    - Compare \$-per-patent implied by (β_2^N, β_2^M) versus (β_1^N, β_1^M)
    - *across regression comparison of same coefficients*

Plausibly Exogenous $: States' Matching Policies

SBIR-STTR Matching Funds

THINKENTUCKY
Cabinet for Economic Development

Kentucky's phenomenally successful SBIR/STTR Matching Funds Program is back. Click below for more information on new guidelines and upcoming deadlines:

Corridor Matching Grants Research Program

THE CORRIDOR
FLORIDA HIGH TECH

The **Florida High Tech Corridor Council** is a regional economic development initiative of the University of Central Florida, University of South Florida and the University of Florida. Its mission is to grow high tech industry and innovation through partnerships that support research, marketing, workforce and entrepreneurship.

Commonwealth Research Commercialization Fund

The Commonwealth Research Commercialization Fund (CRCF) accelerates innovation and economic growth in Virginia by advancing solutions to important state, national, and international problems through technology research, development, and commercialization.

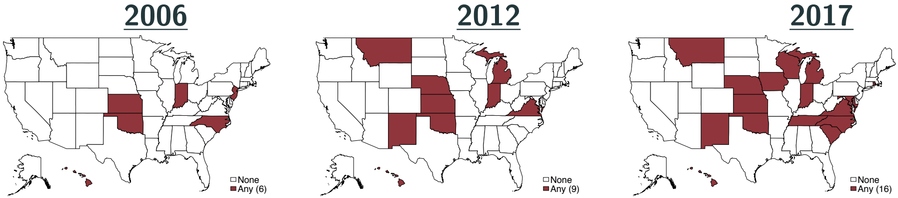
Small Business Innovation Research

Wisconsin's Resource for SBIR/STTR Funding Assistance

Center for Technology Commercialization

One North Carolina Small Business Program

Plausibly Exogenous $: States' Matching Policies



Match bonus ranges between 25-100% of award value

Relevance	tech. pursued by firms in match-states receive "windfalls" of R&D $
Key Assumption	policies unrelated to shocks to tech.
Support	policies uncorr. with small-firm movement and federal SBIR $
Generalizability	a few more states ↑ $-per-award

Main Results on R&D Spillovers

Summary of Magnitudes

	% of net patents	$\frac{\text{patents}}{\$1M}$	$\frac{\$}{\text{patent}}$
Counting all USPTO patents and...			
...only grant recipients	26%	0.75	$ 1,330,000
...only non-recipients nearby	20%	0.60	$ 1,680,000
...all US firms & inventors	60%	1.75	$ 571,000
...all foreign firms & inventors	40%	1.19	$ 839,000
Counting all inventors and...			
...only high match patents	37%	1.10	$ 908,000
...only medium match patents	40%	1.17	$ 852,000
...only low match patents	23%	0.67	$ 1,496,000
Counting all inventors and all patents	100%	2.94	$ 340,000

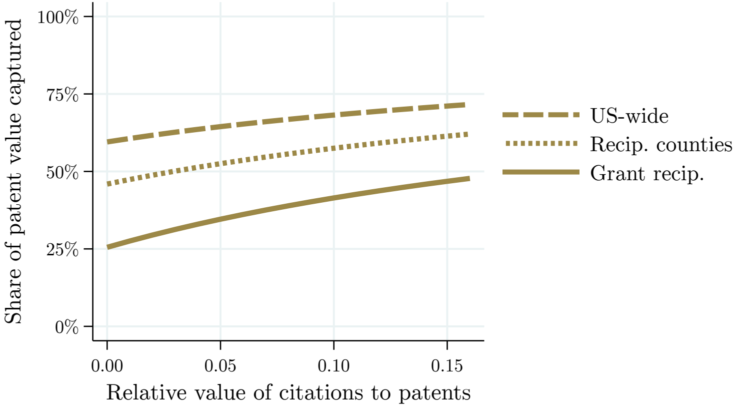
Private vs. Social Value

- Something close we can study: patent value capture
  - What % of net patent value generated does ______ obtain?
  - Patent value: \$-worth of patent + citations

- Add'l regressions: use avg. forward citation count as dep. var.
  - Finding: $\uparrow$ cite-per-patent only for grant recipients

- Need to assume relative value of +1 citation vs. +1 patent
  - Range of assumptions: $[0, 0.15]$
  - Note: at 0, % of net value = % of net patents

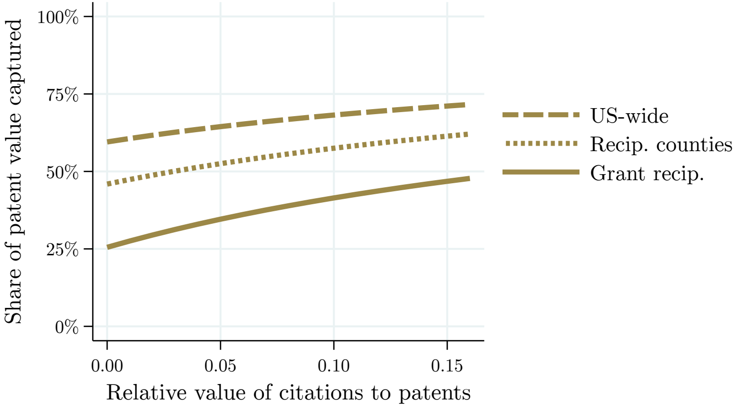
Patent Value Captured, by Firm/Inventor Set



Grant recipients obtain 25-50% of patent value

micro/macro benchmark: 30-50%

Patent Value Captured, by Firm/Inventor Set

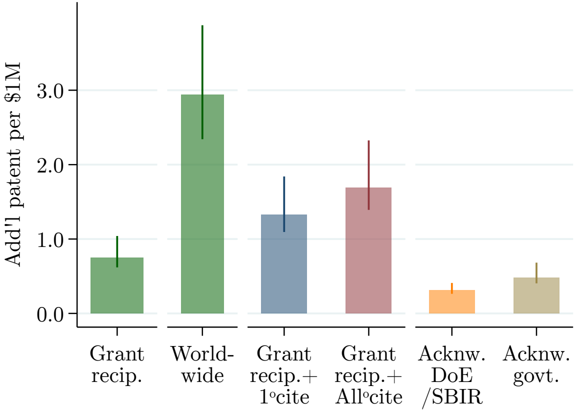


US firms/inventors obtain 60-75% of patent value

macro benchmark: 70-90%

Additional Results & Takeaways

Paper trails miss a lot of spillovers



Direct acknowledgements would yield large underestimates

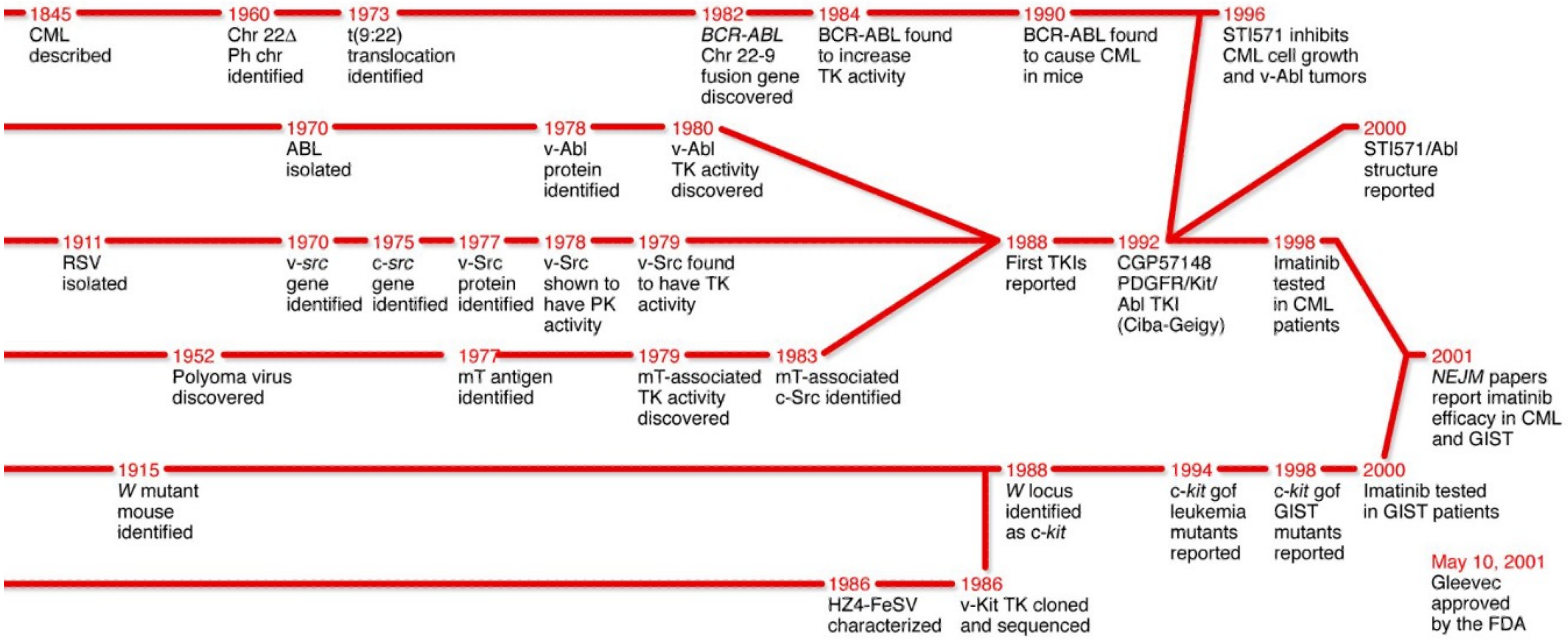
Public R&D Investment and Private Sector Patenting: Evidence from NIH Funding Rules

Azoulay, Li, Graff Zivin, & Sampat

The Review of Economic Studies 86, no. 1 (2019): 117-152

Is Science (eventually) Valuable?

the long road of Gleevec



Azoulay, Li, Graff Zivin, & Sampat (2019)

What are the marginal returns to additional investments in basic science?

- **“Marginal returns” = patents**
  - Why not journal publications?
    - Value is hard to quantify
    - Mechanical connection to linkage method [know your DGP!]

- **“basic science” = US National Institutes of Health**

Unit of analysis?

- Impacts policy-relevance of findings
  - “We estimate the effect of the entire US R&D budget on the world…”
  - “We estimate the effect of receiving a R&D grant on experienced scientists who receive R01 grants by the NIH…”
- Impacts the identifying variation we need:
  - Random funding for a disease: difficult because we pay more attention to high-$ decisions
  - Random funding for a person: difficult because we pay attention to choices that affect individuals
- Possibilities are endless!
  - Individuals, labs, university departments, parts of science-space, parts of geography…
  - This is where computer/data science skills will come in handy (but don’t go crazy)

Unit of analysis: D(isease)**-S**(cience)**-T**(ime)

- No scientist does research “on cancer”
  - Work involves a science area and a disease application (e.g., cell signaling in cancer)
- Here, research area = disease-science area for a given year
  - Work that uses similar **tools / biological-pathways / approaches** (basic; science) to make progress towards treatments or therapies for the same **illness, injury, or disorder** (applied; disease) in the same **year** (time)
- Advantages
  - Allows a policy-relevant question: what happens if we provide more funding for a disease-science area? (e.g. genetic basis of Alzheimer's)
  - D-S-T are not explicit units of funding for NIH administration (which will help with identification)

Defining each D-S-T

Funding	Evaluation
NIAAA National Heart Lung and Blood Institute NIBIB National Cancer Institute NIDA NIMH National Institute of Mental Health NLM	NIH Center for Scientific Review 

Defining each D-S-T

- Defining “**diseases**”:
  - NIH consists of 27 disease(ish)-focused Institutes/Center (e.g., National Cancer Institute; National Institute of Diabetes and Digestive and Kidney Diseases)
  - A grant application must report its disease area to be funded
- Defining “**science**”:
  - Grant review happens in 180 science(ish)-focused “study sections” (e.g., Cellular Signaling and Regulatory Systems; Integrative Nutrition and Metabolic Processes)
  - A grant application must specify its science area to be evaluated
- Defining “**time**”:
  - Fiscal years

Empirics

$$Patents_{???} = a + \beta Funding_{dst} + \epsilon_{dst}$$

- *Where to look for outcomes? (because patents aren't explicitly assigned to DSTs)*
  - It is hard to know a priori what scientific results are relevant for a patent
  - Link grants to patents via:
    - Paper trail: acknowledgements — NIH funding directly used as a part of patenting work
    - Paper trail: citations — patent cites a paper that NIH funded
    - ``Nearby'' in disease-science space (i.e., using similar language as grants/publications)

Finding Patents
connected to NIH investments

- **Direct acknowledgment**: # patents by NIH-funded researchers
  - Grant → Patent
  - *Answers*: Does the NIH directly fund patentable research?
- **Citation-linked**: # patents citing NIH-funded research
  - Grant → Publication → Patent
  - *Answers*: Does the NIH fund research that is directly useful to inventors?
- **``Near-by''**: # patents intellectually related to an NIH funding area
  - Grant → Publication → Related Publication → Patent
  - *Answers*: Does the NIH fund research that is indirectly useful to inventors?

Patent Outcomes

$$Patents_{d(\delta)s(\sigma)t(\tau)} = a + \beta Funding_{dst} + \epsilon_{dst}$$

- $Patents_{d(\delta)s(\sigma)t(\tau)}$ is the # of patents linked to research area dst
- The patents in $Patents_{d(\delta)s(\sigma)t(\tau)}$ can be in different diseases areas, different science areas, and can be issued many years after funding

Identification

$$Patents_{d(\delta)s(\sigma)t(\tau)} = a + \beta Funding_{dst} + \epsilon_{dst}$$

- **Concern**: $Funding_{dst}$ may be correlated with ϵ_{dst}
- **Approach 1**: Fixed effects
  - Assumption: $\epsilon_{dst} = (FE_d \times FE_s) + (FE_d \times FE_t) + (FE_s \times FE_t) + \mu_{dst}$
  - Scientists and the NIH (may) know everything, except for μ_{dst}
- **Approach 2**: Instrumental variable — "windfall" funding due to funding rules
  - DST funding is made up of funding for individual grants.
  - Grant applications are given cardinal scores, but funded on the basis of ordinal scores.
  - Instrument $Funding_{dst}$ with funding for the subset of grants funded for this reason

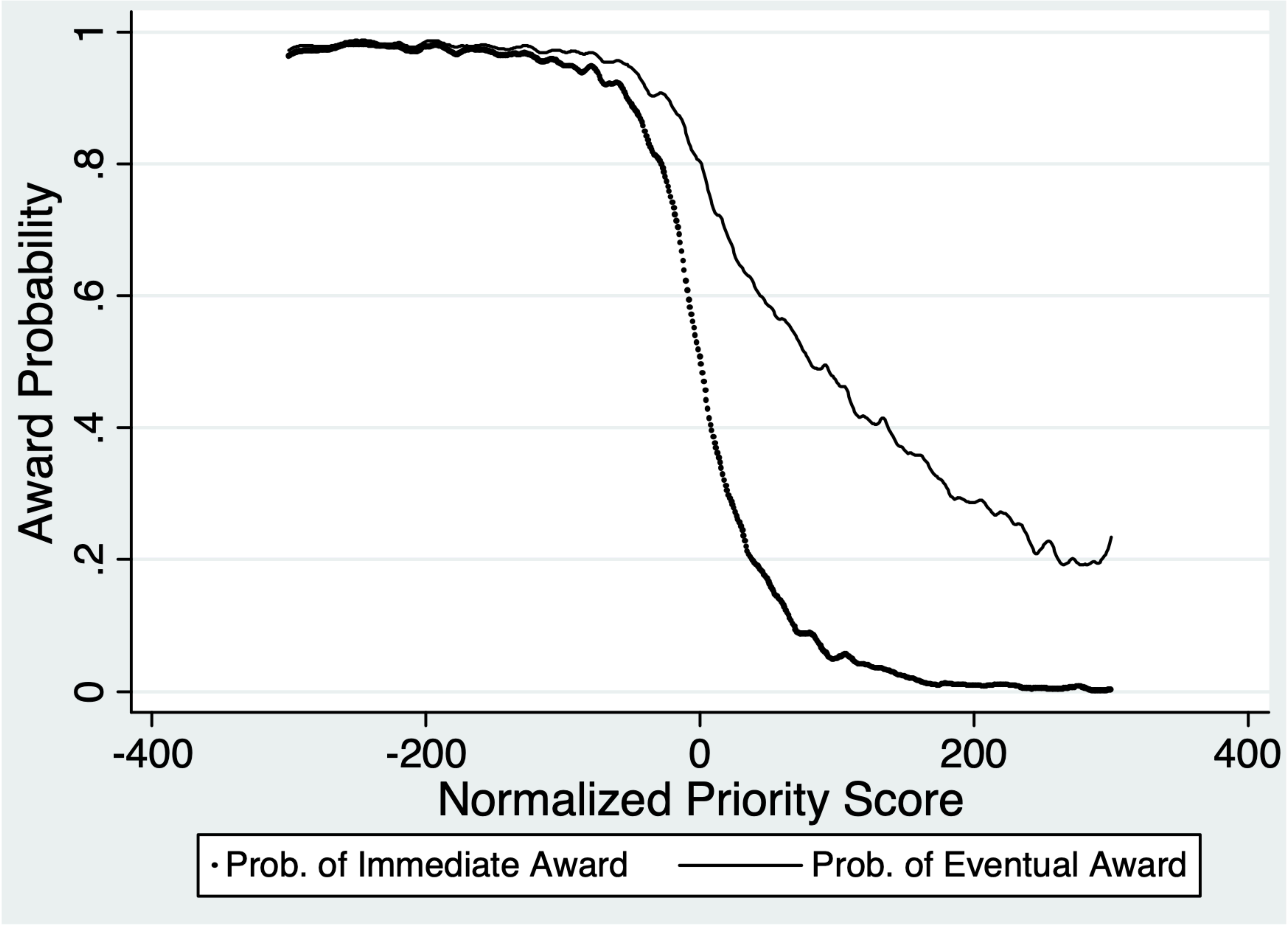
"Windfall" Funding

Cell Signaling Study Section			Tumor Physiology Study Section		
Rank	Disease	Raw Score	Rank	Disease	Raw Score
1	Cancer	10	1	Cancer	8.2
2	Diabetes	9.8	2	Cancer	8.1
3	Cancer	9.2	3	Cancer	7.6
4	Cancer	9.1	4	Cancer	6.4
5	Cancer	8.2	5	Cancer	5.4
6	Diabetes	7.6	6	Diabetes	5.2
7	Cancer	7.6	7	Diabetes	4.8
8	Diabetes	7.5	8	Diabetes	4.4

Aside:
Understanding Investment Functions
(at the NIH)

Know your institutional details!

Source: Jacob & Lefgren (2004)



Notes: Data is smoothed using a lowess estimator with a bandwidth of .03.

Main Results: NIH $ →

- 30% of NIH grants produce research that is cited by a private sector patent
- $10 million of NIH funding → 2.3 more industry patents
- NIH funding increases overall firm R&D investment
  - Increased firm patenting in one area is not offset by declines in another; rather, both appear to increase
- $1 dollar in NIH funding → $0.4 to $1.7 in PDV of drug revenue
- Disease spillovers are large
  - Half of all patents generated by additional NIH investments are for diseases different from the one intended

The Distribution of Science

switching and adjustment costs

- **Myers**. "The Elasticity of Science.”

  American Economic Journal: Applied Economics 12, no. 4 (2020): 103-134.

- **Acemoglu**. "Diversity and technological progress.”

  The Rate and Direction of Inventive Activity Revisited (2011). University of Chicago Press, 319-356.

Aside:
Estimating Demand in Science

We are often focused on scientists' (demand) choices

- And these choices can often be formulated as a discrete choice problem
  - What science to study?
  - What collaborator to work with?
  - What journal to submit to?
  - What results to report? [note: continuous things here too; e.g., *p-hacking*)
- Estimate or motivate (or both)
  - e.g., Krieger, Myers, & Stern. *"How Important is Editorial Gatekeeping? Evidence from Top Biomedical Journals" Review of Economics and Statistics (forthcoming).*

We are often focused on scientists' (demand) choices

e.g., Krieger, Myers, & Stern. "Editorial Gatekeeping"

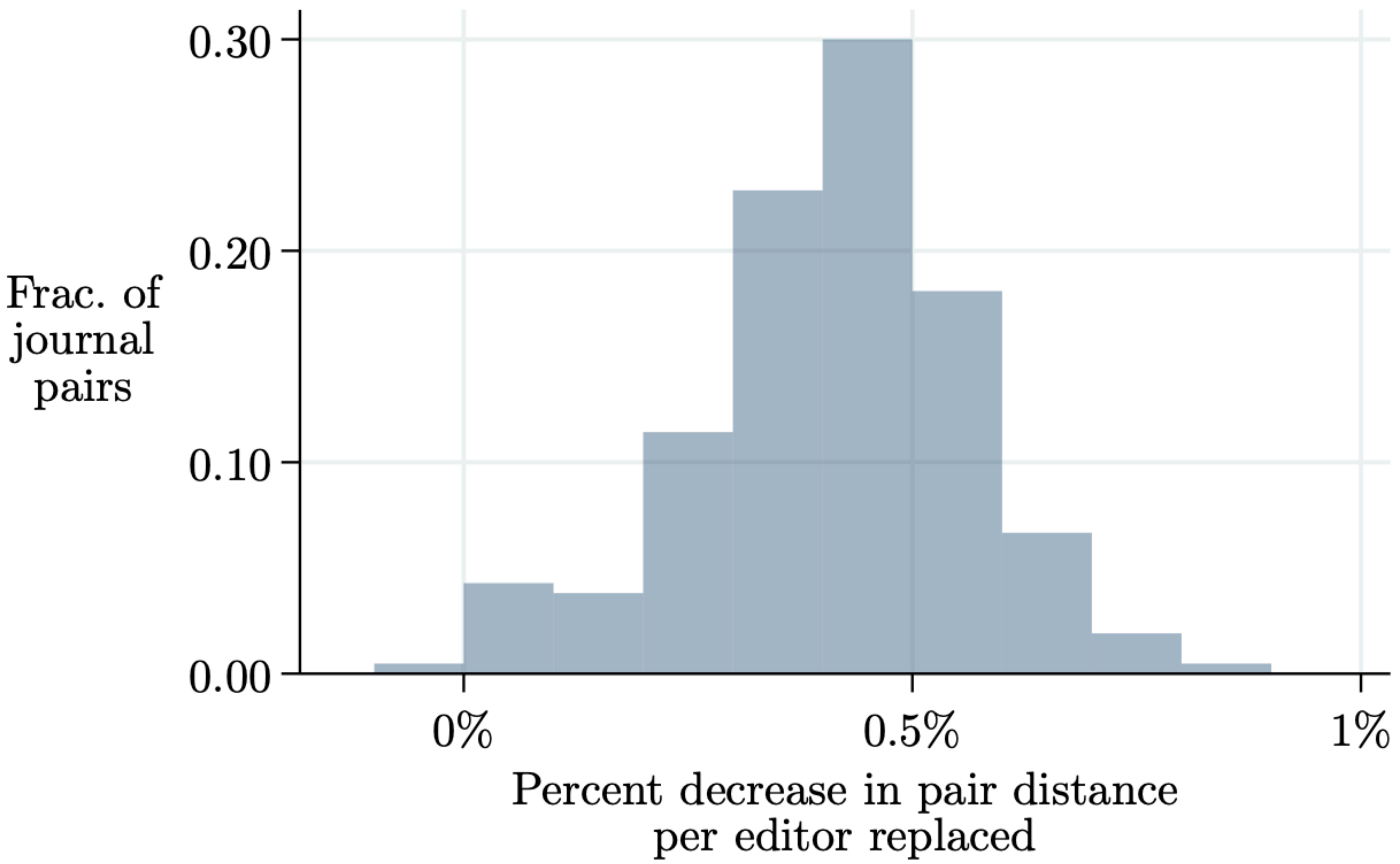
B Motivating Demand Model

The following presents two interconnected demand models of how scientists choose content to publish in journals (which generates variation in our dependent variable), and how they choose to fill editorial positions (which generates variation in our focal independent variable). Besides motivating our regressions, the purpose of this exercise is to formalize our argument as to why our estimate of the scientific homophily effect is likely an upper bound of the true effect.

We are often focused on scientists' (demand) choices

e.g., Krieger, Myers, & Stern. "Editorial Gatekeeping"

(c) Decrease in Distance Post-Takeover, Per Editor Replaced



Often, scientists' "demand" = "entry"

- Standard IO market entry model
  - <u>Decision-maker</u>: firm
  - <u>Competition</u>: other firms
  - <u>Market</u>: geographic location; product space
  - <u>Market features</u>: consumer demand; fixed costs of entry
- See:
  - **Seim**. *"An empirical model of firm entry with endogenous product-type choices." The RAND Journal of Economics (2006).*
  - **Bajari, Hong, Krainer, & Nekipelov**. *"Estimating static models of strategic interactions. Journal of Business & Economic Statistics (2010).*

Often, scientists' "demand" = "entry"

- Standard IO market entry model
  - Decision-maker: **scientists**
  - Competition: **other scientists**
  - Market: **geographic location; science space**
  - Market features: **consumer demand; fixed & variable costs of entry**
- See:
  - **Seim**. *"An empirical model of firm entry with endogenous product-type choices." The RAND Journal of Economics (2006).*
  - **Bajari, Hong, Krainer, & Nekipelov**. *"Estimating static models of strategic interactions. Journal of Business & Economic Statistics (2010).*

The Distribution of Science

switching and adjustment costs

- **Myers**. "The Elasticity of Science."

  American Economic Journal: Applied Economics 12, no. 4 (2020): 103-134.

- **Acemoglu**. "Diversity and technological progress."

  The Rate and Direction of Inventive Activity Revisited (2011). University of Chicago Press, 319-356.

The Elasticity of Science

Myers

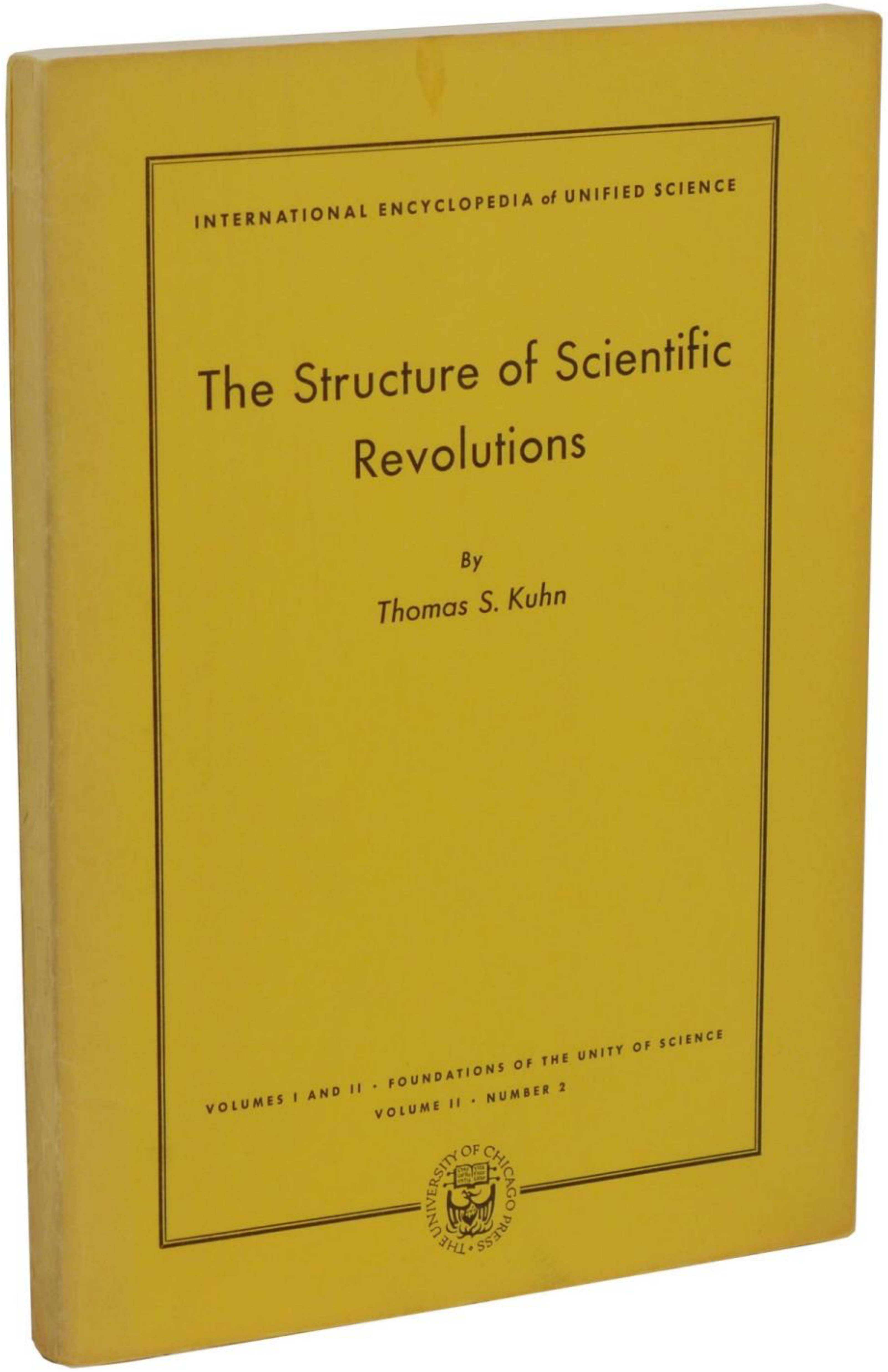
American Economic Journal: Applied Economics 12, no. 4 (2020): 103-134.

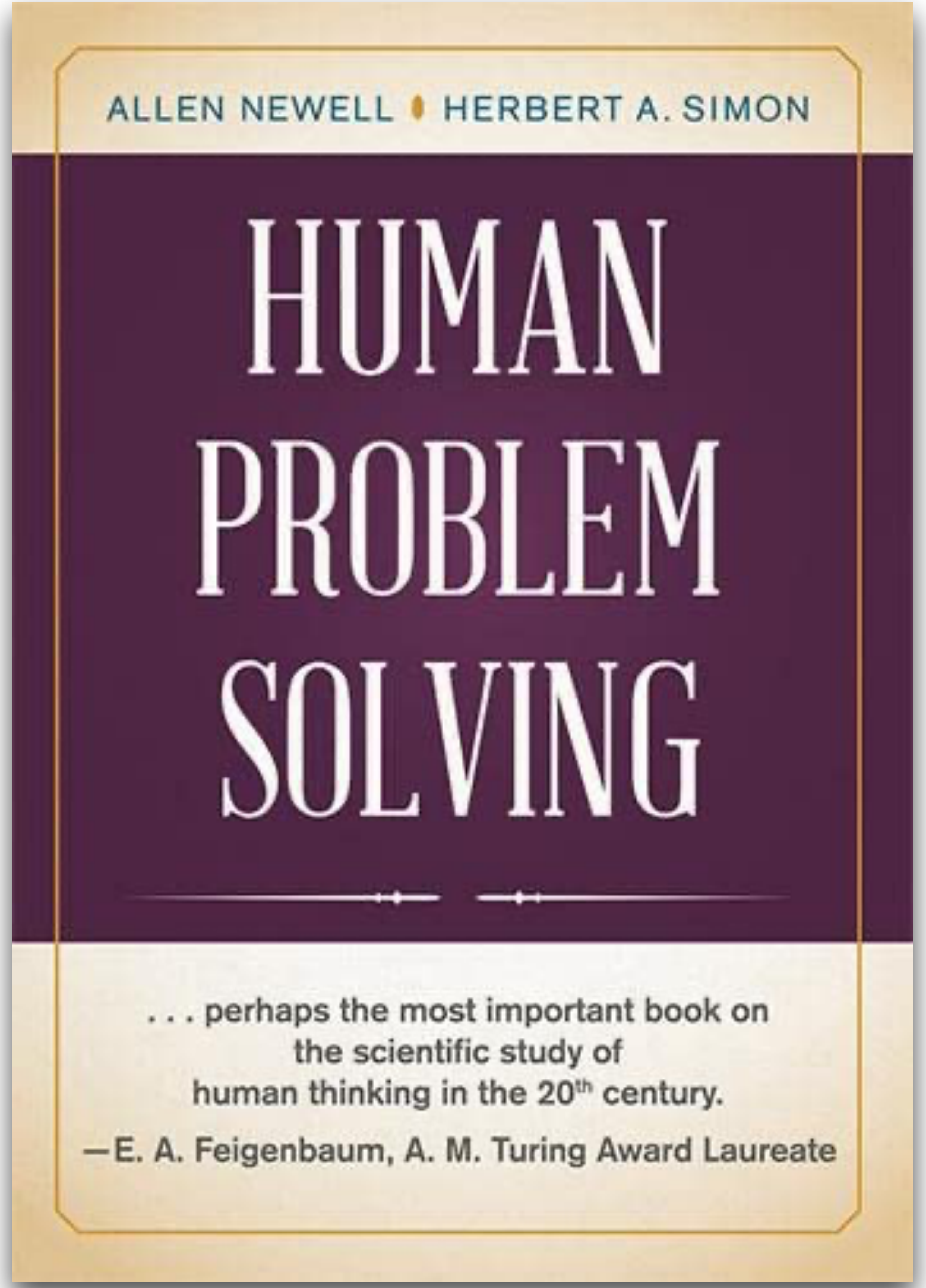
Motivation: The Elasticity of Science

(ex-post rationalization of PhD madness)

- An economy is (generally) more efficient when producers face low adjustment costs
  - Demand shifts → the fast supply catches up, the better
- e.g., the clean energy transition
  - *Acemoglu, Aghion, Bursztyn, & Hemous. "The environment and directed technical change." American Economic Review (2012).*
  - *Aghion, Dechezleprêtre, Hemous, & Van Reenen. "Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry." Journal of Political Economy (2016).*

What actually happened …


INTERNATIONAL ENCYCLOPEDIA of UNIFIED SCIENCE
The Structure of Scientific Revolutions
By
Thomas S. Kuhn
VOLUMES I AND II · FOUNDATIONS OF THE UNITY OF SCIENCE
VOLUME II · NUMBER 2
THE UNIVERSITY OF CHICAGO PRESS


ALLEN NEWELL • HERBERT A. SIMON
HUMAN PROBLEM SOLVING
. . . perhaps the most important book on the scientific study of human thinking in the 20th century.
—E. A. Feigenbaum, A. M. Turing Award Laureate

Technical ``Outsiders'' Perform Better

Organization Science
Vol. 21, No. 5, September–October 2010, pp. 1016–1033
ISSN 1047-7039 | EISSN 1526-5455 | 10 | 2105 | 1016

INFORMS
DOI 10.1287/orsc.1090.0491

Marginality and Problem-Solving Effectiveness in Broadcast Search

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Karim R. Lakhani
Technology and Operations Management Unit, Harvard Business School, Boston, Massachusetts 02163, klakhani@hbs.edu

We examine who the winners are in science problem-solving contests characterized by open broadcast of problem information, self-selection of external solvers to discrete problems from the laboratories of large research and development intensive companies, and blind review of solution submissions. Analyzing a unique data set of 166 science challenges involving over 12,000 scientists revealed that technical and social marginality, being a source of different perspectives and heuristics, plays an important role in explaining individual success in problem solving. The provision of a winning solution was positively related to increasing distance between the solver's field of technical expertise and the focal field of the problem. Female solvers—known to be in the "outer circle" of the scientific establishment—performed significantly better than men in developing successful solutions. Our findings contribute to the emerging literature on open and distributed innovation by demonstrating the value of openness, at least narrowly defined by disclosing problems, in removing barriers to entry to nonobvious individuals. We also contribute to the knowledge-based theory of the firm by showing the effectiveness of a market mechanism to draw out knowledge from diverse external sources to solve internal problems.

Key words: open innovation; problem solving; marginality; gender; broadcast search
History: Published online in *Articles in Advance* February 22, 2010.

Targeted Funding at the NIH

MANAGEMENT SCIENCE
Vol. 61, No. 10, October 2015, pp. 2281–2298
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

informs

http://dx.doi.org/10.1287/mnsc.2014.2107

Can Private Money Buy Public Science? Disease Group Lobbying and Federal Funding for Biomedical Research

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Bhaven Sampat
Mailman School of Public Health, Columbia University, New York, New York 10032, bns3@columbia.edu

Private interest groups lobby politicians to influence public policy. However, little is known about how lobbying influences the policy decisions made by federal agencies. We study this through examining lobbying by advocacy groups associated with rare diseases for funding by the National Institutes of Health (NIH), the world's largest funder of biomedical research. Disease group lobbying for NIH funding has been controversial, with critics alleging that it distorts public funding toward research on diseases backed by powerful groups. Our data reveal that lobbying is associated with higher political support, in the form of congressional "soft earmarks" for the diseases. Lobbying increases with disease burden and is more likely to be associated with changes in NIH funding for diseases with higher scientific opportunity, suggesting that it may have a useful informational role. Only special grant mechanisms that steer funding toward particular diseases, which comprise less than a third of the NIH's grants, are related to earmarks. Thus, our results suggest that lobbying by private groups influences federal funding for biomedical research. However, the channels of political influence are subtle, affect a small portion of funding, and may not necessarily have a distortive effect on public science.

Keywords: research and development; lobbying; earmarks; National Institutes of Health
History: Received December 9, 2012; accepted July 30, 2014, by Bruno Cassiman, business strategy. Published online in *Articles in Advance* April 8, 2015.

Requests For Applications (RFAs)

an example

Title: Development of New Technologies Needed for Studying the Human Microbiome (R01)

Announcement Type
This Funding Opportunity Announcement (FOA) is a reissue of RFA-RM-08-026.

Request for Applications (RFA) Number: RFA-RM-09-008

Key Dates
Release/Posted Date: July 16, 2009
Opening Date: August 14, 2009 (Earliest date an application may be submitted to Grants.gov)
Letters of Intent Receipt Date(s): August 17, 2009
NOTE: On-time submission requires that applications be successfully submitted to Grants.gov no later than 5:00 p.m. local time (of the applicant institution/organization).
Application Due Date(s): September 14, 2009
Peer Review Date(s): February-March 2010
Council Review Date(s): May 2010
Earliest Anticipated Start Date(s): July 2010
Additional Information To Be Available Date (Activation Date): Not Applicable
Expiration Date: September 15, 2009

Requests For Applications (RFAs)

an example

Executive Summary

- **Purpose.** The purpose of this FOA is to solicit applications to develop new and improved technologies for obtaining samples of individual microbial isolates or strains, from the human microbiota, suitable for complete genomic sequence analysis. The goal is to expand the number of "reference" microbial genome sequences, which in turn will aid in the analysis of the complex microbial populations resident in and on the human body.
- **Mechanism of Support.** This FOA will utilize the NIH Research Project Grant (R01) grant mechanism and runs in parallel with a FOA of identical scientific scope, RFA-RM-09-009 that solicits applications under the R21 mechanism.
- **Funds Available and Anticipated Number of Awards.** $2 million is available in FY10 for this FOA and the parallel R21 FOA in combination. It is anticipated that 2-4 R01 grants (of duration up to 3 years) and 2-6 R21 grants will be awarded. . Awards issued under this FOA are contingent upon the availability of funds and the submission of a sufficient number of meritorious applications.
- **Budget and Project Period.** Because the nature and scope of the proposed research will vary from application to application, it is anticipated that the size and duration of each award will also vary. Applicants for R01 grants may request a project period of up to 3 years.

Requests For Applications (RFAs)

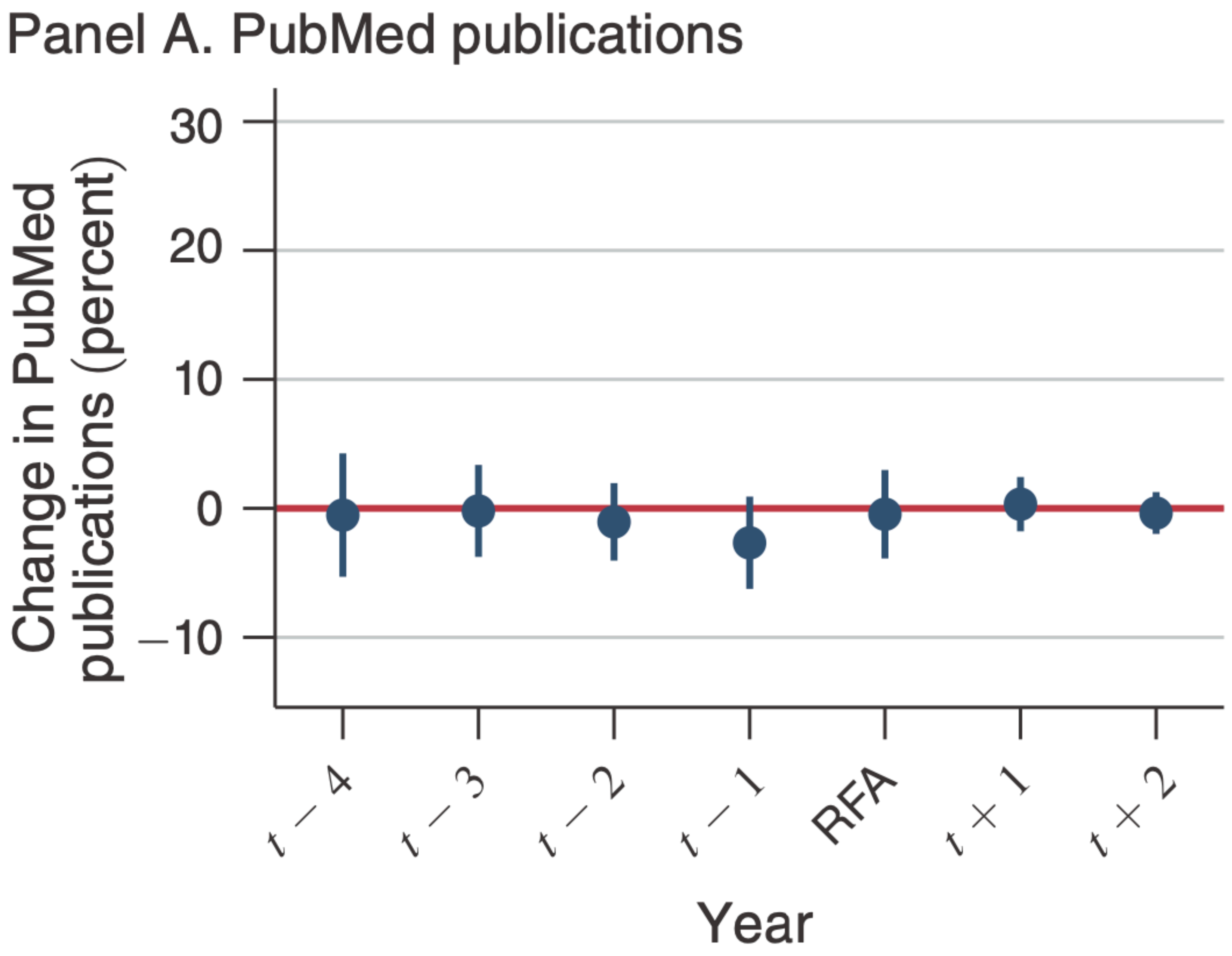
an example

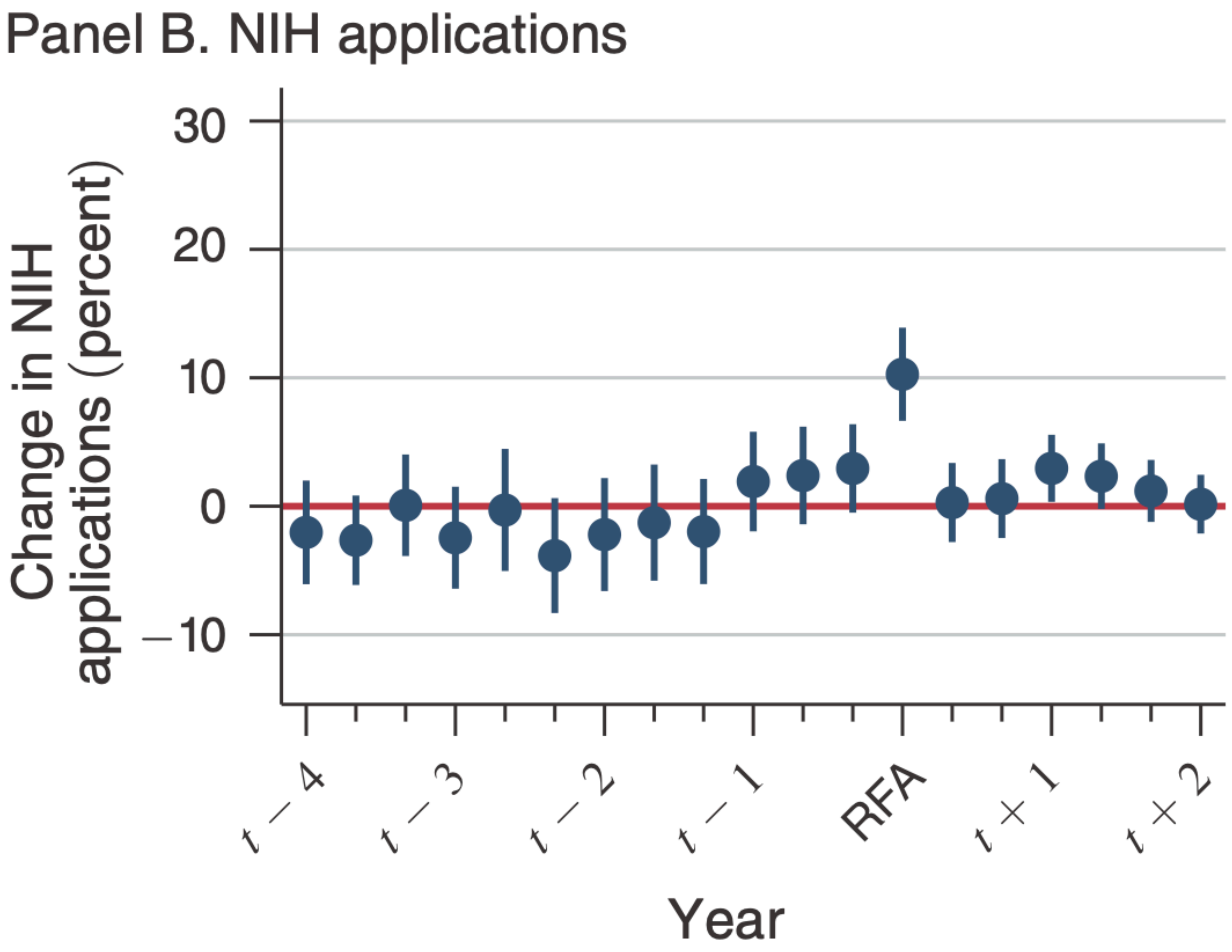
RESEARCH SCOPE: The interpretation of metagenomic sequence data is greatly aided by comparison to the genomic sequence of isolated species and genetically different strains of the same species. Yet, only a small proportion of the microbial species resident in or on the human body has been isolated and sequenced. The purpose of this FOA is to support the development of technologies that will allow the determination of the complete, individual genome sequences of substantial numbers of previously uncharacterized members of the human microbiota, to aid in the interpretation of metagenomic datasets obtained from sampling the human body. The following list, which is certainly incomplete, presents examples of strategies that would be supportable under this FOA:

- Development of methods to isolate single microbial cells. These methods would enable the identification, analysis and isolation of individual cells in the human microbiota that satisfy a specified set of criteria.
- New approaches to obtain pure cultures or simple mixed cultures of small numbers of previously uncultivated species would advance the objective of genomic analysis of the human microbiota. Proposed methods that can be applied to a large number of species rather than to any one particular species will take high priority.
- Development, optimization and validation of methods to isolate, amplify, or clone unamplified or amplified DNA of whole genomes from individual cells at high fidelity (e.g., complete coverage, low bias, low chimerism).
- Development of methods to “normalize” the complexity of the population, at either the cellular or DNA level. Such methods would facilitate either the ability to isolate single cells that are rare within a population, or to perform bioinformatics analysis on metagenomic sequences (e.g., by improving the representation of “rare” members).
- Development of methods to enrich the cells of a given species to essential purity. This is the inverse of reducing redundancy, and might be most effective for species whose abundance is already high. Such methods might substitute, at least for DNA sequencing studies, for the ability to establish pure cultures.
- Development of methods that (as a prelude to isolating single microbial cells, or conducting enrichment or normalization) disaggregate cells from the complex mixtures of microbial cells, human cells, and extracellular materials (e.g., biofilms) that comprise human microbial samples. Methods for cell disaggregation should be developed in conjunction with associated methods such as those described above.

RFAs don't appear to target "hot" topics

regression results





Scientists like being “close” to “big” RFAs

raw data

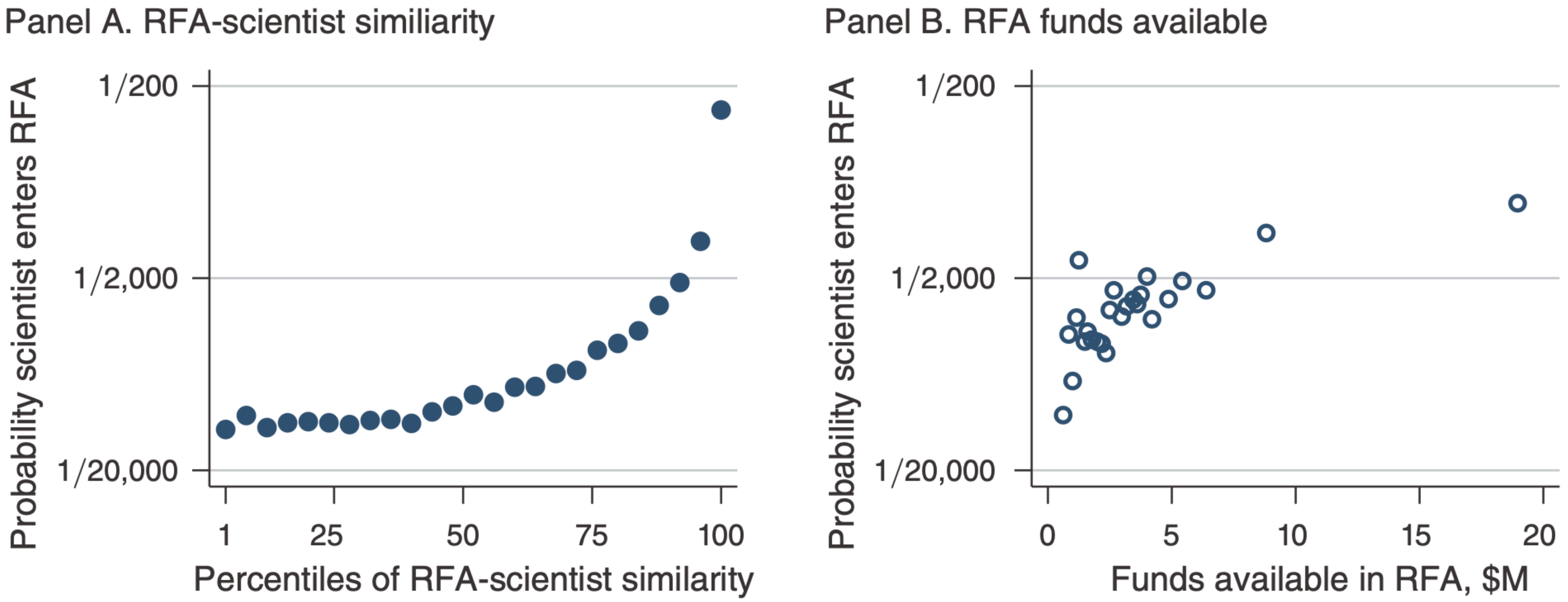


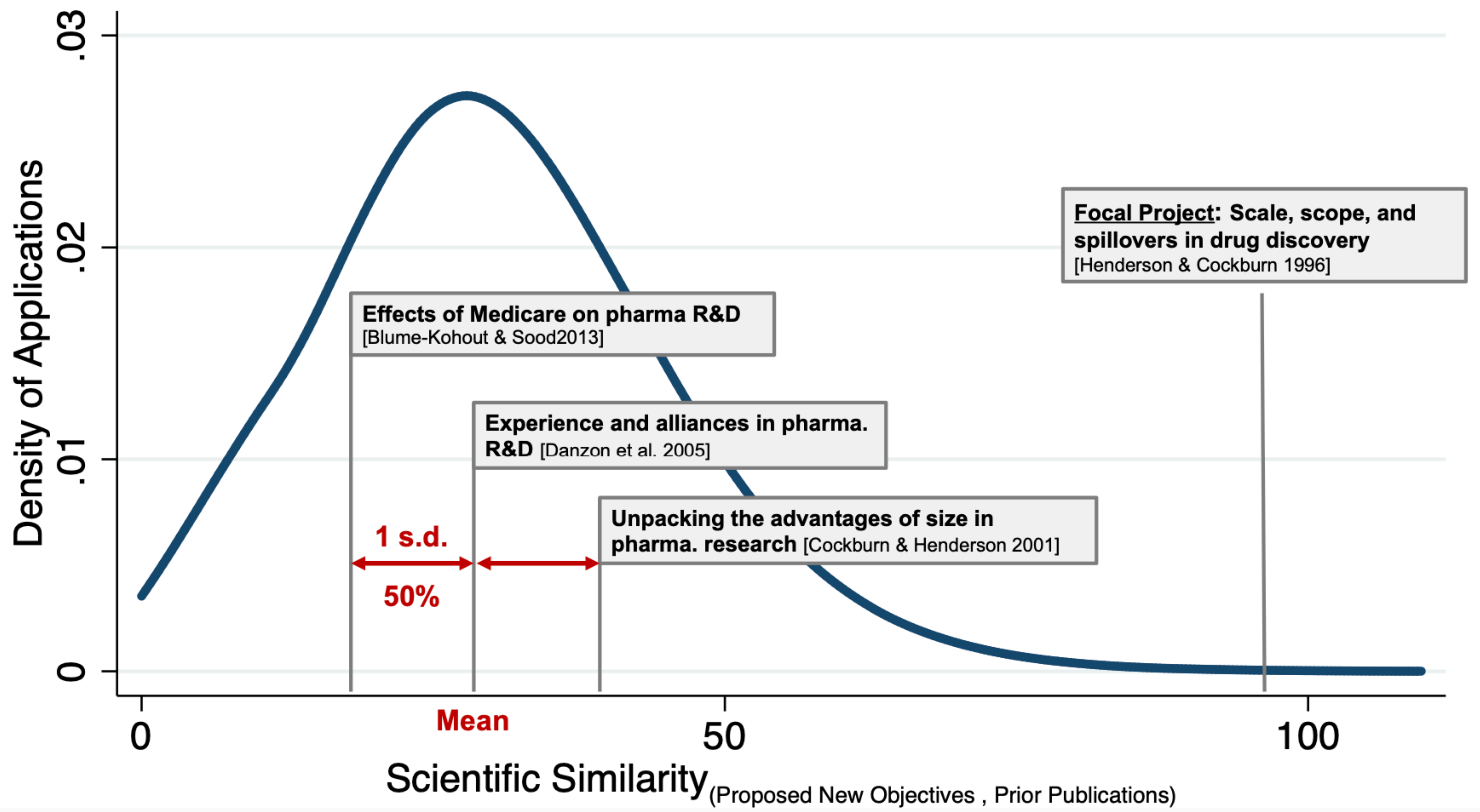
FIGURE 1. PROBABILITY OF RFA ENTRY PER SIMILARITY AND FUNDING

Notes: The figure shows binned scatterplots of entry probabilities per panel A, similarity of scientists’ prior publications to the research objectives of the RFA (larger scores indicate greater overlap), and panel B, the amount of funds made available in the RFA. The figure is based on approximately 110,000 scientists and 390 RFAs. Note the log scale of the *y*-axis.

Measuring Scientific Similarity

(and communicating it too)

Figure III.6: *pmra* Distribution: Economics Examples



A Simple Entry Model
handling competitive expectations

- **Concern**: If scientists like RFAs that are bigger ($) …
  - … ***scientists will know*** that RFAs with larger "purses" will attract many others …
    - … which increases competitive expectations …
      - … which could mute the effect of purse size on Pr(apply)
- **Concern**: If scientists like RFAs that are (scientifically) similar…
  - … ***scientists will know*** that RFAs in dense areas will attract many others …
    - … which increases competitive expectations …
      - … which could mute the effect of scientific similarity on Pr(apply)

A Simple Entry Model
handling competitive expectations (Bajari et al. 2010)

- Estimate scientists' expectations of how many others will enter:
  - $\Pr(Entry_{ij}) = a + \beta Similarity_{ij} + \gamma Purse_j + \epsilon_{ij}$
  - $\mathbf{E}[\Pr(Entry_{ij})] = \hat{a} + \hat{\beta} Similarity_{ij} + \hat{\gamma} Purse_j$
  - $\tilde{n}_{ij} = \sum_{i' \neq i} \left(\hat{a} + \hat{\beta} Similarity_{i'j} + \hat{\gamma} Purse_j \right)$
- Estimate scientists' own probability of entering, given these expectations:
  - $\Pr(Entry_{ij}) = \alpha + \sigma Similarity_{ij} + \phi Purse_j + \delta \tilde{n}_{ij} + \varepsilon_{ij}$

Results: Entry Model

Table 1—Determinants of RFA Entry

	$\mathbf{1}\{Entry_{ij}\}$				
	(1)	(2)	(3)	(4)	(5)
$Purse_j$				$\boxed{2.32}$	$\boxed{4.07}$
				$\boxed{(0.551)}$	$\boxed{(0.503)}$
$Similarity_{ij}$				2.33	2.55
				(0.911)	(0.964)
$Competitive\ Expectations_{ij}$					−4.37
					(0.271)
Includes similarity bins					
RFA controls				Y	Y
Scientist fixed effects				Y	Y

ignoring competition severely biases (downward) responsiveness to $

Notes: All models include 20,221,541 scientist-RFA (ij) pair observations, where the mean entry probability is 5.47×10^{-4}. Independent variables are standardized in regression, so coefficients indicate the change in entry probability associated with a one standard deviation increase in the variable; all coefficients are scaled by 10^{-4}.

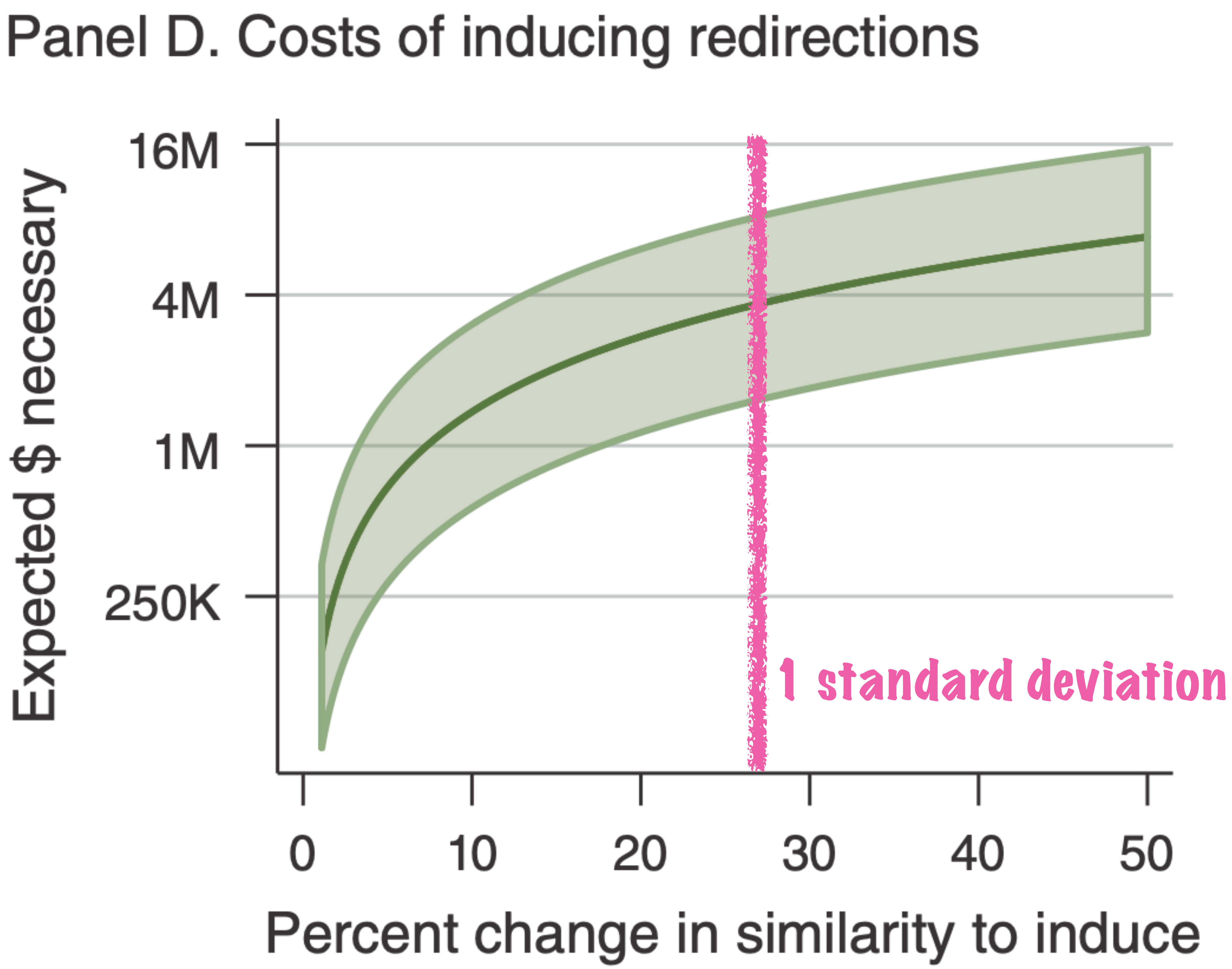
The Elasticity of Science

from entry model parameters to adjustment costs

- Estimate scientists' own probability of entering, given these expectations:
  - $\Pr(Entry_{ij}) = \alpha + \sigma Similarity_{ij} + \phi Purse_j + \delta \widetilde{n}_{ij} + \varepsilon_{ij}$
  - $\sigma \equiv \partial \Pr(Entry)/\partial Similarity$
  - $\phi \equiv \partial \Pr(Entry)/\partial Purse$
- Elasticity of science: the percent change in scientific similarity that can be induced with a percent change in (expected) funding
  - EoS: $\dfrac{\sigma/S}{\phi/P}$

How much $ does it take?

elasticity of science ≈ 0.1



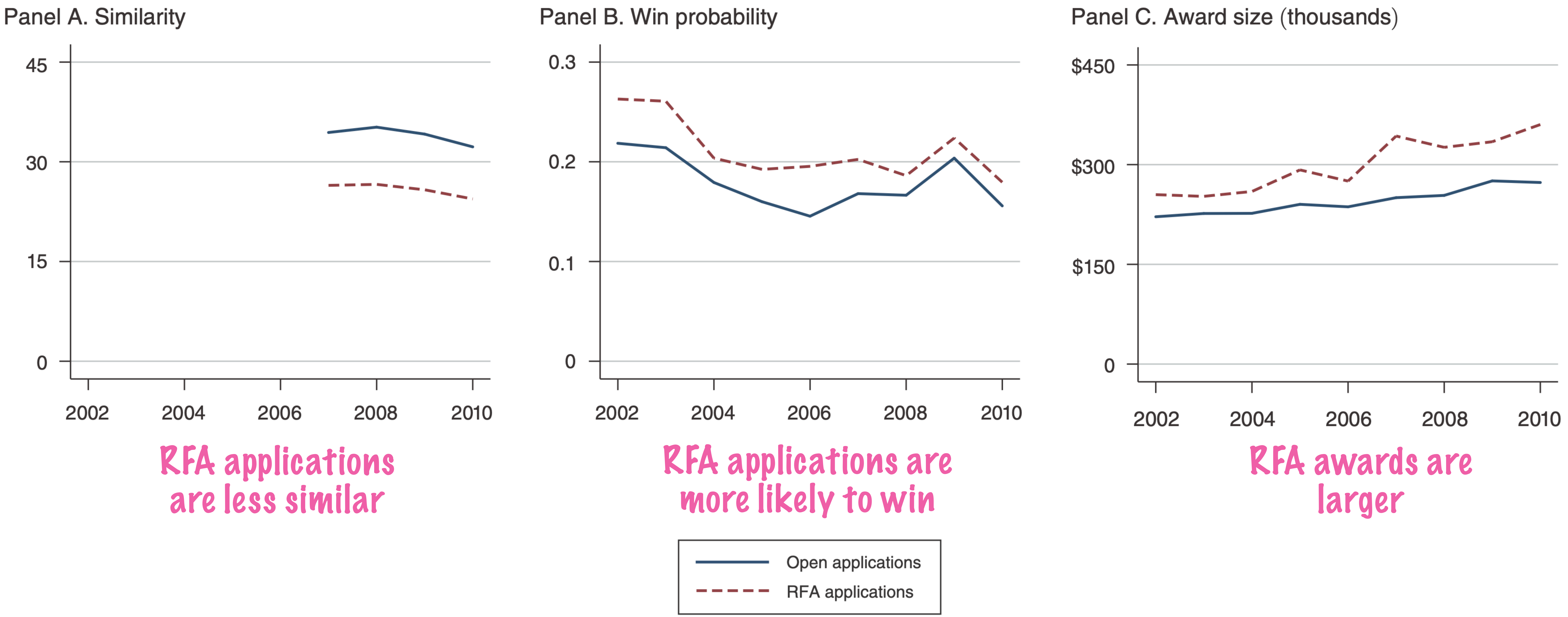
Adjustment Costs Look Large!

but, are they policy-relevant?

- Two major channels at the NIH:
  - “Investigator-initiated” / “open”: propose (almost) whatever you want
  - RFAs: propose something within the scope of objectives
- If adjustment costs are first-order and there aren’t a ton of scientists close to each RFA, then in equilibrium:
  - Scientists will see the RFAs and compare the extra adjustment costs relative to the extra expected payoff
  - But, they will never fully dissipate all (expected) rents in the RFAs
  - And, the size of those rents will equal the adjustment costs

Expected Costs and Benefits

RFAs versus Open channels



Are re-directions persistent?

yes

TABLE 4—GRANT PRODUCTIVITY—PUBLICATION SIMILARITY

	IHS(*Publication-RFA Similarity$_{jk}$*)		
	(1)	(2)	(3)
$\mathbf{1}\{Win, RFA_{jk}\}$	0.131	0.334	0.317
	(0.0328)	(0.166)	(0.136)
Semielasticity *RFA*	0.140	0.378	0.361
Observations	4,949	4,949	4,949
IV		Y	Y
F-statistic		57.5	58.2
Project, people **X**			Y
Funding group fixed effects	Y	Y	Y
pmra controls	Y	Y	Y
$LASSO\ var_{sel/poss}$	3/21	6/21	12/350

Summary & Take-aways

Myers (2020). *"The Elasticity of Science"*

- **The adjustment costs of modern (biomedical-like) science are very large**
  - In both absolute terms, and relative to current grant sizes
- Targeted funding mechanisms:
  - Give rents to scientists who apply
  - Cause significant changes in trajectory for winners
  - Cause as many (if not more) total publications compared to "open" channels
  - $\Rightarrow$ **there could be a pseudo-deadweight-loss of intervening in science with $**
    - *[caveat: on the scale of how RFAs are used at the NIH in this period]*
    - *[caveat: don't forget Sampat (2012) Hegde & Sampat (2015)]*

Diversity and Technological Progress

Acemoglu

The Rate and Direction of Inventive Activity Revisited (2011)

Simple Model: Setup
Acemoglu (2011)

- Two periods $t = \{1,2\}$; no discounting
- Two technologies j (sellable at $t = 1$) and j' (un-sellable at $t = 1$)
  - Sellable ("active"): if scientist makes improvement, they're rewarded
  - At $t = 1$, "quality" of both technologies = 1
- A scientist as 1 unit of time, can devote some share x to studying tech.
  - Quality of tech. improves with prob. $h(x)$; $h()$ is concave and well-behaved
  - Improvement moves quality from 1 to $(1 + \lambda)$, where $\lambda > 0$
  - Receive payoff of $(1 + \lambda)$ if successful

Expected payoff

x_j : scientists share of effort devoted to tech. j (note: $x_{j'} = 1 - x_j$)

v : prob. other scientist wins in either tech.

p : prob. of switch from tech. j to j'

$$\pi(x_j) = \underbrace{h(x_j)}_{\text{prob. win } j} \times \underbrace{(1+\lambda)}_{\text{payoff in } t=1} + \underbrace{h(x_j)[(1-v)(1-p)]}_{\text{prob. still winner \& no demand shift}} \times \underbrace{(1+\lambda)}_{\text{payoff in } t=2}$$

$$+ \underbrace{h(1-x_j)[(1-v)p]}_{\text{prob. win } j' \text{ \& no demand shift}} \times \underbrace{(1+\lambda)}_{\text{payoff in } t=2}$$

Comparative static

x_j^* **is increasing in v (= prob. other scientist wins)**

- Invest more in active tech. when “competition” is stronger

- Examples of v in practice?
  - Actual competition from other scientists
  - Knowledge / skill / ability / etc.
  - Fixed costs

Social Planner's Expected Payoff

(it doesn't matter who wins)

$$\Pi(x_j) = h(x_j)[\underbrace{(1 + (1 - v)(1 - p)(1 + \lambda))}_{\text{private returns in } j} + \underbrace{v(1 - p)(1 + \lambda)^2}_{\text{social returns in } j}]$$

$$h(1 - x_j)[\underbrace{[(1 - v)p(1 + \lambda))}_{\text{private returns in } j'} + \underbrace{vp(1 + \lambda)^2}_{\text{social returns in } j'}]$$

Private vs. Social Optimum

Key result: $x_{j'}^{social*} > x_{j'}^{private*}$

- Social planner wants more effort in the alternative tech. (j') than scientist does

- Comparative static
  - Invest more in active tech. when "competition" is weaker, i.e., $\partial x_j^{social*} / \partial v < 0$
  - Recall, the opposite is true for the scientists' problem

$\Rightarrow$**Wedge between private and social optimum grows with "competition"!**

Counter-acting forces

that push against distortionary profit-seeking

- Adjustment costs
- Forecast (belief) differences
- Technology-specific competencies or preferences

- In other words, getting “stuck” in a certain field is great if your field happens to be valuable in the future!
- <u>Thesis I’d love to see</u>: *how close are observed adjustment costs of science to the socially optimal adjustment costs?*

Kortum's Comment
(in the same volume)

- In Acemoglu, early progress in non-active tech. quickly becomes superseded
- **Kortum: what about differing returns to scale?**

- How large are the dis-incentives from competition relative to the incentives from learning from more scientists?
  - *Is separating these forces from the aggregate returns to scale policy-relevant?*

The Allocation of Science

- **Jones**. *"The burden of knowledge and the “death of the renaissance man”: Is innovation getting harder?" The Review of Economic Studies (2009).*
- **Bryan & Lemus**. *"The direction of innovation." Journal of Economic Theory (2017).*
- **Hopenhayn & Squintani**. *"On the direction of innovation." Journal of Political (2021).*

- See also, work in experimental socio-psych. on how scientists generate, perceive, and evaluate ideas
  - *Note: much to be done on connecting socio-psych. findings with macro models*

Sourcing Research Ideas from Macro Models

as an applied micro-economist

- Macroeconomic models tell us what parameters "matter"

- Parameters are either:
  - In the model
    - Informed by prior empirical work **[but is that work good, or still true?]**
  - Not in the model
    - Implicitly assumed to be 0 or 1 **[but is it!?]**

Innovation 2023

NBER Summer Institute Redux

Innovation and Appropriability: Revisiting the Role of Intellectual Property

Filippo Mezzanotti, Northwestern University
Timothy Simcoe, Boston University and NBER

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This paper was distributed as **Working Paper 31428**, where an updated version may be available.

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Scott Stern, Massachusetts Institute of Technology and NBER

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Discussant:
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Judith A. Chevalier, Yale University and NBER

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Joel Waldfogel, University of Minnesota and NBER

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Sendhil Mullainathan, University of Chicago and NBER
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Daron Acemoglu, Massachusetts Institute of Technology and NBER

View abstract ›

This paper was distributed as **Working Paper 30922**, where an updated version may be available.

Discussant:
Manuel Trajtenberg, Tel Aviv University and NBER

The Economics of Science

always happy to talk!

kmyers@hbs.edu

Kyle R. Myers

Innovation Research Boot Camp, Summer 2023