The Lasting Effects of Government R&D

Jason Hall

Minnesota

Federal Reserve Bank of Minneapolis
October 27, 2026

Any views expressed are those of the author and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 3126. (CBDRB-FY26-P3126-R13126)

Graduate Programs are Dramatically Reducing Admissions


The Washington Post
Democracy Dies In Darkness

Higher Education

Admissions to top PhD programs down 15% amid federal funding cuts, uncertainty

U.S. universities have warned Trump policies will narrow the talent pipeline. Already global applications are down, though domestic applications are up slightly.

July 6, 2026


The Washington Post
Democracy Dies In Darkness

Higher Education

MIT president blames federal policy shifts for big drop in research on campus

Funding cuts and restrictive immigration policies are throttling scientific work as other nations are investing heavily, education experts say.

May 15, 2026

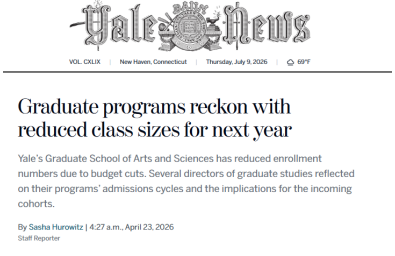

The Washington Post
Democracy Dies In Darkness

Higher Education

At Harvard, Trump administration cuts hit young scientists hard

More than 700 graduate students and nearly 800 postdoctoral researchers at Harvard get salaries, stipends or tuition support from federally funded research.

August 24, 2025


Yale News

VOL. CXLIX | New Haven, Connecticut | Thursday, July 9, 2026 | 69°F

Graduate programs reckon with reduced class sizes for next year

Yale's Graduate School of Arts and Sciences has reduced enrollment numbers due to budget cuts. Several directors of graduate studies reflected on their programs' admissions cycles and the implications for the incoming cohorts.

By Sasha Hurowitz | 4:27 a.m., April 23, 2026
Staff Reporter

Research Questions

- Large cuts in STEM Ph.D. programs following uncertainty in government funding.

- Questions:
  1. What role do STEM Ph.D.s play in U.S. innovation?
  2. How does cutting federal funding for universities affect growth and welfare?

What I do

1. **Data:** Measure relationships between federal funding, PhDs, and doctoral innovation.

2. **Model:** Construct positive model of PhD training and growth.

3. **Counterfactual:** Use model as a laboratory to evaluate policy.

What I do

1. **Data:** Measure relationships between federal funding, PhDs, and doctoral innovation.
   - 1% higher appropriations/GDP $\Rightarrow \approx 0.55\%$ higher PhD yield
   - Construct new dataset linking 2M dissertations to patents
   - PhDs appear on $\approx 50\%$ of critical-technology patents
   - Substantial ex-ante uncertainty about ability
2. **Model:** Construct positive model of PhD training and growth.
   - Assume that PhDs are crucial for some subset of growth.
   - Students sort across university tiers on a noisy public signal of research ability
   - Federal funding $\rightarrow$ PhD supply $\rightarrow$ aggregate growth
3. **Counterfactual:** Use model as a laboratory to evaluate policy.
   - Consider 50% reductions to federal R&D
   - 3-year cut has a welfare cost of 0.09% of permanent consumption.
   - 23-year cut costs $\approx 1.3\%$ of permanent consumption.

Related Literature

- **Innovation, growth, and the allocation of talent**
  Romer, 1990; Aghion and Howitt, 1992; Murphy et al., 1991; Aghion et al., 2017; Bell et al., 2019; Hsieh et al., 2019; Pearce, 2020; Akcigit et al., 2025
  ↪ New patent dataset; model of endogenous PhD capacity → future talent distribution.

- **Education as experimentation and public learning**
  Manski, 1989; Terviö, 2009; Chade et al., 2014; Hendricks and Leukhina, 2018; Wu, 2026
  ↪ Infer ex ante uncertainty about ability → quantify the value of experimentation.

- **Returns to government R&D**
  Azoulay et al., 2019; Myers and Lanahan, 2022; Babina et al., 2023; Tham et al., 2024; Dyevre, 2023; Fieldhouse and Mertens, 2025; Campbell et al., 2026
  ↪ Quantify the growth effects of government R&D through PhD training capacity.

Empirics

Government Funding Effects on New PhDs

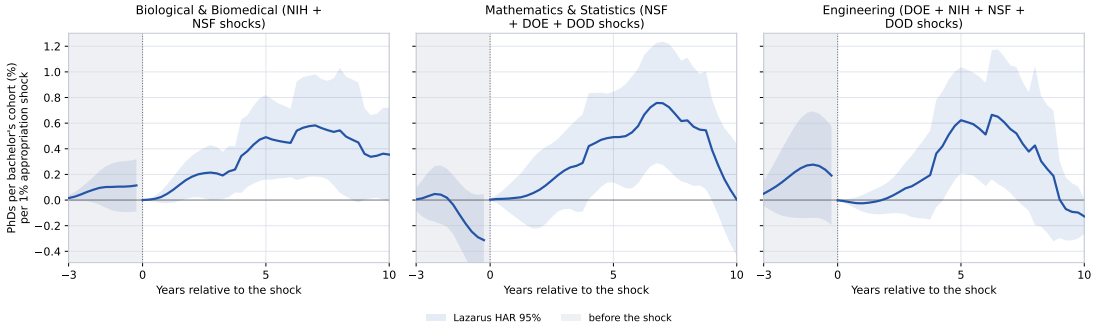
- Want to know how increases in government funding affect supply of PhDs
- OLS is biased because of contemporaneous productivity concerns.

Government Funding Effects on New PhDs

- Want to know how increases in government funding affect supply of PhDs
- OLS is biased because of contemporaneous productivity concerns.
- Use Fieldhouse and Mertens (2025) narrative R&D account shocks:
  - Map R&D account to fields
  - Scale by university-linked obligation shares
  - 1974–present
- Estimate field-by-field local projections:

$$\overline{\ln \text{PhD}}_{f,t+h} = \alpha + \beta_h \cdot \text{shock}_{f,t} + \sum_{j=1}^{12} \gamma_j \ln A_{f,t-j} + \sum_{j=1}^{12} \delta_j \ln \text{PhD}_{f,t-j} + \sum_{j=1}^{12} \boldsymbol{\phi}_j \mathbf{X}_{t-j} + \varepsilon_{f,t+h}$$

A 1% Increase in G/Y causes $\approx$ 0.55% Increase in PhD Yield



All Fields | Basic Specification | Funding Responses | All Field Funding Responses | Pooled | Predetermined Shares

Data

Goal: Measure the role of PhDs in U.S. innovation.

Challenge: Systematic data on U.S. inventor education is limited.

- Restricted use datasets
- Time-limited (typically post-2000)
- Limited institutional coverage.

Data

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Match two datasets:

1. ProQuest Dissertations and Theses Global Coverage
   - PhD Dissertations from 1950 to the present.
2. PatentsView Coverage
   - Patents granted from January 1976 to December 2025
   - Focus on assigned patents with at least one US-based inventor

Ultimate sample:

- 3.83 million patents, 1.70 million inventors, 1.96 million Ph.D.s

Matching Example

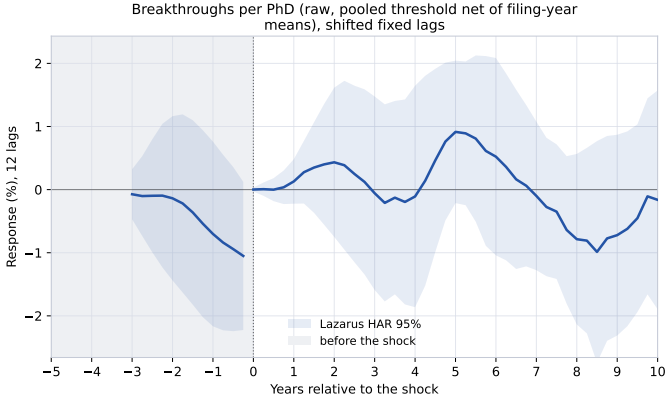
In Critical Technologies, Half of Patents have a PhD Inventor

	Patents	PhD Share
All Critical Tech	443,000	49.3%
Technology Area		
AI/ML & Autonomy	32,000	52.5%
HPC & Semiconductors	34,000	69.9%
Biotech & Medical	125,000	55.4%

Patents granted 2018–2023. PhD share = fraction with ≥ 1 matched STEM PhD inventor.

Full table

Breakthroughs per PhD after a Funding Shock



No strong evidence of average quality degradation in response to quantity increases.

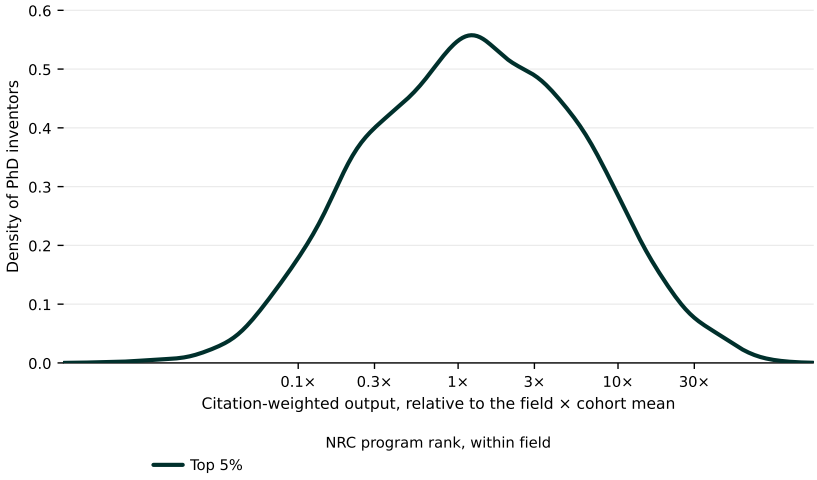
Quality LPs | Funding | PhDs per Bachelor's | Patents per PhD (Adjusted) | Patents per PhD (Raw)
Fixed Lags | Breakthroughs (Adjusted) | Breakthroughs (Raw) | No Year Adjustment | KPST Flag (Adjusted) | KPST Flag (Raw)

Inferring Ability

- Output effects depend on the quality of marginal entrant.
- Leverage sorting patterns to measure ex-ante uncertainty.
  - Programs rank candidates on expected quality, so better candidates sort to better programs.
  - Under perfect information, ex-post outcomes would not overlap across program tiers.
  - Measure tiers using National Research Council Rankings Details

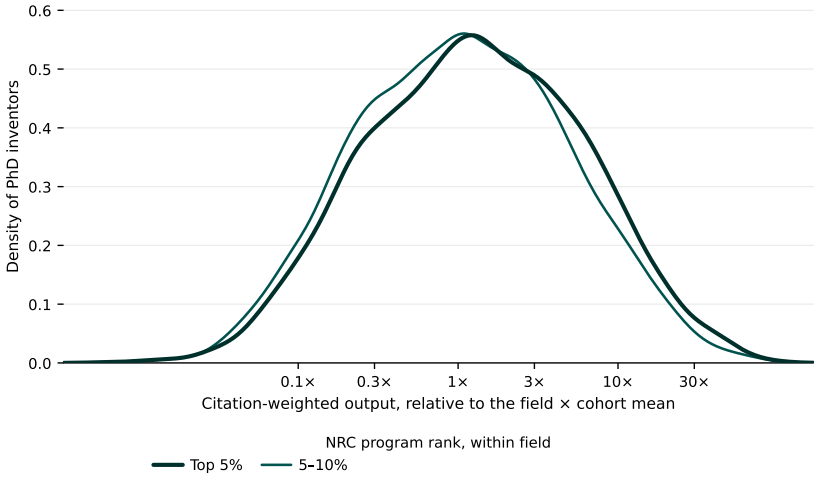
LP Evidence

Institution Explains Little Variance in 10 Year Patenting



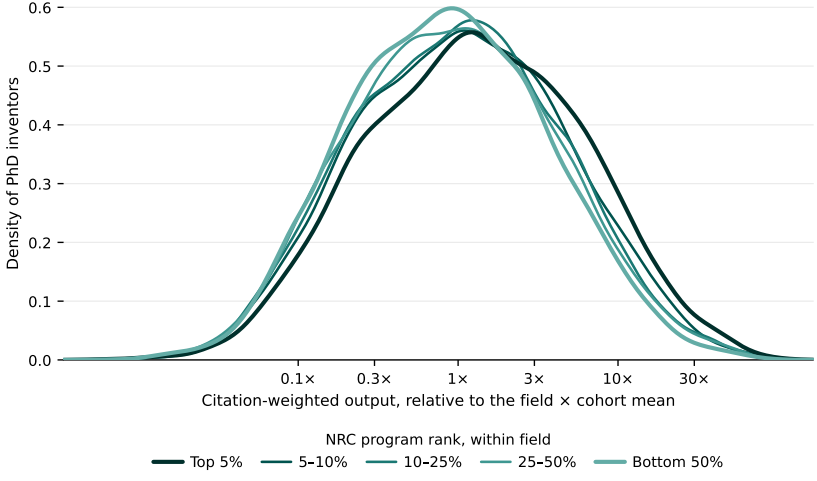
Variance Decomposition | Quality Adjusted by Field | Raw Patents | Raw Patents by Field | Beats Statistics

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Three Facts

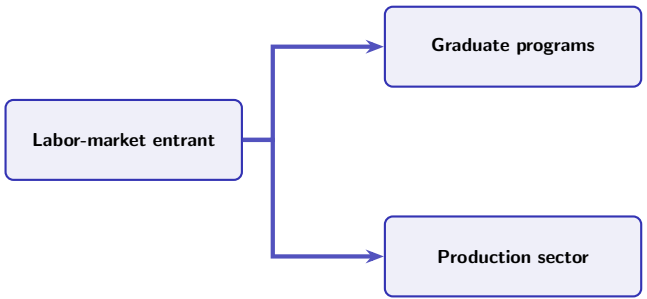
1. Individuals with doctorates appear on $\approx 50\%$ of high-tech patents.
2. A 1% exogenous increase in appropriations to GDP increases PhD yield by $\approx 0.55\%$.
3. PhD institution conveys very little information about ex-post patenting.

Three Facts

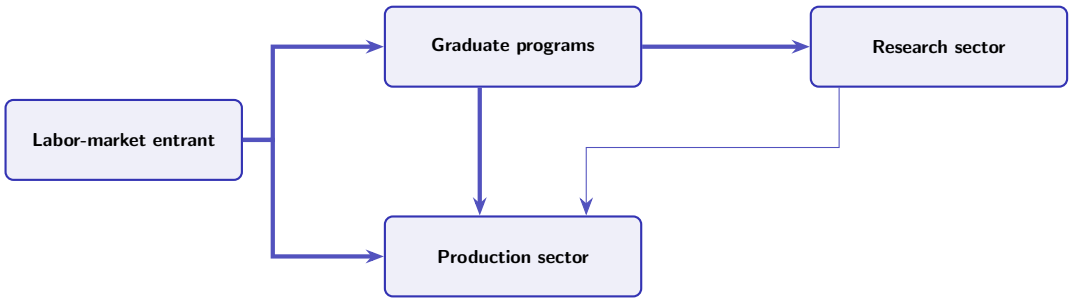
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- Model allows me to handle selection into research and patenting.
- Evaluate the effects of cuts in federal funding to R&D over the long-run.

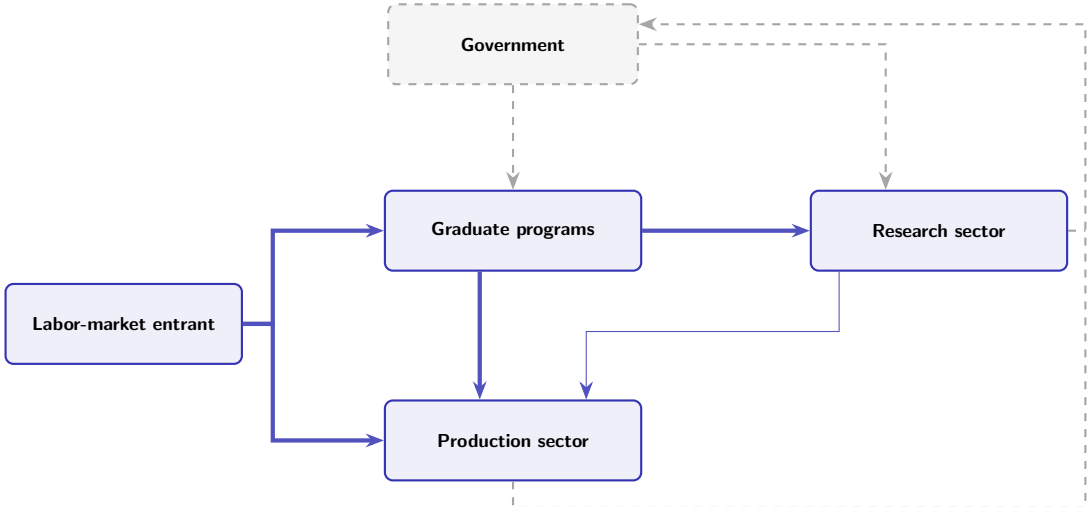
Model Overview



Model Overview



Model Overview



Worker Endowments and Utility

- Hand to mouth, value flow consumption according to:

$$u(c) = \ln(c)$$

- Die at rate δ, discount rate ρ
- Fraction $1 - \pi$ workers enter production with skill $\xi_1 z_P$
- Fraction π workers can be researchers or production with skill z_P.
- Draw unobserved research skill:

$$\ln(z_R) = \underbrace{X}_{\sim\mathcal{N}(0,\sigma_z^2)} + \underbrace{Y}_{\sim Exp(\tau)}$$

- See public signal:

$$\ln(n_R) = X + \underbrace{\varepsilon}_{\sim\mathcal{N}(0,\sigma_\varepsilon^2)}$$

- Endowed with share in mutual fund that owns all firms.

Eligible Worker Choices

- If they go to production:
  - Earn $w_t z_P$.
- If graduate school:
  - Earn stipend $s_t(n_R)$.
  - $\mathcal{O}$ stages, finish stage at rate $\mathcal{O}\mu$
- At graduation:
  - Learn z_R
  - Decide to go to production or continue to research sector.
  - If go to production, have skill $\xi_2 z_P$
- If research, Nash bargain with innovative firm, receive $\mathcal{P}_t(z_R)$.

▸ Worker HJBs ▸ Timeline

The Research Sector

- A match between a PhD and an innovative firm generates new ideas at rate:

$$I_t = \varphi_R z_R$$

- Wages are renegotiated instant by instant holding continuation values fixed.
- Outside option is 0 for innovative firms.
- Surplus is divided via Nash bargaining, with researcher weight θ:

$$\mathcal{P}_t(z_R) = \arg\max_p \left(\mathcal{R}_t(z_R; p) - \mathcal{W}_t\right)^{\theta} \left(\mathcal{V}_t(z_R; p)\right)^{1-\theta}$$

Researcher HJBs

Graduate Programs

- Their objective is to maximize ability of admitted students:

$$\int \mathbb{E}\left[z_R \mid n_R\right] a_{j,t}(dn_R), \qquad x_{j,t} \equiv a_{j,t}(\mathcal{N}_R)$$

- *Commit* to a stipend schedule $Q_t s_t(n_R)$ per cohort.
- States of a tier-j program:
  1. α_j : productivity
  2. $N_{j,t}$: enrollment
  3. $Rev_{j,t} \equiv Q_t \int \left[\alpha_j \mathbb{E}\left[z_R \mid n_R\right] - s_t(n_R)\right] N_{j,t}(dn_R)$: net revenue due to the enrolled stock
- Receive a per-body subsidy $Q_t f_t$.
- Pay real admissions cost $Q_t \frac{\kappa x_{jt}^{1+\nu}}{1+\nu}$
- Can borrow from abroad at interest rate r^*.
- Graduate programs are non-profits who break even **per cohort**.

▸ Sequence Problem ▸ Sorting

Production Firms

- Unit mass of product lines with endogenous quality q_{jt}

$$y_{jt} = q_{jt}\ell_{jt}$$

- Final goods technology:

$$\ln(Y_t) = \int_0^1 \ln(y_{jt})dj$$

- HJB:

$$(r^* + \iota_t)V_t - \dot{V}_t = \pi_t$$

Innovation

- Innovations arrive on each line at rate

$$\iota_t = \underbrace{\chi}_{\text{Exogenous idea flow}} + \varphi_R \int_{z \geq z_t^*} z \, dG_R(z)$$

- Growth rate is given by:

$$g_t = \ln(\lambda) \times \iota_t$$

- Researcher of ability z_R produces patents according to:

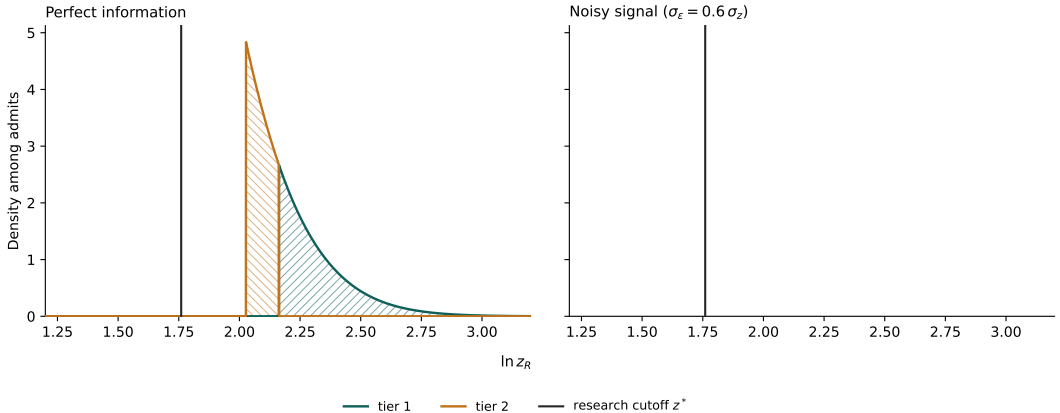
$$N \mid z \sim \mathrm{NB}\big(Az_R, r\big)$$

Equilibrium Definition

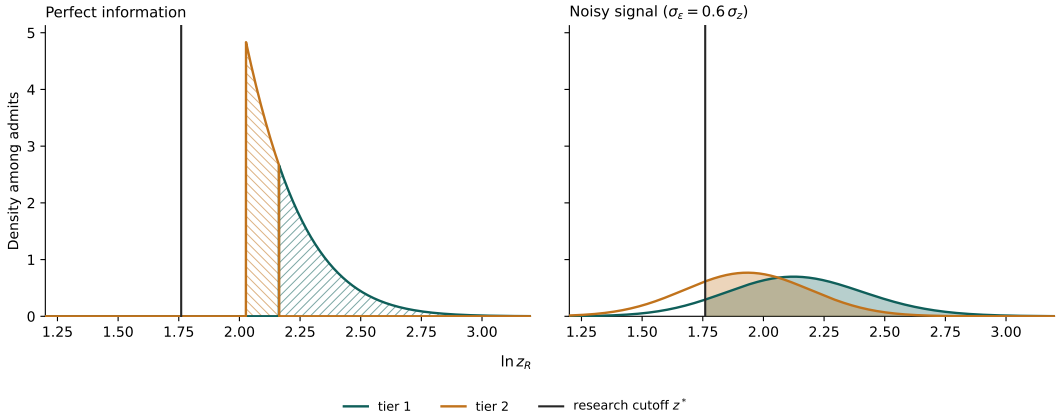
Given the world interest rate r^* and the policy path $\{f_t, s_R, \tau_t\}$, a perfect-foresight competitive equilibrium is prices $\{p_{jt}, w_t\}$, the value of a product line V_t, the stipend schedule $s_t(n_R)$, researcher payments $\mathcal{P}_t(z_R)$, the dividend d_t; admission measures $a_{jt}(n_R)$; stocks of students, graduates and researchers; and output Y_t, growth g_t and consumption $\{c_{it}\}$ such that:

- Workers choose optimally given (n_R, z_R).
- Firms maximize profits.
- Research firms maximize profits and $\mathcal{P}_t(z_R)$ solves the Nash bargain.
- $a_{jt}(n_R)$ solves each program's problem.
- The government's budget balances.
- Stocks are consistent.
- Labor and goods markets clear.

Heuristic Identification of Uncertainty



Heuristic Identification of Uncertainty



Estimated Parameters

Calibration

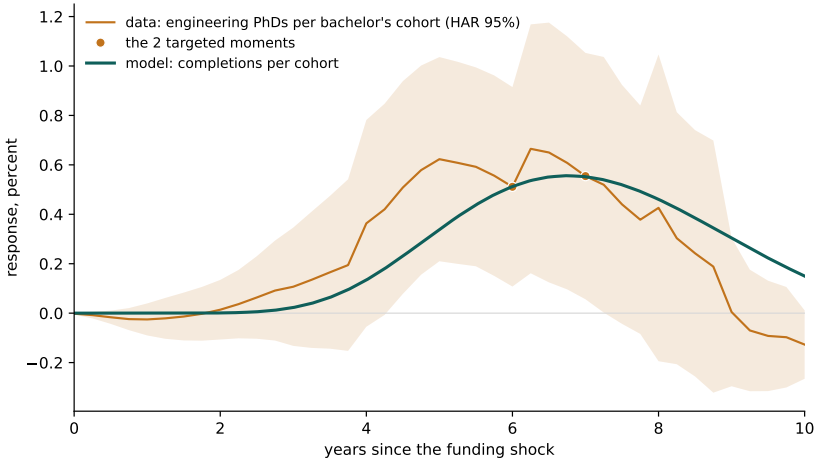
Externally Calibrated Parameters

Parameter	Description	Value	Source
Panel A. Preferences and demography			
ρ	Discount rate	0.03	Standard
δ	Death rate	0.025	Expected working life of 40 years
r^*	World interest rate	0.03	Small open economy
Panel B. Graduate education and the labor market			
π_R	Eligible cohort share	0.46	CPS, labor force aged 25+
ξ_1	Relative productivity of ineligible workers	0.62	BLS median weekly earnings, 2024
ξ_2	Relative productivity of PhDs who exit research	1.20	PSEO, engineering: master's earnings premium
$1/\mu$	Mean time to degree (years)	5.5	Survey of Earned Doctorates
$\mathcal{O}$	Erlang stages (sd of time to degree 1.5 years)	14	Survey of Earned Doctorates
Panel C. Innovation			
$\chi \ln \lambda$	Growth from non-PhD sources (p.p.)	1.12	$2\% \times (1-\text{Patent Share})$
Panel D. Normalizations			
$\mathbb{E}[X]$	Mean of log normal portion of research productivity	0	
z_P	Baseline production productivity	1	

Internally Calibrated Parameters: Aggregates and Programs

Parameter	Description	Value	Targeted moment	Model	Data
Panel A. Aggregates					
λ	Innovation step size	1.0231	growth rate g	0.0200	0.0200
φ_R	Research productivity	8.154	PhD research payroll / GDP	0.0060	0.0060
θ	Researcher bargaining weight	0.246	incumbent rent passthrough (KPZW)	0.61	0.60
Panel B. Graduate programs					
κ	Admission cost, level	59	PhD holders / labor force (SDR)	0.0041	0.0040
ν	Admission cost, curvature	0.072	completions IRF, years 6 and 7	0.3% / 0.4%	
α_1	Program productivity, top tier	0.386	university services / GDP	0.0035	0.0035
$\alpha_1, \ldots, \alpha_{10}$	Program productivity profile	0.39–0.30	relative decile sizes	0.4% / 1.4%	
Panel C. Policy instruments					
f	Federal subsidy per student	2.724	federal R&D to universities / GDP	0.0020	0.0020
s_R	R&D tax credit rate	0.101	R&D credit tax expenditures / GDP	0.0006	0.0006

Identifying the Graduate Cost Elasticity

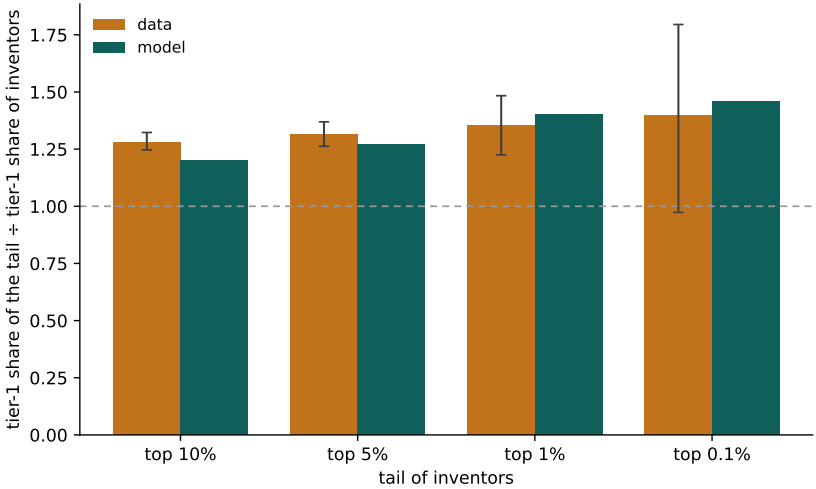


Funding Shock

Internally Calibrated Parameters: Ability, Information and Luck

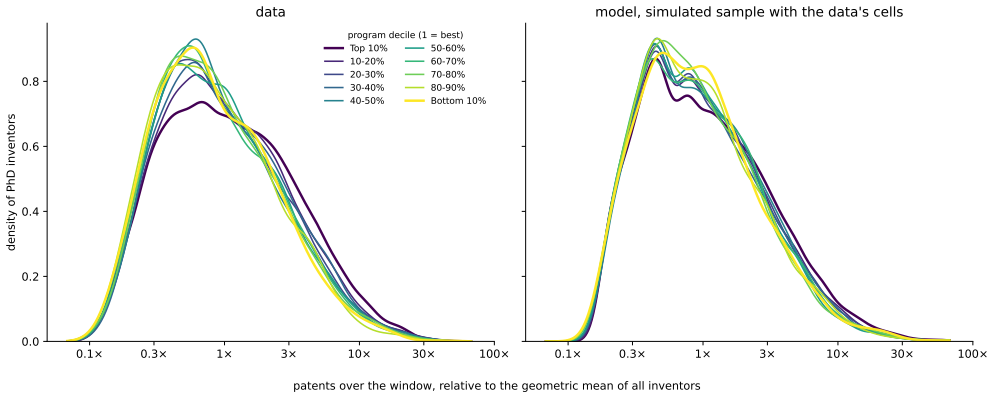
Parameter	Description	Value	Identifying moments	Fit
Panel A. Research ability				
σ_R	Dispersion of the normal component	0.84	Within-decile variance of log output	3.7% / 6.5%
τ	Scale of the star component	0.48	Pooled tail index of patent counts (Hill, top 5%)	1.99 / 2.06
			Elite capture at four depths	4.5% / 6.3%
Panel B. Information at admission				
σ_ε	Signal noise (reliability $\beta = 0.62$)	0.66	Research share among PhD holders (SDR)	0.688 / 0.681
			Between-decile gradient of the patenting share	4.8% / 17.4%
Panel C. Luck and measurement				
ϱ	Within-person dispersion of output	0.13	Patenting share, pooled	0.178 / 0.179
A	Nuisance parameter	0.0101	Mean patents among patenters	5.41 / 5.60
			Mean log count among patenters, by decile	3.5% / 7.4%

Identifying the Tail



▸ Tail Index by Decile

Identifying the Body of Ability



▸ Means ▸ Variances ▸ Cell Rate Adjusted ▸ By Decile

Untargeted Moments

	decile 1 (best)		decile 10		abs. % error, 10 deciles	
Untargeted moment	Model	Data	Model	Data	mean	max
share of patenters with exactly one patent	0.323	0.332	0.354	0.409	6.2%	13.3%
share of patenters with exactly two patents	0.163	0.166	0.175	0.163	2.8%	9.4%
share of patents held by the top 1% of PhDs	0.341	0.362	0.400	0.466	9.4%	14.1%
kurtosis of ln N among patenters	3.00	2.56	3.09	2.78	8.8%	17.4%
skewness of ln N among patenters	0.73	0.47	0.79	0.66	23.1%	54.9%

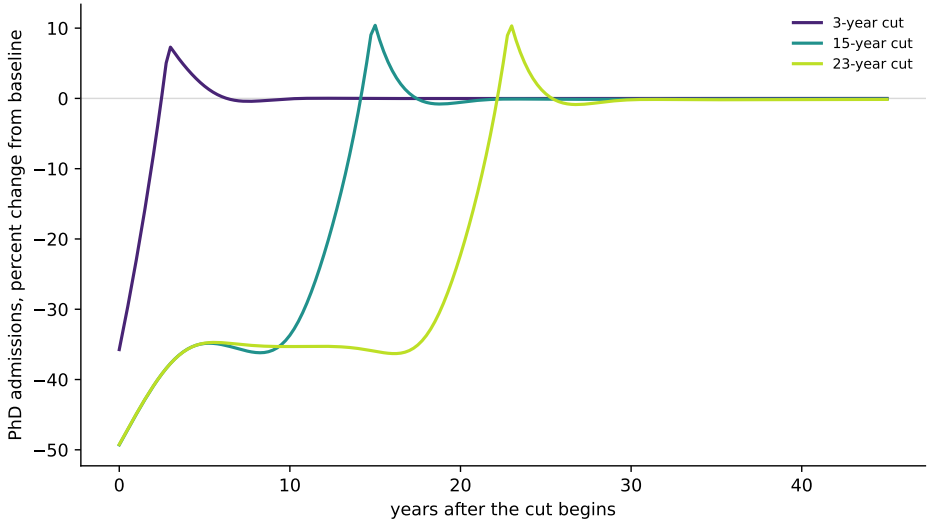
▸ Ones and Twos ▸ Top 1% Share ▸ Log-Count Shape ▸ Tail Index by Decile ▸ Tail Composition ▸ Danish Expansion ▸ Rank-Rank Slope

Results

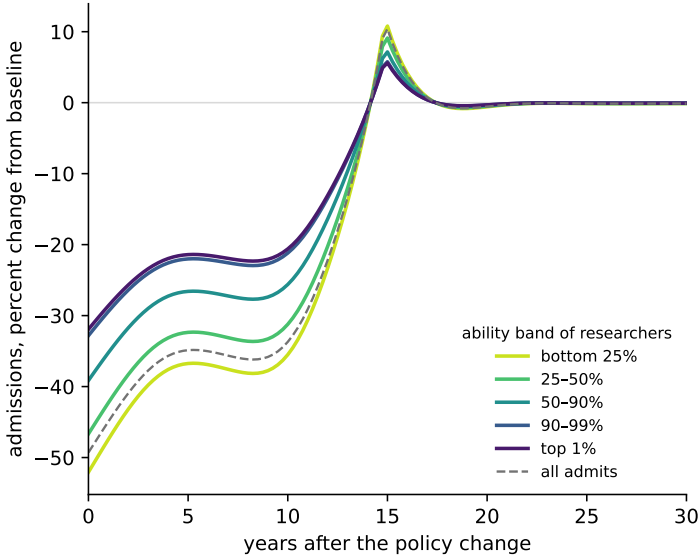
The Proposed Cuts

- Current administration has effectively proposed to cut federal R&D by $\approx 40\%$ for past two years.
- I implement this as a 50% reduction in federal funding.
- Will make different assumptions about how long Congress takes to reverse cut.
  1. 3 years
  2. 15 years
  3. 23 years

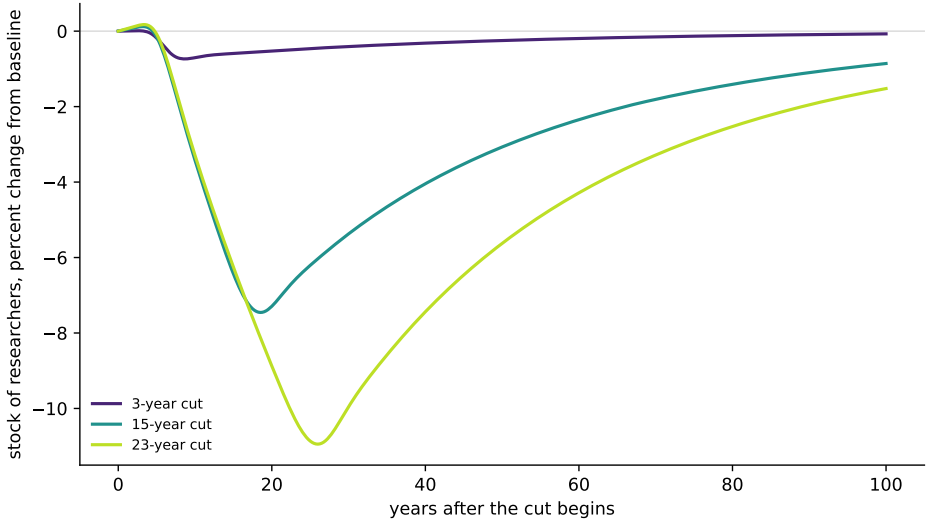
Admissions Response



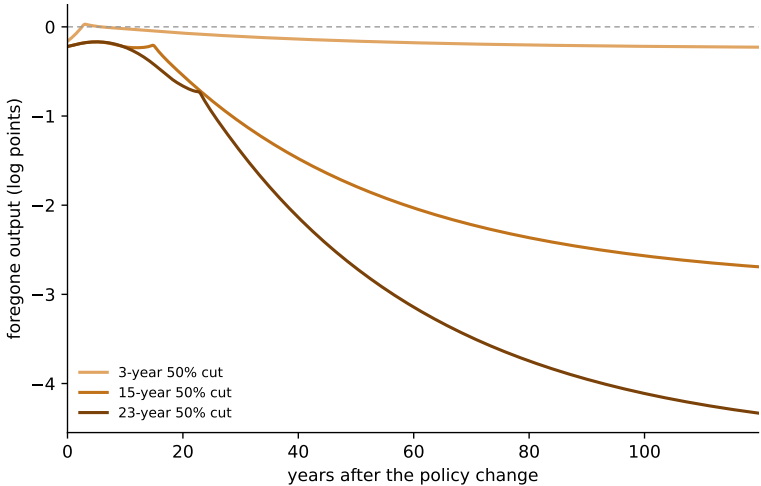
Quantifying Lost Einsteins



Researcher Stocks

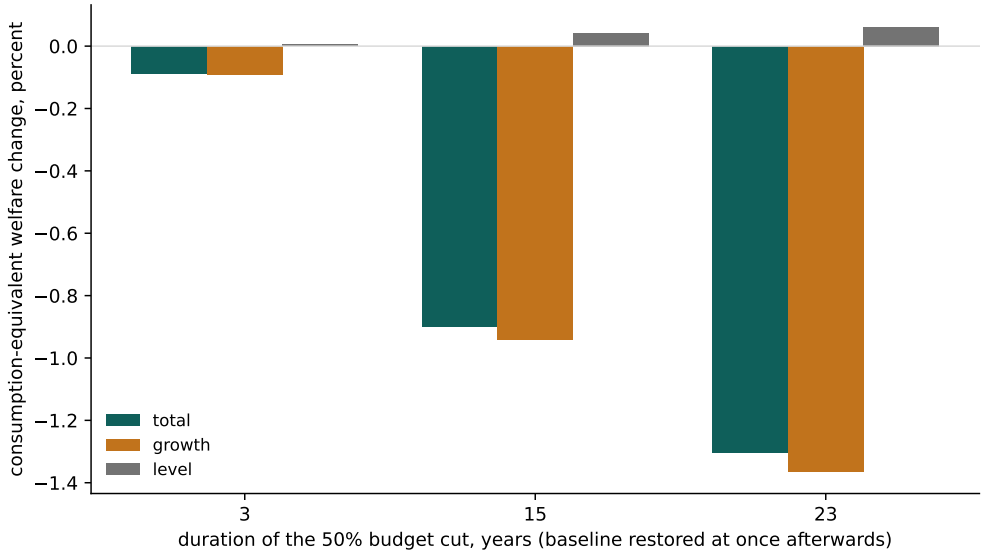


The Output Effects of Funding Cuts



Growth Rates

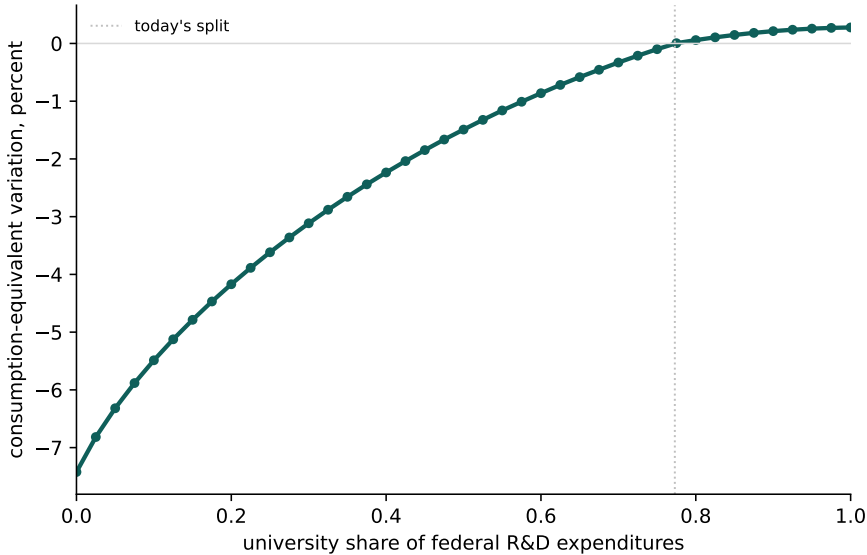
Aggregate Welfare



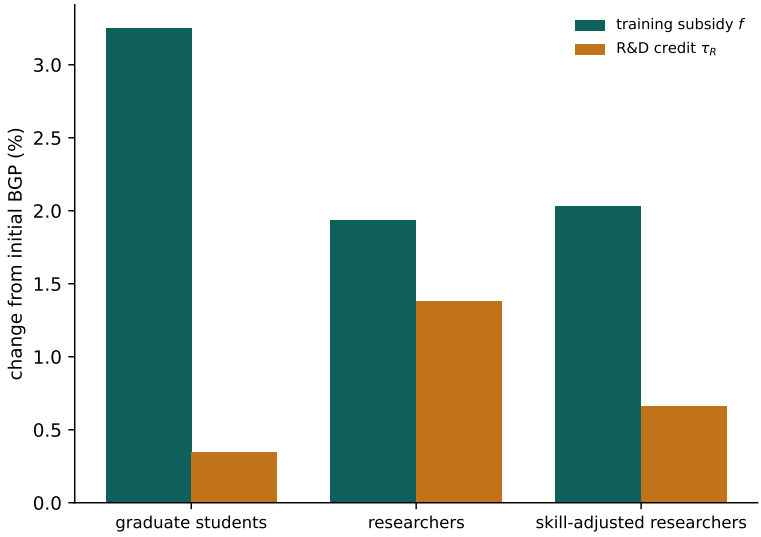
Comparing Policy Instruments

- Consider problem of a fiscally constrained government.
- Holding existing level of spending fixed, vary composition across instruments.

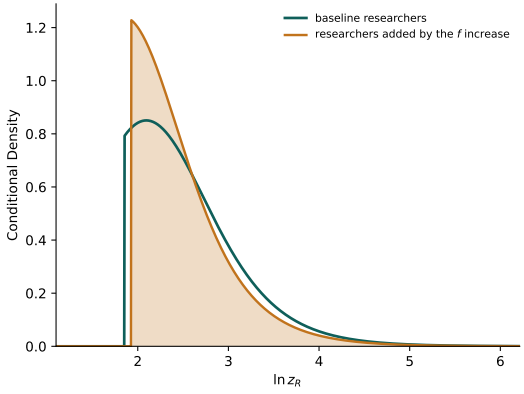
Welfare Frontier

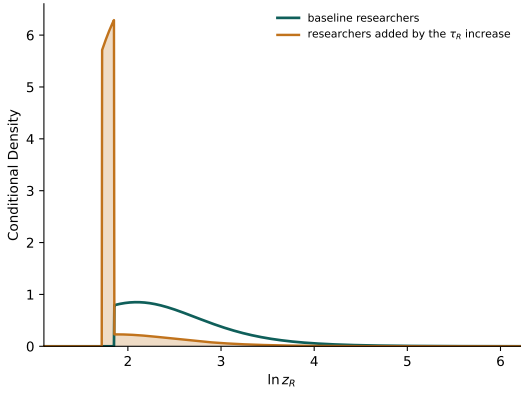


Changes in Stocks

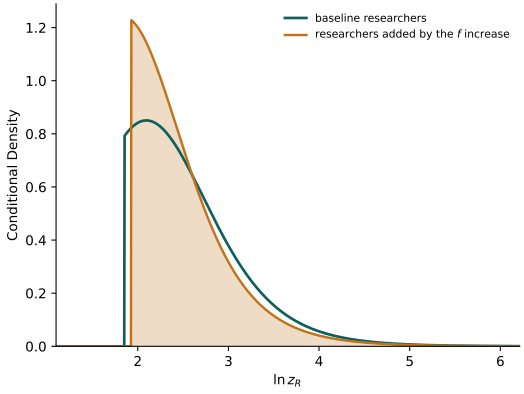


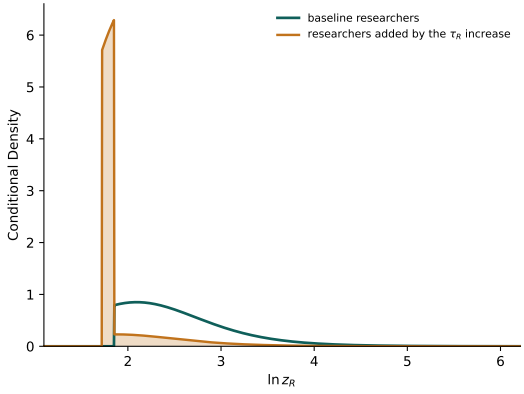
Selection Under Different Instruments





Selection Under Different Instruments





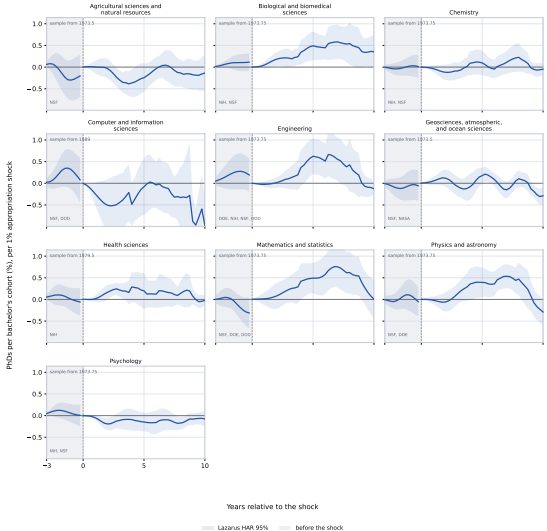
- Long-run growth rate $\uparrow \approx$ 6 basis points.
- 0.28% increase in welfare.
  - Across BGPs, 2.1% increase in welfare.

Conclusion

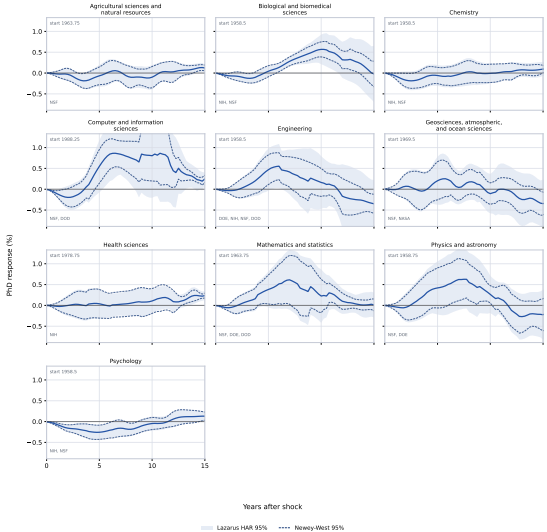
- Doctoral education is important for economic growth.
- It is hard to identify research talent ex-ante.
- This means the marginal entrant is much closer to the average ceteris paribus.
- Short-term cuts reduce welfare, but long-term cuts reduce welfare substantially more.
- University support is substantially more effective than R&D tax credits at increasing growth.

Appendices

All Fields — Cyclical Stock Controls

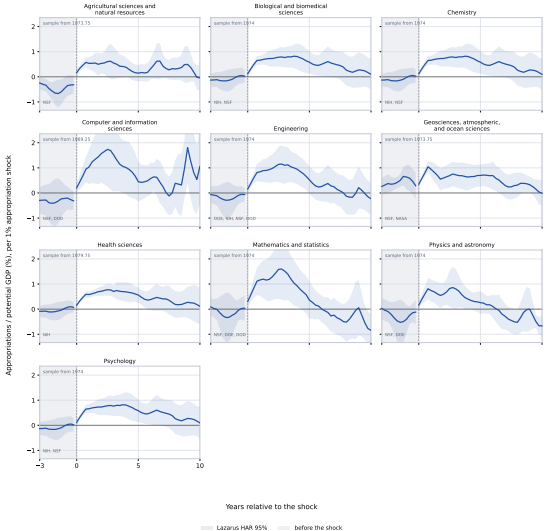


All Fields — Basic Specification



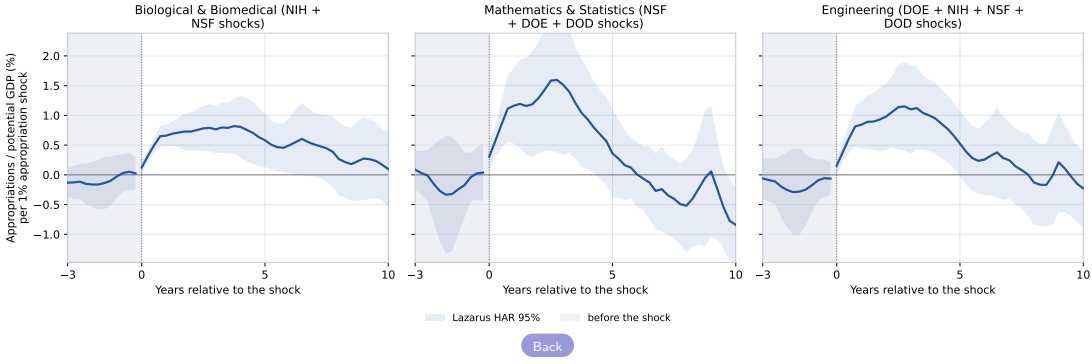
Back

First Stage: Appropriation Responses

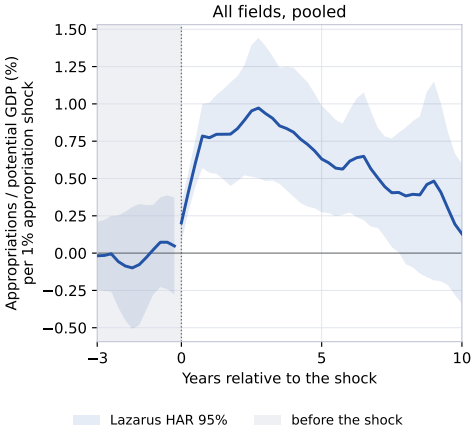


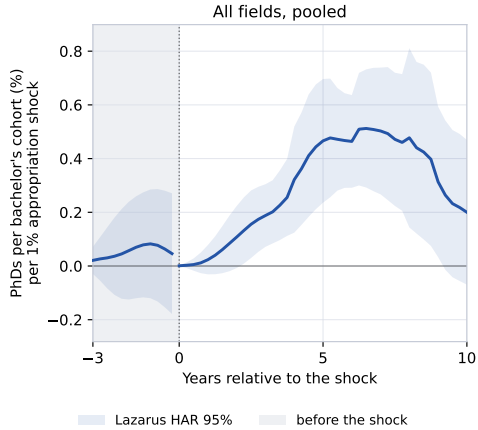
Back

First Stage: Appropriation Responses



All Fields Pooled

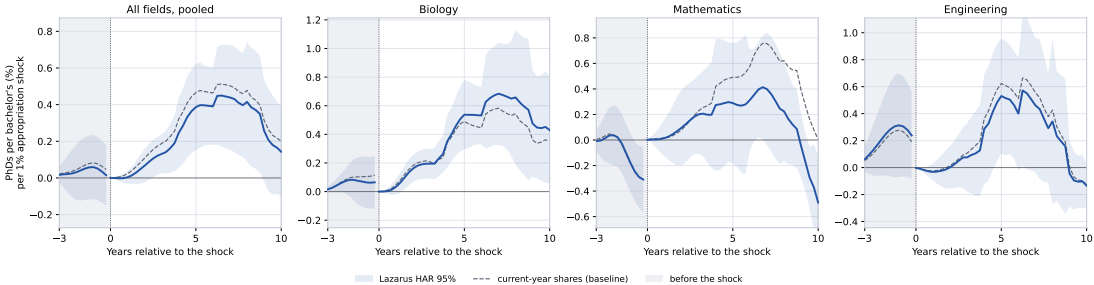




The ten fields stacked on the same sample as the field panels: field fixed effects, one shock coefficient, common lag and control coefficients.

Back

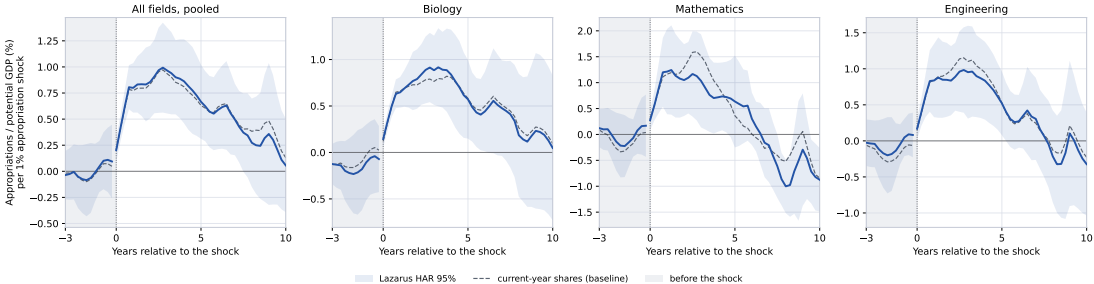
Predetermined Agency Shares



Agency weights from fiscal years before the shock's (two years earlier); dashed: current-year weights (baseline). Sample from 1975.

Funding Back

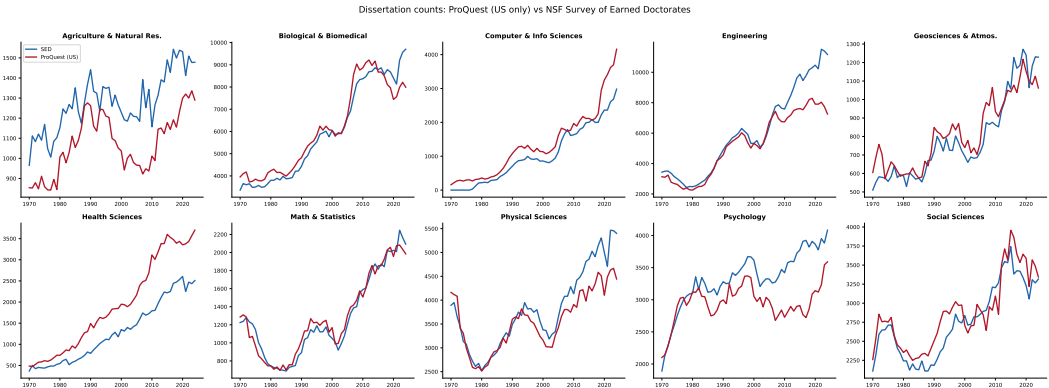
Predetermined Agency Shares: Funding



Appropriations / potential GDP. Agency weights from fiscal years before the shock's (two years earlier); dashed: current-year weights (baseline). Sample from 1975.

PhDs per Bachelor's Back

ProQuest Coverage



Back

PatentsView

- Restrict to patents with ≥ 1 currently domiciled U.S. inventor.
  - 4,391,716 patents.
- Further restrict to assigned patents.
  - 3,832,919 patents.

Back

Sample by Decade

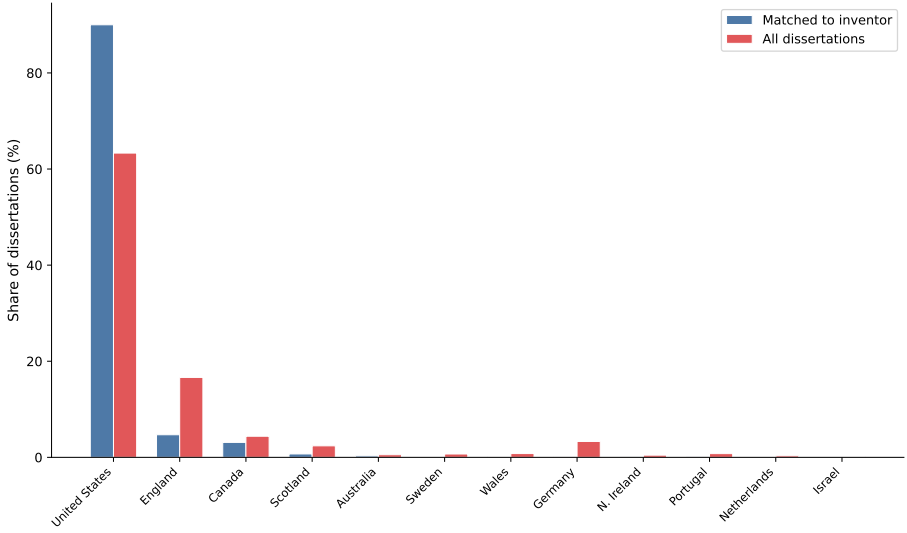
	Patents			Inventors		
Decade	Total	w/ PhD	%	Total	PhD	%
1970s	120,904	30,650	25.4%	100,088	14,037	14.0%
1980s	305,681	84,739	27.7%	223,504	32,762	14.7%
1990s	485,380	168,060	34.6%	379,543	62,805	16.5%
2000s	745,716	300,225	40.3%	533,813	93,236	17.5%
2010s	1,307,905	562,084	43.0%	777,951	139,420	17.9%
2020s	867,333	388,978	44.8%	633,466	120,667	19.0%
Total	3,832,919	1,534,736	40.0%	1,706,516	264,996	15.5%

Assigned patents with ≥ 1 US-located inventor, by grant year.

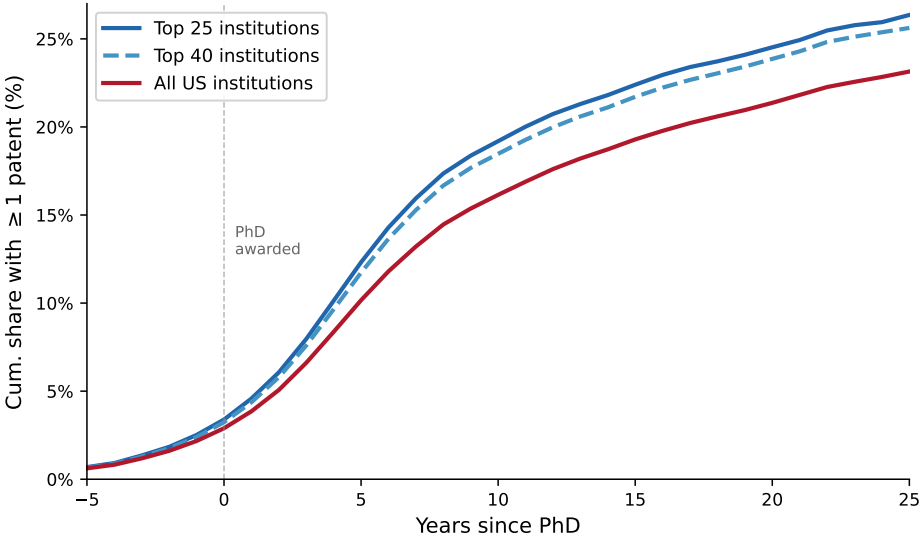
Inventors in a decade are counted once per decade; the total counts each once.

Back

Dissertations by Country



Cumulative Patenting Rate of STEM PhDs



Matching: An Example

PatentsView: matched patents

Method for determining a border in a complex scene with applications to image masking

Gregg D. Wilensky; **Scott Cohen**
Filed 2000-05-08 · Granted 2002 · Adobe
G06T7/12 edge segmentation (2 CPC)

Classifying colors of objects in digital images

Scott Cohen and 3 co-inventors
Filed 2019-07-22 · Granted 2022 · Adobe
G06T7/90 colour characteristics (9 CPC)

ProQuest dissertations

Finding color and shape patterns in images

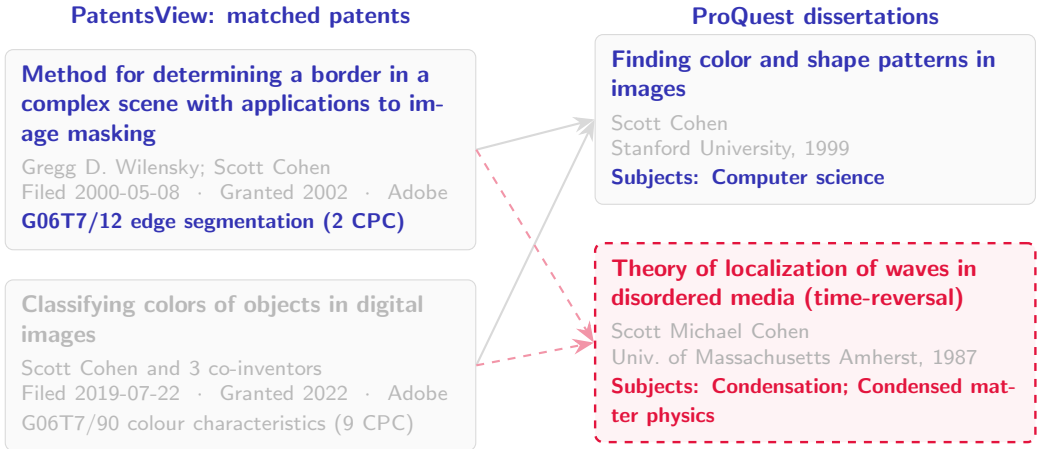
Scott Cohen
Stanford University, 1999
Subjects: Computer science

Theory of localization of waves in disordered media (time-reversal)

Scott Michael Cohen
Univ. of Massachusetts Amherst, 1987
Subjects: Condensation; Condensed matter physics

Algorithm Details · Back

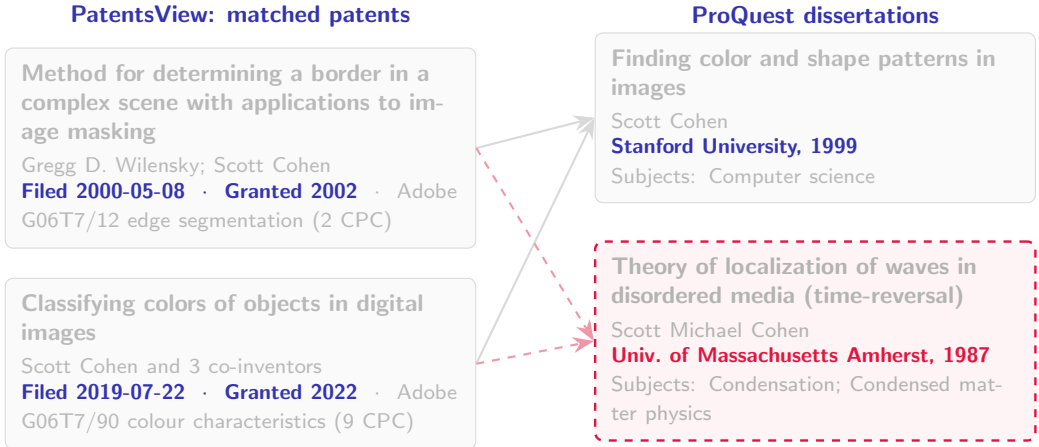
Matching: An Example



Text. SPECTER2 cosine 0.891 mean vs. 0.795 for the alternative.

Algorithm Details · Back

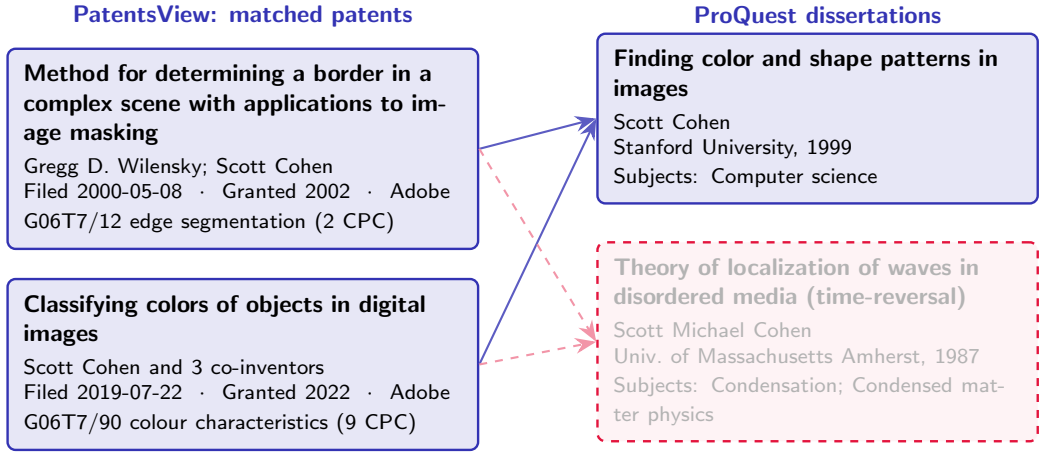
Matching: An Example



Timing. Degree conferred 1999 (alternative: 1987); first filing 2000-05-08.

Algorithm Details · Back

Matching: An Example



Corroboration. 148 patents related to dissertation. Validation

Algorithm Details · Back

Example CPC Classes

CPC Classes

A01 Agriculture
A61 Medical / pharma / devices
B33 Additive manufacturing / 3D printing
B60 Vehicles
B81 MEMS / microstructural tech
B82 Nanotechnology
C07 Organic chemistry
C08 Polymers
C12 Biochem / genetic engineering
C22 Metallurgy / alloys
C23 Thin-film coating (CVD/PVD)
C30 Crystal growth
G01 Measurement / sensing
G02 Optics / photonics / displays
G05 Control / automation / autonomous
G06 Computing / AI / image
G11 Information storage
G16 ICT (bio/health informatics)
G21 Nuclear (fission + fusion)
H01 Basic electric elements / semiconductors
H02 Power
H03 Electronic circuitry
H04 Communications
H05 Electronics NEC
H10 Semiconductor devices

CPC Subclasses

B25J Robotics / manipulators
F03D Wind power
G03F Photolithography
G10L Speech analysis / synthesis

Matching Algorithm

1. Embed (dissertation titles + subjects) and (patent titles + abstracts) using SPECTER
2. Block on inventor surname + given name variants (4 stages, strict $\rightarrow$ loose)
3. Within each block, compute cosine similarity of embeddings
4. Score = text similarity + name quality + temporal proximity + advisor co-invention
5. Greedy 1-to-1 assignment (each inventor $\leftrightarrow$ one dissertation)
6. Filter: mean text similarity ≥ 0.80, corroboration ratio ≥ 0.80 or ≥ 8 corroborating patents

488,775 raw matches $\rightarrow$ 264,996 pass threshold. STEM fields only.

Back

ORCID Precision

Stage	TP	FP	N	Precision
1 (name + corroboration)	311	12	323	96.3%
2 (name only)	328	38	366	89.6%
3 (advisor)	6	1	7	85.7%
Total	**645**	**51**	**696**	**92.7%**

696 ORCID PhD holders linked to analysis sample via patent + name.
School matching determines TP/FP.

Back

Constructed Match vs. Administrative Data

		Inventor Share (%)			Patent Share (%)		
CPC	Description	Admin	ProQuest	Diff	Admin	ProQuest	Diff
H10	Semiconductors	29.5	23.1	−6.4	61.1	60.7	−0.4
H01	Basic electronics	17.6	14.9	−2.7	38.3	36.6	−1.7
A61	Medical/pharma	14.4	12.3	−2.1	25.2	26.9	+1.7
G01	Instruments	16.7	14.7	−2.0	32.2	32.8	+0.6
G06	Computing	9.0	7.6	−1.4	22.5	23.4	+0.9
H04	Telecom	8.0	7.6	−0.4	25.9	27.6	+1.7
B60	Vehicles	5.7	5.4	−0.3	12.5	14.9	+2.4
H02	Power generation	10.0	9.7	−0.3	22.6	23.2	+0.6
A01	Agriculture	9.1	9.7	+0.6	20.0	24.1	+4.1
Mean abs. diff				**1.8pp**			**1.6pp**
Rank corr. ρ				**0.98**			

Admin: SED–PatentsView linkage (Goldschlag et al.). US STEM PhDs 2000–2017, patents 2018–2023.

Back

University Specialization

CPC Class	University	Share (%)	Patents	Total
C08 Polymers	SUNY ESF	17.8	309	1,738
	Southern Miss	23.4	1,062	4,531
	Akron	23.7	3,034	12,816
	All universities avg.	*1.7*		
G02 Optics	Kent State	19.0	675	3,555
	U. Arizona	8.4	2,807	33,244
	UCF	7.8	482	6,201
	Rochester	7.9	2,460	30,985
	All universities avg.	*1.2*		
A01 Agriculture	North Dakota State	16.5	708	4,299
	Nebraska	10.9	1,079	9,918
	Iowa State	9.2	3,392	36,672
	All universities avg.	*1.8*		
B60 Vehicles	U. Detroit Mercy	15.4	170	1,106
	Wayne State	5.1	785	15,425
	Michigan	2.8	2,106	75,985
	All universities avg.	*1.4*		

Share = % of university's matched PhD-inventor patents in that CPC class.

P(PhD Field | CPC Subclass)

Subclass	CS/IT	Chem	EE	Bio	Biomed	Phys
G06F Computing	**42**		24			5
C07D Heterocyclic		**77**		9	10	
A61K Pharma		**41**		22	24	
H04L Digital transm	29		**48**			
C07K Peptides		30		**43**	17	
H04W Wireless	14		**70**			
G01N Material anal.		**28**	7	21	11	12
H01L Semiconductors		13	29			**35**
C12N Genetic eng.		22		**52**	10	
A61B Diagnosis	6	8	16	8	**26**	8

Each row sums to 100% across all 12 fields (6 largest shown). Bold = modal field. Cells $< 5\%$ omitted.

Additional Tables

PhD Share of Critical & Emerging Technology Patents

	Technology Area	Patents	All PhD	US-Trained	
1	AI/ML & Autonomy	31,731	52.5%	49.5%	CPC
2	HPC & Semiconductors	33,678	69.9%	67.6%	CPC
3	Quantum Information	1,119	76.1%	73.2%	CPC
4	Robotics & Adv. Manufacturing	15,077	42.8%	40.2%	CPC
5	Disaster Prevention	3,808	30.7%	27.2%	CPC
6	Communications & Immersive	148,660	44.2%	41.3%	CPC
7	Biotech & Medical	124,735	55.4%	52.0%	CPC
8	Data Storage & Cybersecurity	63,858	33.2%	30.6%	CPC
9	Energy & Batteries	19,179	51.8%	49.2%	CPC
10	Advanced Materials	15,740	69.8%	66.7%	CPC
	All Critical Tech	443,339	49.3%	46.3%	
	All Patents	891,018	44.1%	41.1%	

Technology areas from CHIPS & Science Act §10331. Patents granted 2018–2023, first-listed CPC code only.

(1) AI/ML & Autonomy — 52.5% PhD

CPC	Description	Patents	All PhD	US-Trained
G06N	ML/Neural Networks	8,132	63.4%	60.4%
G01S	Radio Navigation/Radar	6,540	53.6%	50.3%
G06V	Image Analysis	6,114	51.7%	48.6%
B60W	Vehicle Control Systems	3,734	47.1%	44.0%
G01C	Navigation/Surveying	3,609	41.3%	38.8%
G05D	Control Systems	3,602	43.9%	41.1%
	Total	31,731	52.5%	49.5%

Summary

(2) HPC & Semiconductors — 69.9% PhD

CPC	Description	Patents	All PhD	US-Trained
H01L	Semiconductor Devices	11,078	67.5%	65.0%
H10D	Semiconductors (reclassified)	7,991	83.0%	80.9%
G11C	Static Stores/Memories	6,289	49.8%	47.5%
H10F	Photovoltaic Devices	2,238	72.3%	70.2%
H10N	Electric Solid-State Devices	1,836	80.2%	77.9%
H10P	Semiconductor Mfg. Processes	1,255	72.8%	70.8%
H10H	Semiconductor Light Sources	1,127	78.8%	76.1%
H10K	Organic Semiconductors	944	79.9%	78.7%
H10W	Semiconductor Packaging	920	71.8%	69.2%
	Total	33,678	69.9%	67.6%

Summary

(3) Quantum Information — 76.1% PhD

CPC	Description	Patents	All PhD	US-Trained
G06N10	Quantum Computing	523	79.3%	73.8%
H10N60	Superconducting Devices	249	81.5%	80.7%
H04L9/0852-58	Quantum Key Distribution	109	49.5%	49.5%
H10D48	Quantum Effect Devices	98	68.4%	68.4%
B82Y10	Nano Info Processing	77	87.0%	84.4%
H01F6	Superconducting Magnets	40	60.0%	60.0%
H10N69	Superconducting Integrated	23	95.7%	95.7%
	Total	1,119	76.1%	73.2%

Grey: fewer than 100 patents.

Summary

(4) Robotics & Adv. Manufacturing — 42.8% PhD

CPC	Description	Patents	All PhD	US-Trained
B29C	Shaping of Plastics	6,144	40.8%	38.3%
G05B	Control/Regulating Systems	4,096	41.6%	37.9%
B25J	Manipulators/Robots	2,408	53.8%	51.9%
B23K	Soldering/Welding	2,380	39.1%	36.9%
B33Y	Additive Manufacturing	49	42.9%	40.8%
	Total	15,077	42.8%	40.2%

Grey: fewer than 100 patents.

Summary

(5) Disaster Prevention — 30.7% PhD

CPC	Description	Patents	All PhD	US-Trained
G08B	Signalling/Alarm Systems	3,542	28.9%	25.6%
G01W	Meteorology	266	54.9%	48.9%
	Total	3,808	30.7%	27.2%

Summary

(6) Communications & Immersive — 44.2% PhD

CPC	Description	Patents	All PhD	US-Trained
H04L	Digital Transmission	63,269	38.6%	35.6%
H04W	Wireless Networks	28,363	52.3%	49.1%
H04N	Pictorial Communication	21,835	41.0%	38.6%
G06T	Image Processing	14,889	50.1%	47.6%
H04B	Transmission Systems	11,162	62.6%	59.0%
H04M	Telephonic Communication	4,219	26.4%	23.8%
H04R	Loudspeakers/Microphones	4,185	36.6%	32.1%
H04J	Multiplex Communication	738	62.3%	60.0%
	Total	148,660	44.2%	41.3%

Summary

(7) Biotech & Medical — 55.4% PhD

CPC	Description	Patents	All PhD	US-Trained
A61B	Diagnosis/Surgery	38,018	43.9%	40.7%
A61K	Pharmaceuticals	25,990	68.5%	64.8%
A61F	Prostheses/Implants	12,564	33.3%	30.2%
A61M	Devices for Body Cavities	10,701	36.9%	33.3%
C12N	Genetic Engineering	8,308	80.5%	77.2%
C07K	Peptides	7,497	80.3%	76.9%
A61N	Electrotherapy/Radiation	6,491	57.2%	54.0%
C12Q	Measuring/Testing (Bio)	5,424	80.0%	75.2%
G16H	Health Informatics	5,359	43.5%	39.6%
C12P	Fermentation Processes	1,257	78.1%	75.7%
G16B	Bioinformatics	852	77.1%	74.8%
C12M	Bioreactors	848	67.3%	65.4%
A61P	Therapeutic Activity	840	84.3%	81.0%
C07H	Sugars/Nucleosides	586	79.2%	73.4%
	Total	124,735	55.4%	52.0%

Summary

(8) Data Storage & Cybersecurity — 33.2% PhD

CPC	Description	Patents	All PhD	US-Trained
G06Q	Data Processing/Business	34,979	28.4%	25.6%
G06F21	Security Arrangements	11,718	33.8%	30.8%
G11C	Static Stores/Memories	6,289	49.8%	47.5%
H04L9	Cryptography/Security Protocols	5,042	33.7%	32.1%
G11B	Recording/Reproducing	2,855	50.4%	47.8%
G06K	Graphical Data Reading	2,855	34.7%	32.3%
H04K	Secret Communication	120	45.8%	40.8%
	Total	63,858	33.2%	30.6%

Summary

(9) Energy & Batteries — 51.8% PhD

CPC	Description	Patents	All PhD	US-Trained
H01M	Batteries/Fuel Cells	6,259	60.7%	58.1%
H02J	Power Distribution	5,047	37.5%	34.8%
H02K	Electric Machines	2,003	39.0%	36.7%
H10N	Electric Solid-State Devices	1,836	80.2%	77.9%
H02S	Solar Electric Generators	840	39.4%	37.0%
H01G	Capacitors	728	59.9%	58.4%
F03D	Wind Motors	662	41.4%	39.1%
G21C	Nuclear Reactors	552	49.8%	43.3%
C10L	Fuels	473	56.9%	53.7%
F24S	Solar Heat Collectors	237	43.5%	43.0%
G21F	Radiation Protection	177	36.2%	34.5%
G21K	Nuclear Techniques	109	67.0%	63.3%
G21G	Nuclear Transmutation	87	57.5%	56.3%
G21B	Fusion Reactors	80	58.8%	58.8%
G21D	Nuclear Power Plant	54	59.3%	55.6%
G21H	Nuclear Energy Sources	35	71.4%	71.4%
	Total	19,179	51.8%	49.2%

Grey: fewer than 100 patents.

Summary

(10) Advanced Materials — 69.8% PhD

CPC	Description	Patents	All PhD	US-Trained
C09D	Coating Compositions	2,117	67.5%	64.0%
C23C	Coating Metallic Material	2,087	69.2%	66.6%
C08G	Polycondensation Polymers	1,839	77.7%	75.8%
C08F	Addition Polymers	1,771	81.1%	77.3%
C08L	Polymer Compositions	1,444	67.0%	62.9%
C04B	Lime/Ceramics	1,237	57.5%	54.6%
C01B	Non-Metallic Elements/Compounds	1,195	69.8%	66.9%
C08J	Polymer Processing	1,123	65.4%	63.2%
C08K	Polymer Additives	637	66.4%	64.1%
C22C	Alloys	564	65.2%	62.4%
C30	Crystal Growth	384	70.8%	69.3%
B81B	Microstructural Devices	342	70.2%	61.1%
B81C	Microstructural Fabrication	279	74.6%	72.4%
C22B	Production/Refining of Metals	228	53.5%	49.1%
C22F	Working Metallic Powder	212	65.1%	61.3%
C01G	Metallic Compounds	140	77.9%	75.0%
B82Y	Nanotechnology Applications	105	86.7%	83.8%
B82B	Nanostructures	36	97.2%	97.2%
	Total	15,740	69.8%	66.7%

Grey: fewer than 100 patents.

Summary

Ranking Programs

- Use National Research Council 2010 ranking of graduate programs, aggregated to 11 broad fields.
  - Ranking is survey based and covers $\approx$ 5000 programs
  - Survey was run from 2005 to 2006 (restrict to 1990-2010 cohorts to minimize rank drift)
  - Aggregate by averaging over percentile rank of programs within an institution.
  - Robust to other aggregations and running on singletons.
- This ranking predicts:
  1. The intensive margin Show
  2. The extensive margin Show
  3. The exit margin Show

Back

Validation

Precision: ORCID → out of 696 patenting PhDs, 645 correctly matched (92.7%)

Recall: Census match of patents to 2000–2017 PhDs → share of patents differ by 1.6pp

ORCID Census Specialist Universities Fields ◂ Back

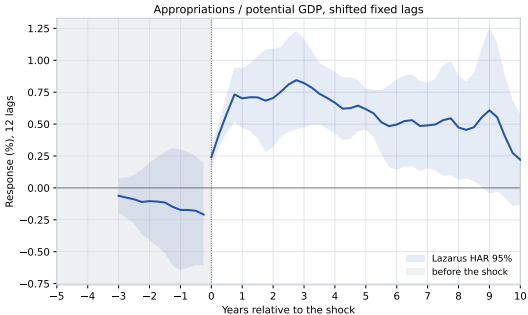
Quality Local Projections

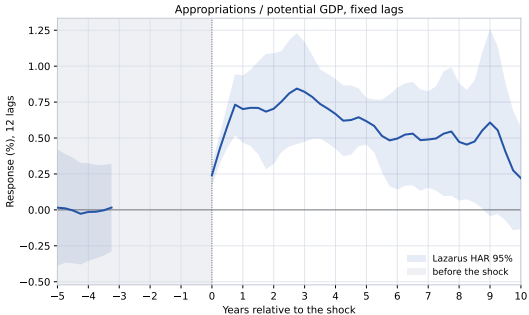
- Patent outcomes need a 10-year window ⇒ only the 1980–2010 cohorts.
- Stack the nine fields: field fixed effects, common coefficients on the shock, lags and controls, 12 lags:

$$\overline{\ln Y}_{f,t+h} = \alpha_f + b_h \varepsilon_{f,t} + \sum_{k=1}^{12} \beta_{h,k} \ln Y_{f,t-k} + \sum_{k=1}^{12} \gamma_{h,k} \ln G_{f,t-k} + \sum_{k=1}^{12} \delta'_{h,k} X_{t-k} + u_{f,t+h}$$

- Patenting boomed in the mid-1990s to early 2000s ⇒ year-adjusted patents per PhD: cohort effects from a Poisson of a cohort's patents on cohort and filing-year effects.
- Outcomes: funding / potential GDP, PhDs per bachelor's, patents per PhD and breakthroughs per PhD (Kelly et al., 2021), each year-adjusted and raw.
- Breakthrough = top decile of KPST importance: ranked within filing year (baseline), net of filing-year means (main slide), KPST's released flag, or one threshold on the unadjusted score.
- Breakthroughs counted over each cohort's first 8 filing years (KPST scores cover the latest cohorts only in part).
- Before the shock: controls fixed at $t-27, \ldots, t-16$ for the last 3 years (left) and at $t-12, \ldots, t-1$ (right, de Fraisse et al. (2026)); Lazarus HAR 95% bands.

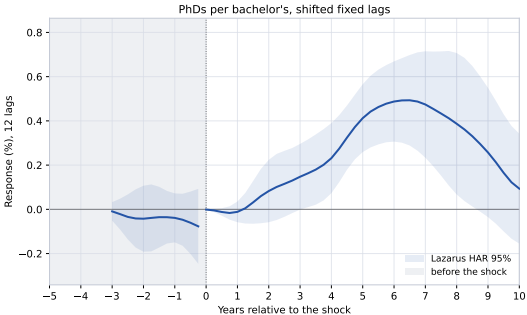
Quality Sample: Funding

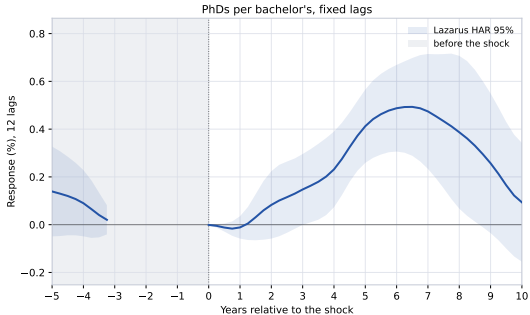




Back

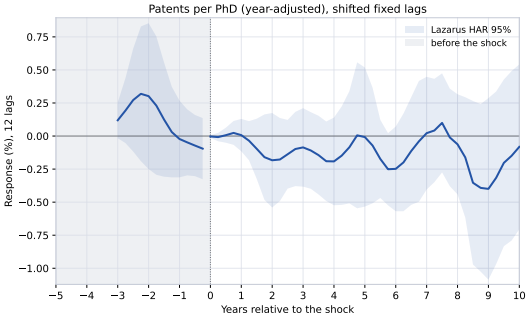
Quality Sample: PhDs per Bachelor's

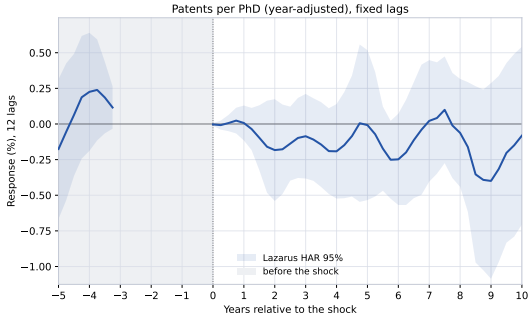




Back

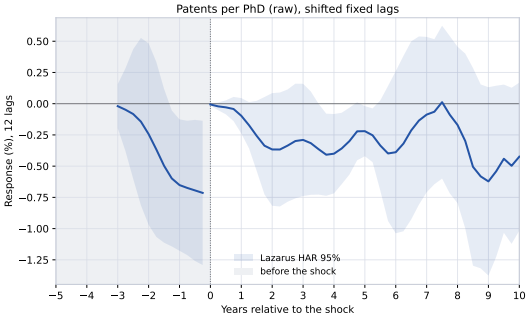
Patents per PhD (Year-Adjusted)

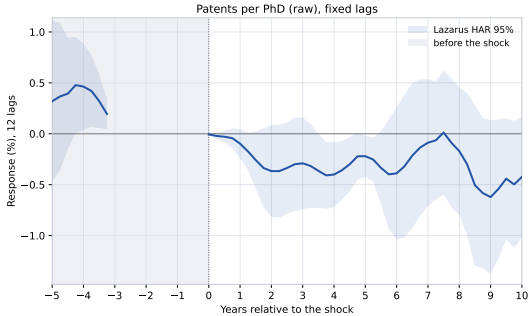




Back

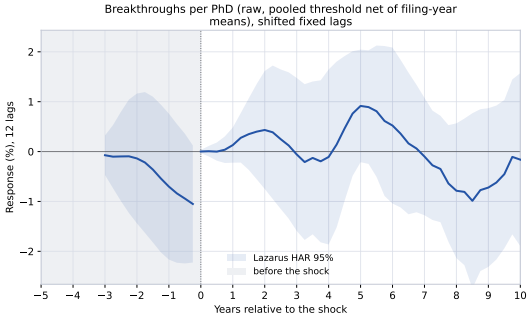
Patents per PhD (Raw)

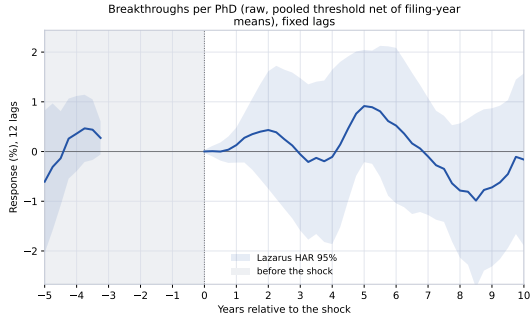




Back

Breakthroughs per PhD (Raw, Net of Filing-Year Means)

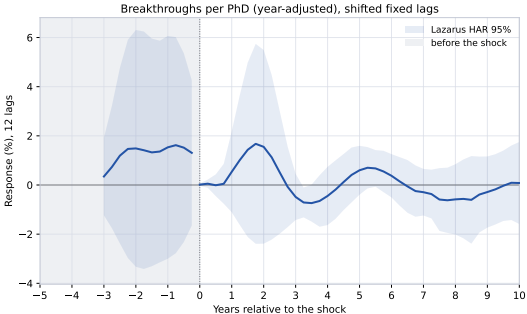


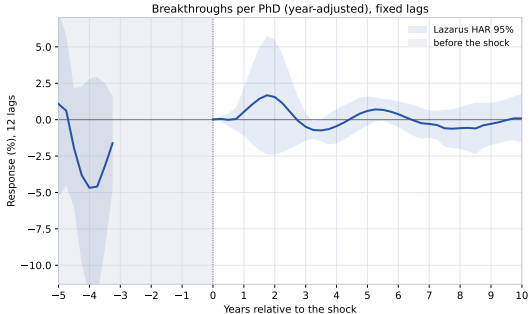


Breakthrough: top decile of KPST importance among all patents, net of filing-year means.

Back

Breakthroughs per PhD (Year-Adjusted)

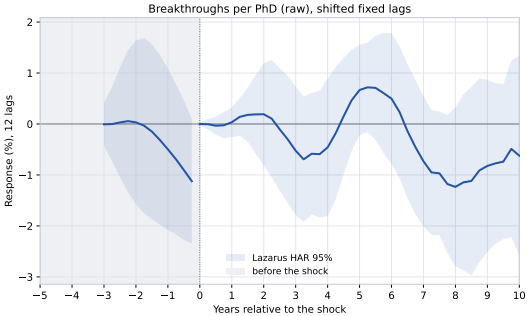


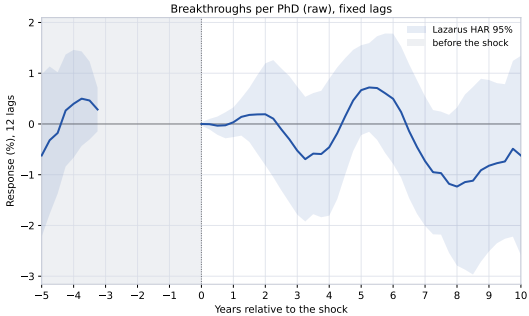


Breakthrough: top decile of KPST importance within filing year.

Back

Breakthroughs per PhD (Raw)

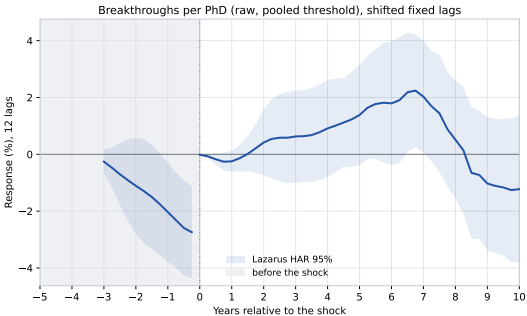


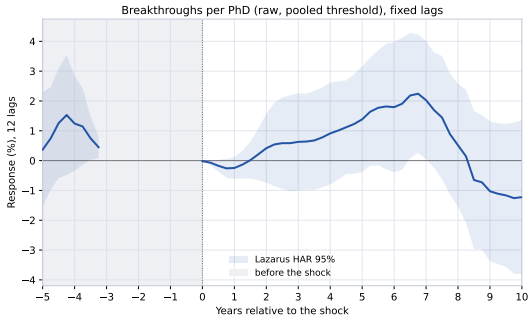


Breakthrough: top decile of KPST importance within filing year.

Back

Breakthroughs per PhD (Raw, No Year Adjustment)

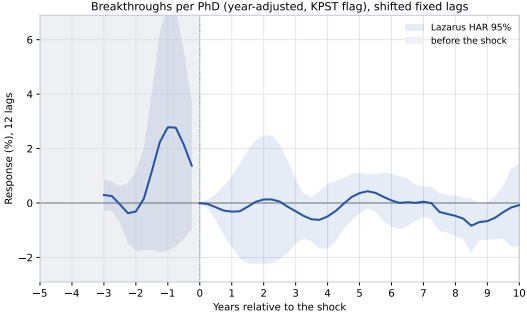


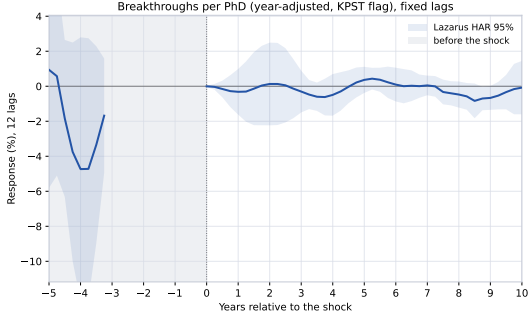


Breakthrough: top decile of KPST importance among all patents, one threshold for every filing year (not ranked within filing year).

Back

Breakthroughs per PhD (KPST Flag, Year-Adjusted)

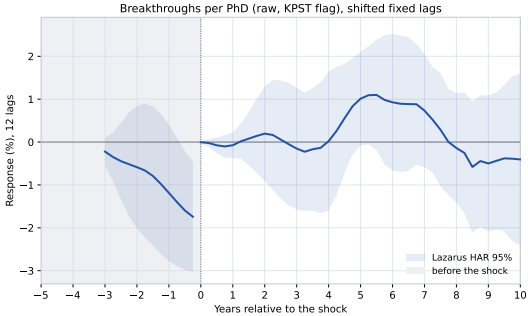


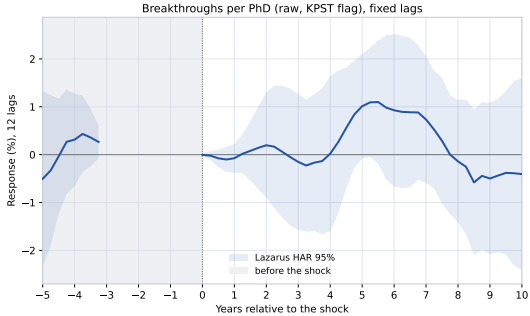


Breakthrough: KPST's released flag (top decile of importance net of issue-year means).

Back

Breakthroughs per PhD (KPST Flag, Raw)

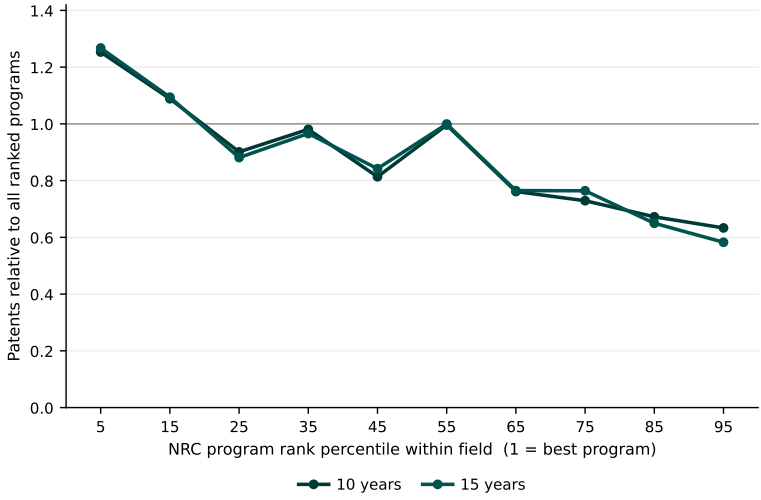




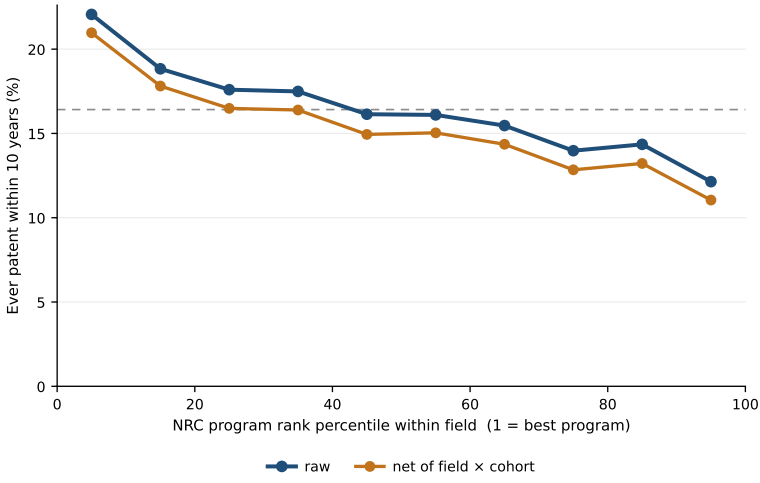
Breakthrough: KPST's released flag (top decile of importance net of issue-year means).

Back

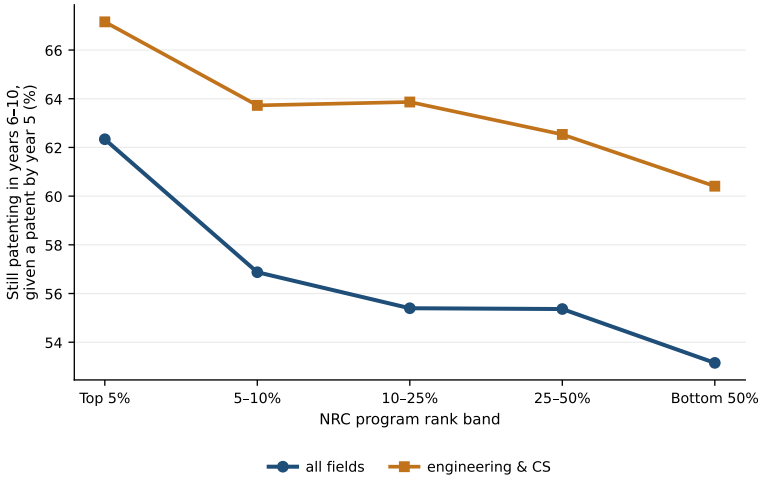
NRC Rank Predicts the Intensive Margin



NRC Rank Predicts the Extensive Margin

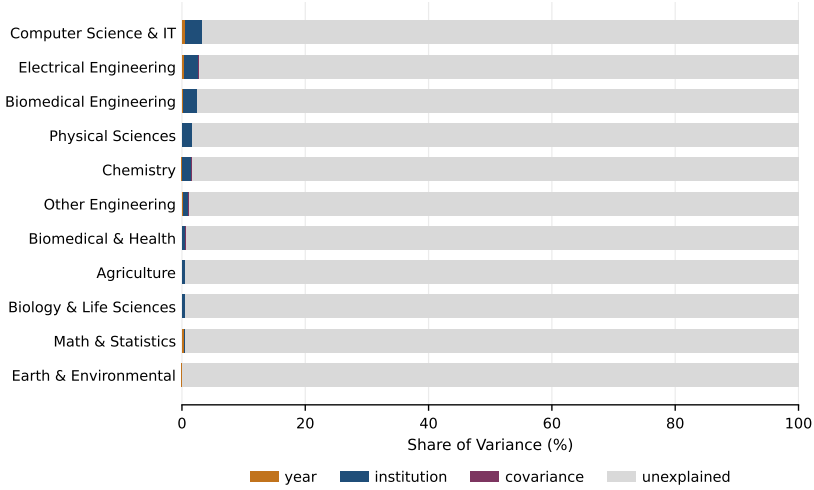


NRC Rank Predicts Exit from Patenting



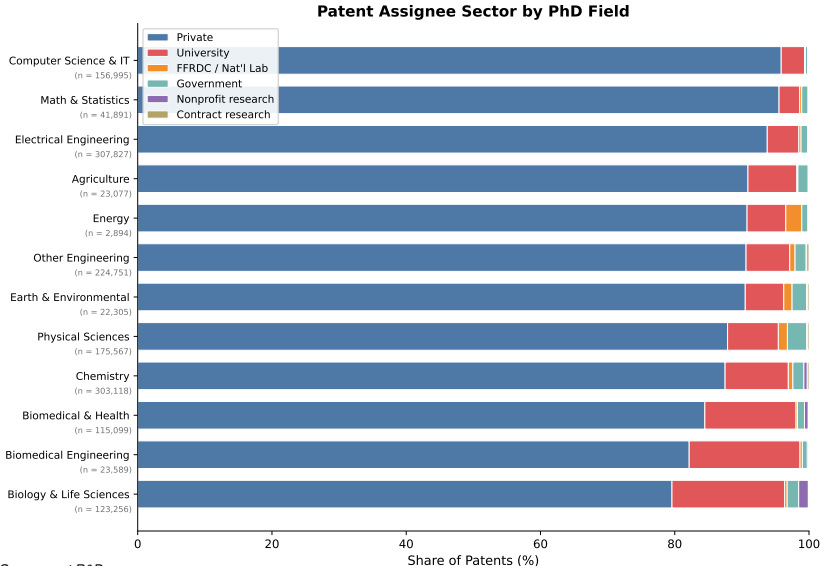
Empirical Robustness

Institutions Explain 1.5% of the Variance in 10 Year Patenting

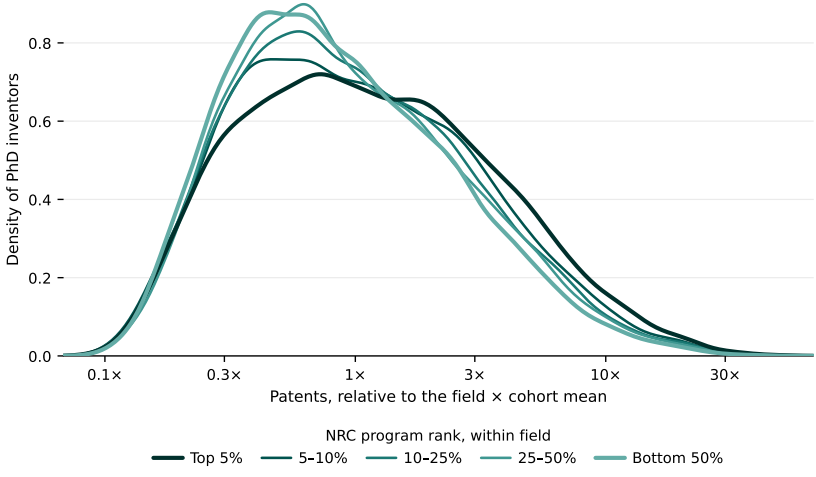


Heteroskedasticity | Capture Curves | Tail Index by Tier | Back

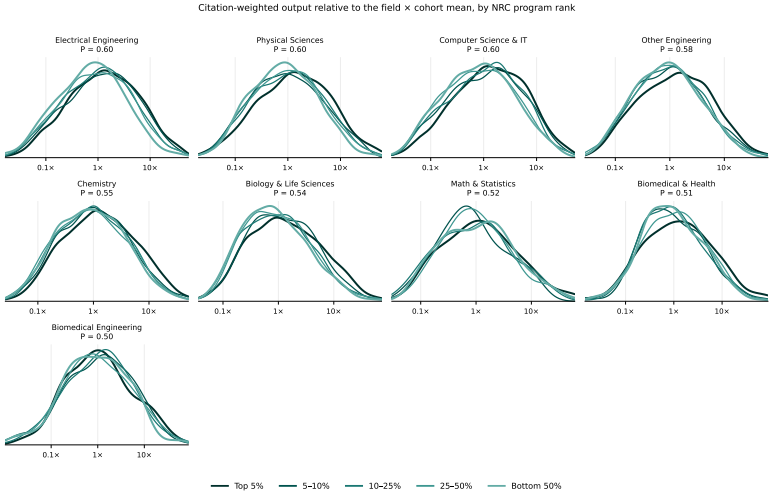
Most PhD Patents Are Assigned to Private Sector Firms



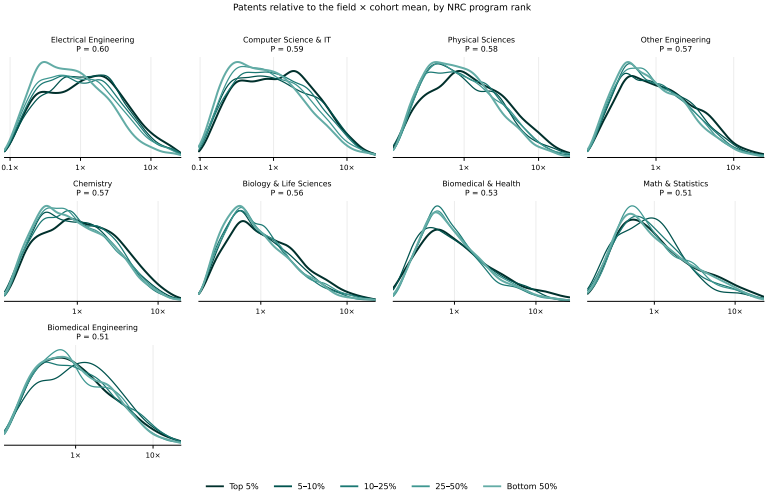
Raw Patent Density



Raw Density by Field



Raw Density by Field



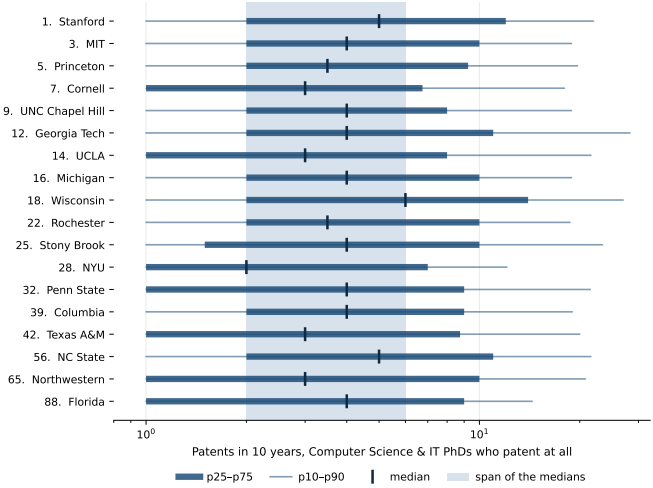
How Often Does a Bottom-50% Program Beat a Top-5% Program?

	Inventors		Mann–Whitney			van Elteren		
Field	Bottom 50%	Top 5%	P(beats)	95% CI	p	P(beats)	95% CI	p
All fields	13,680	11,430	0.420	[0.402, 0.437]	<0.001	0.426	[0.413, 0.440]	<0.001
Biology	1,752	1,128	0.458	[0.426, 0.484]	0.005	0.454	[0.421, 0.484]	0.004
Biomed. & health	792	365	0.486	[0.417, 0.544]	0.661	0.467	[0.392, 0.534]	0.367
Biomed. eng.	592	323	0.497	[0.443, 0.561]	0.918	0.500	[0.445, 0.566]	0.991
Chemistry	2,924	2,326	0.447	[0.424, 0.470]	<0.001	0.435	[0.412, 0.460]	<0.001
CS & IT	1,127	1,520	0.401	[0.369, 0.431]	<0.001	0.404	[0.374, 0.431]	<0.001
Elec. eng.	1,657	2,201	0.396	[0.345, 0.448]	<0.001	0.395	[0.346, 0.447]	<0.001
Math & stat.	328	217	0.477	[0.429, 0.534]	0.386	0.477	[0.427, 0.528]	0.364
Other eng.	1,979	1,930	0.417	[0.395, 0.454]	<0.001	0.422	[0.401, 0.459]	<0.001
Physical sci.	1,811	1,338	0.401	[0.369, 0.431]	<0.001	0.400	[0.367, 0.431]	<0.001

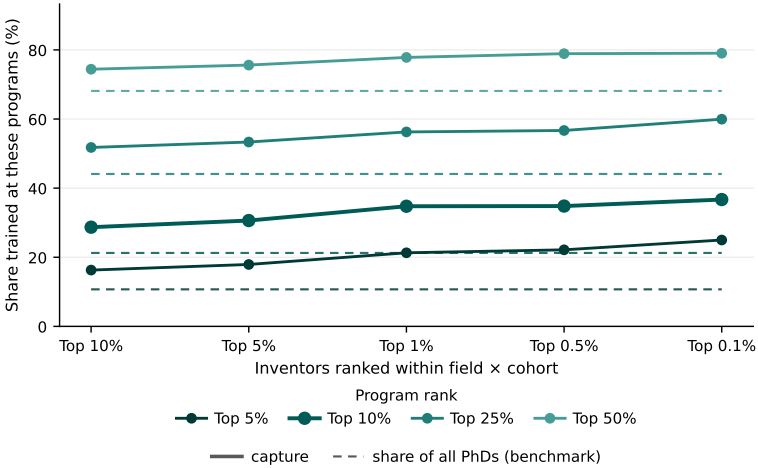
P(beats): the probability that a Ph.D. inventor from a bottom-50% program has more quality-adjusted patents filed within ten years of the degree than one from a top-5% program, output relative to the field $\times$ degree-year geometric mean, ties counted one half. Mann–Whitney compares every pair in the row, van Elteren only pairs in the same field and degree year. Intervals and p-values (P(beats) $= 0.5$) resample whole programs, 9,999 draws. Fields with fewer than 100 inventors in either group are omitted: Agriculture, Earth & Environmental.

Back

Within Dispersion is not Concentrated at Top Programs

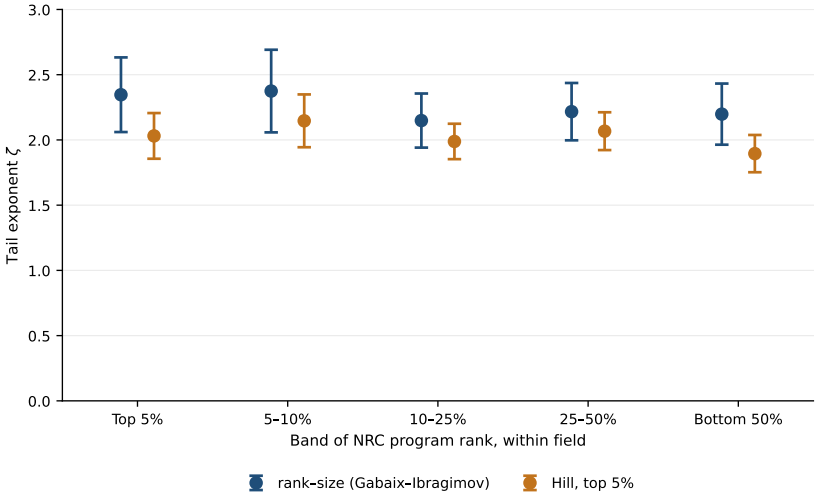


The Tail is not Captured by the Top



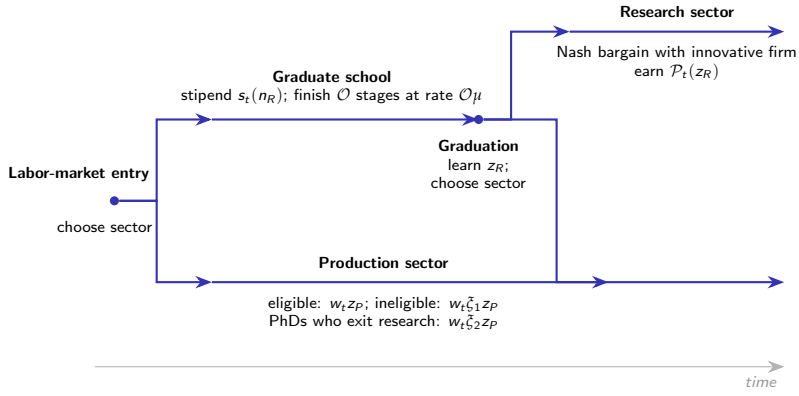
Back

Tail Index by Tier



Baseline Model

Timeline



Back

Individual HJBs

- Production worker with efficiency units $z \in \{\xi_1 z_P,\ z_P,\ \xi_2 z_P\}$

$$(\rho + \delta) W_t(z) - \dot{W}_t(z) = \ln\big((1 - \tau_W)(w_t z + \Pi_t)\big)$$

- Graduate student in stage o of an $\mathcal{O}$-stage Erlang

$$(\rho + \delta + \mathcal{O}\mu) G_t(o, n_R) - \dot{G}_t(o, n_R) = \ln\big((1 - \tau_W)(s_t(n_R) + \Pi_t)\big) + \mathcal{O}\mu\, G_t(o+1, n_R)$$
$$G_t(\mathcal{O}+1, n_R) = \mathbb{E}\big[\max\big\{R_t(z_R), W_t(\xi_2 z_P)\big\} \mid n_R\big]$$

Back

Research Details

- Researcher

$$(\rho + \delta)R_t(z_R) - \dot{R}_t = \ln((1 - \tau_W)(\mathcal{P}_t(z_R) + \Pi_t))$$

- Matched innovative firm has value:

$$(r^* + \delta)\mathcal{V}_t(z_R; P_t(z_R)) - \dot{\mathcal{V}}_t = V_t\phi_r z_R - \mathcal{P}_t(z_R)$$

- Bargaining at every instant takes future path of payments as given.

Back

Proposition 1

Proposition 1: *Suppose that $K(\cdot)$ is strictly convex and $K(0) = 0$. Then, along the balanced growth path, the equilibrium exhibits a positive ranking on expected research skill: if $\alpha_j > \alpha_{j'}$, then $\bar{m}_j \geq \bar{m}_{j'}$, where $\bar{m}_j$ is the average of $\mathbb{E}[z_R|n_R]$ among program j's admits. If the distribution of n_R is atomless, then this ranking is strict.*

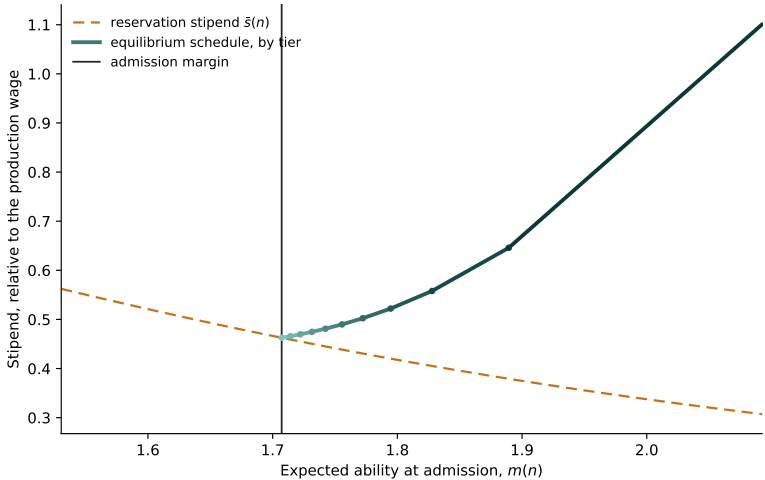
▸ Affine Schedule Lemma ▸ Schedule ◂ Back

Characterizing the Stipend Schedule

Lemma 1: *Order university tiers by productivity so that* $\alpha_1 > \alpha_2 > \cdots > \alpha_J$. *Then the equilibrium stipend schedule at any* t *is piecewise affine in posterior expected productivity,* $\mathbb{E}[z_R|n_R]$, *continuous, and convex.*

Back

The Stipend Schedule



Quantitative Model

Graduate Program: sequence problem

- Tier j college chooses admission measure $x_{j,t} = \int x_{j,t}(n)\, dn$:

$$\max_{\{x_{j,t}(\cdot)\}} \int_0^\infty e^{-r^* t} \int a(n)\, x_{j,t}(n)\, dn\, dt, \qquad a(n) = \mathbb{E}[z_R \mid n]$$

- Subject to cohort break-even:

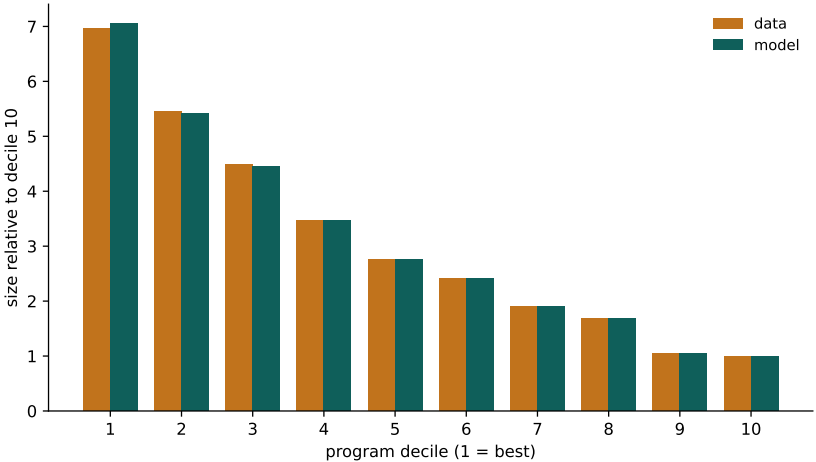
$$K(x_{j,t}) = \int \left[A_{\lambda,t}\big(\alpha_j a(n) - s_t(n)\big) + \mathcal{F}_t \right] x_{j,t}(n)\, dn$$

$$A_{\lambda,t} = \int_0^\infty e^{-\int_0^u (r^* + \delta - g_{t+v})\, dv}\, S(u)\, du, \qquad \mathcal{F}_t = \int_0^\infty e^{-\int_0^u (r^* + \delta - g_{t+v})\, dv}\, S(u)\, f_{t+u}\, du$$

- Functional form: $K(x) = \kappa x^{1+\nu}/(1+\nu)$

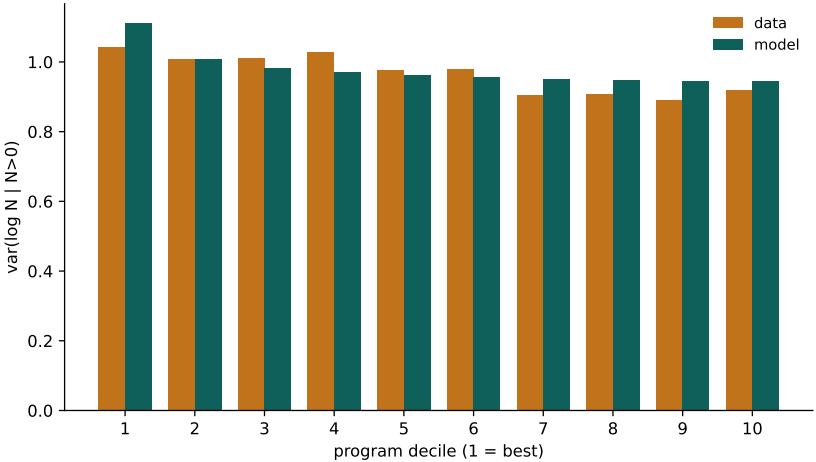
Back

Program Sizes



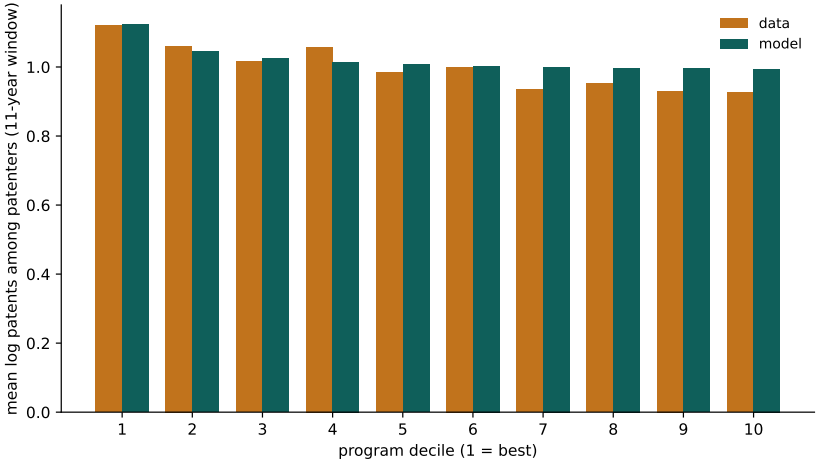
Back

Within-Decile Variance



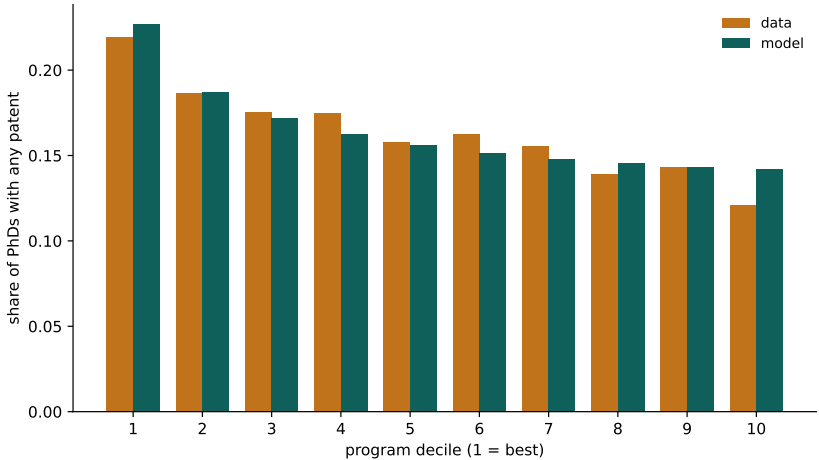
Back

Mean Log Count



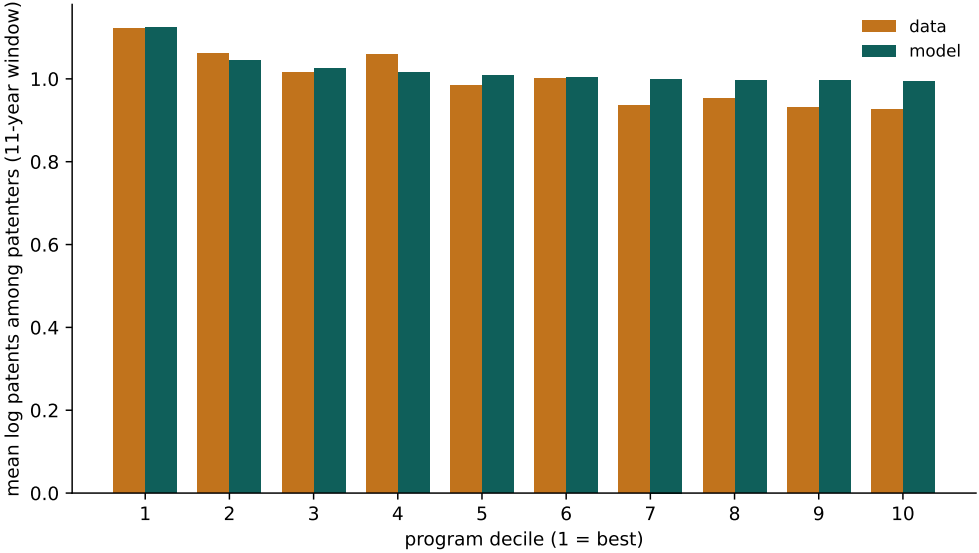
Back

Patent Share

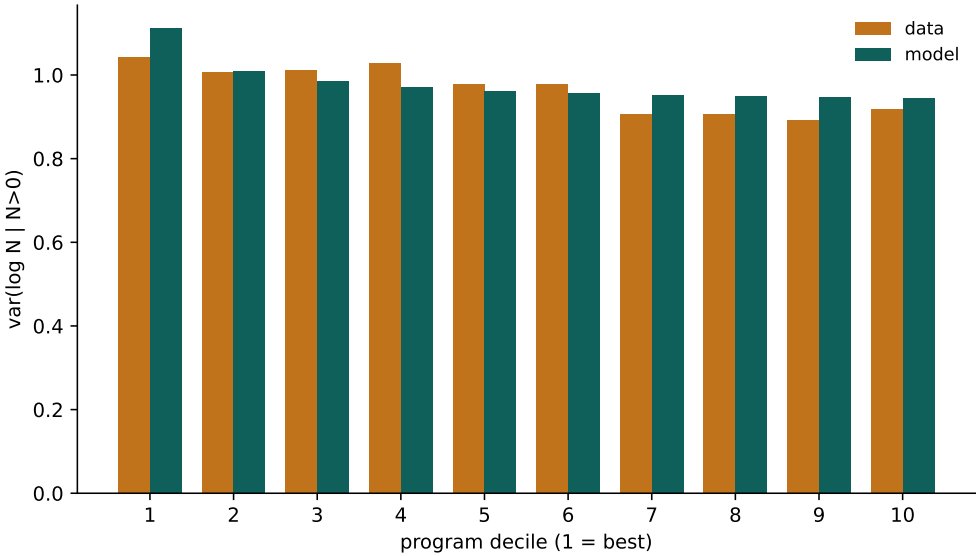


Back

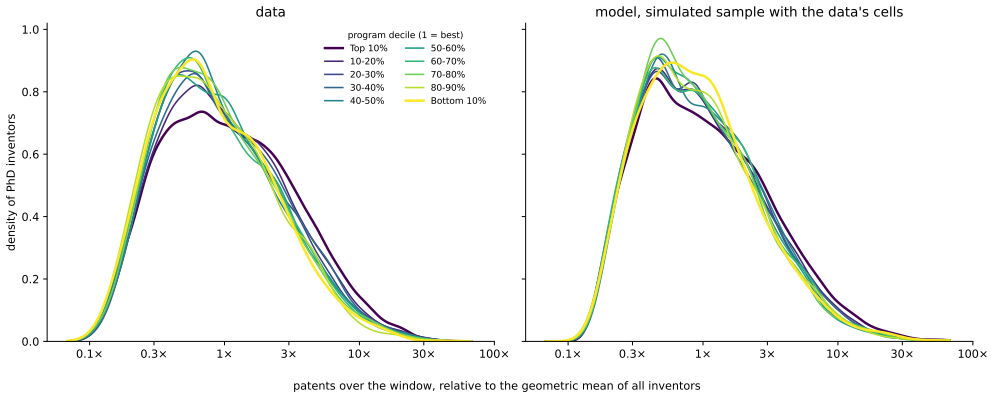
Means


data
model
mean log patents among patenters (11-year window)
0.0
0.2
0.4
0.6
0.8
1.0
1
2
3
4
5
6
7
8
9
10
program decile (1 = best)

Variances

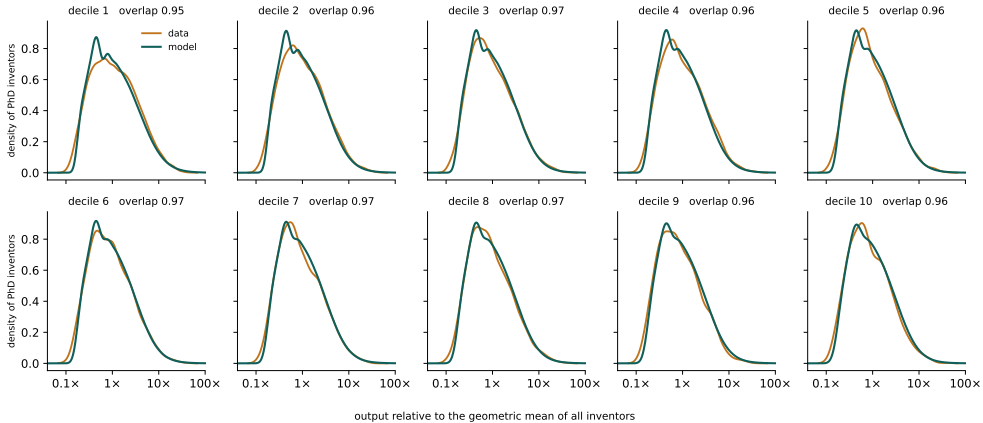

data
model
var(log N | N>0)
0.0
0.2
0.4
0.6
0.8
1.0
1
2
3
4
5
6
7
8
9
10
program decile (1 = best)

Cell Rate Adjusted



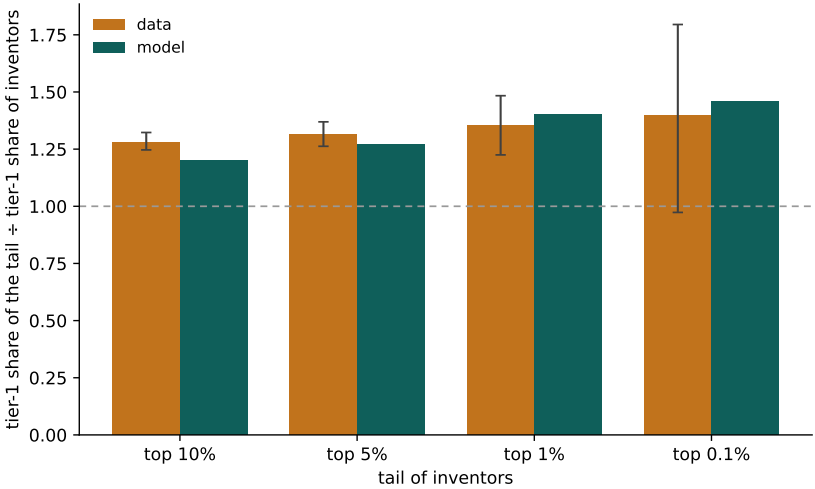
Back

By Decile



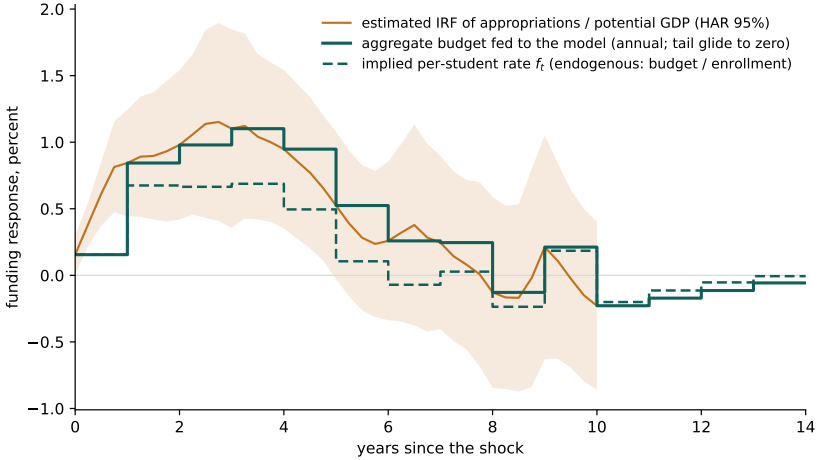
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Capture Curve



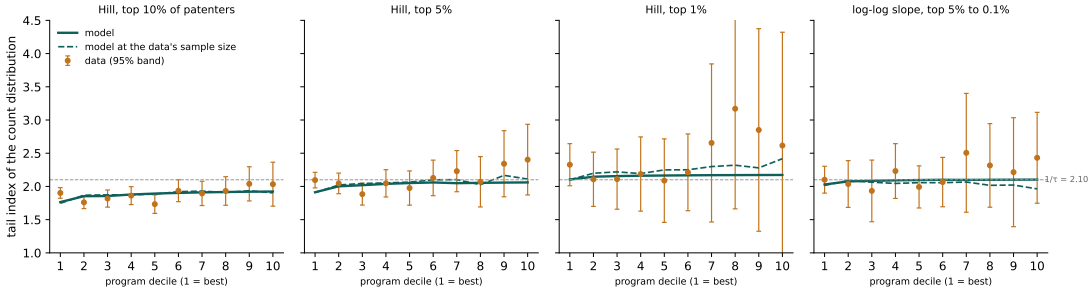
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Funding Input



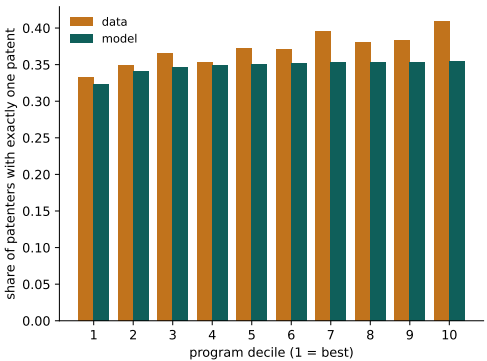
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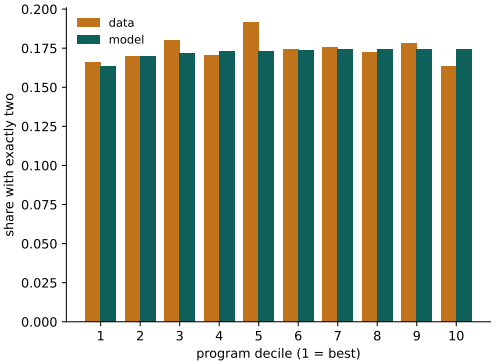
Tail Index: Model vs. Data



◂ Identifying the Tail ◂ Untargeted Moments

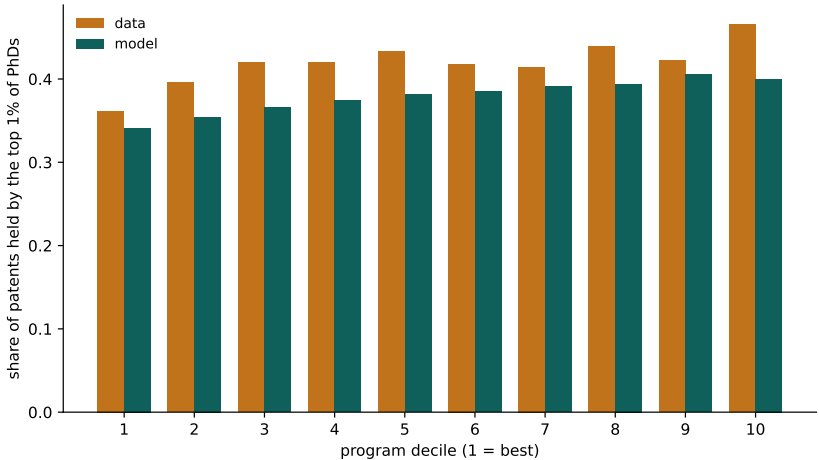
Ones and Twos





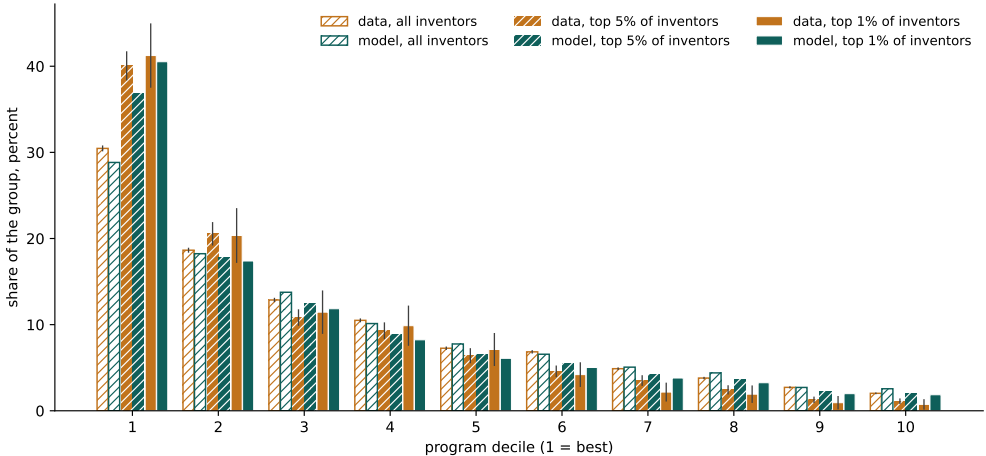
Back

Top 1% Share



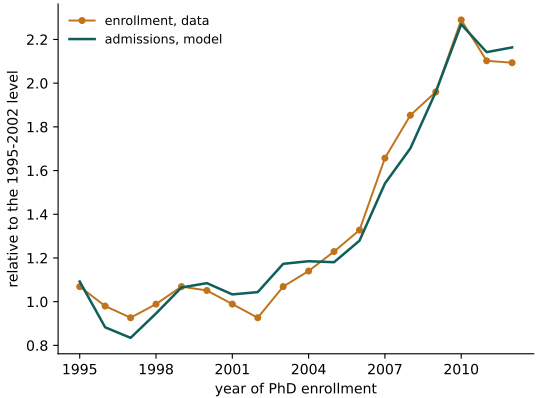
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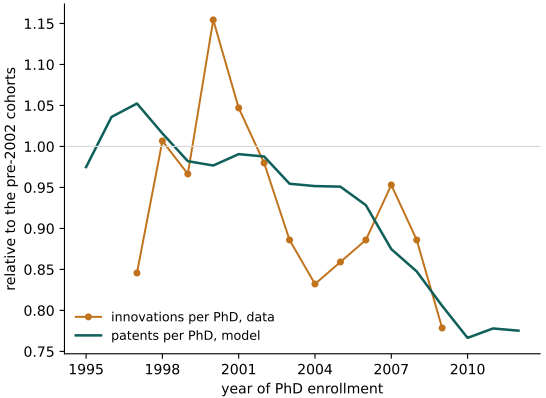
Tail Composition by Decile



Back

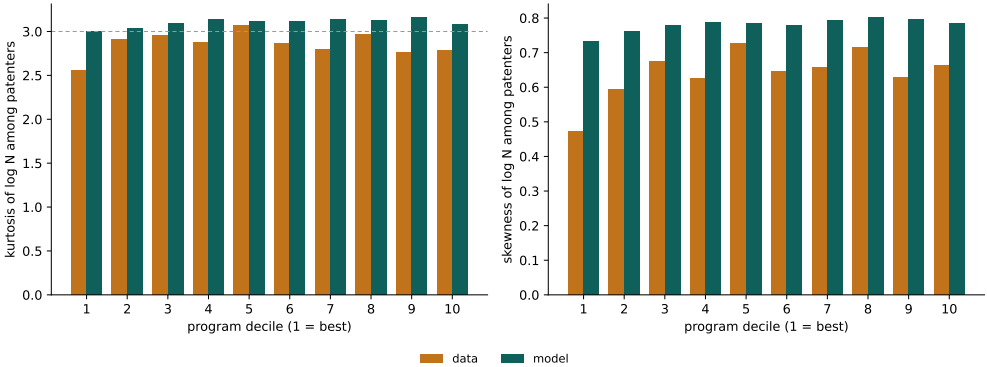
The Danish PhD Expansion: Data and Model





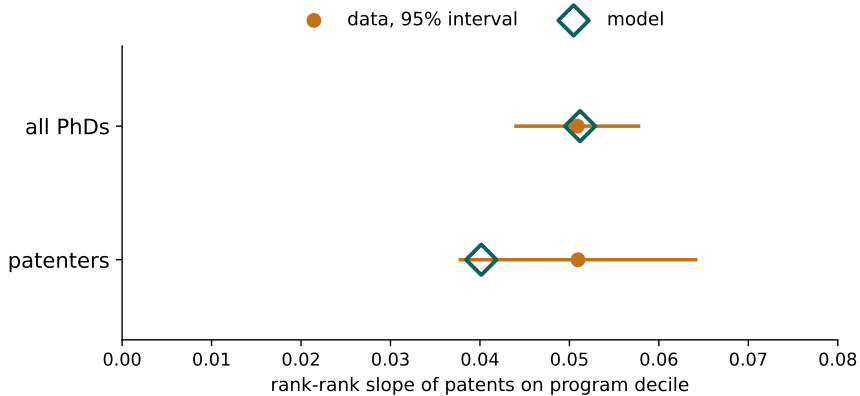
Back

Log-Count Shape



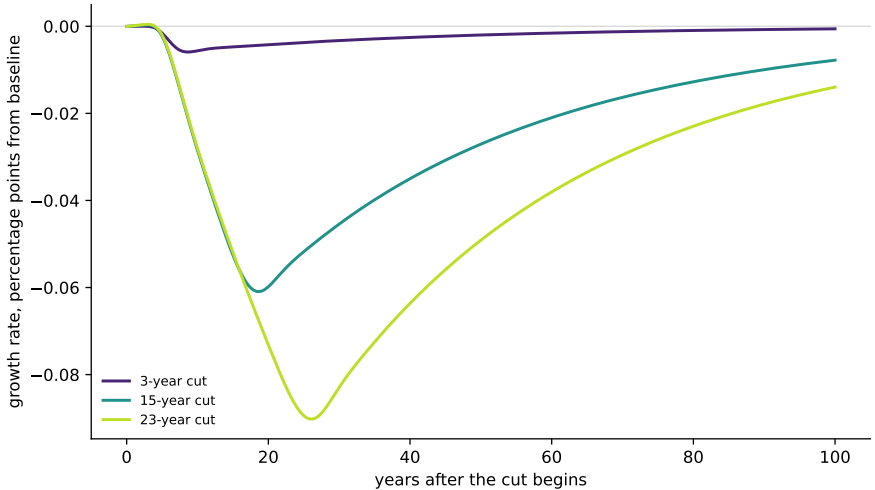
Back

Rank-Rank Slope: Model vs. Data



Back

The Growth Effect of Funding Cuts



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