Direct R&D Subsidies

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Innovation Policy: The "Lightbulb" Table

(1) Policy	(2) Quality of evidence	(3) Conclusiveness of evidence	(4) Benefit - Cost	(5) Time frame:	(6) Effect on inequality
Direct R&D Grants	Medium	Medium		Medium-Run	↑
R&D tax credits	High	High		Short-Run	↑
Patent Box	Medium	Medium	Negative	n/a	↑
Skilled Immigration	High	High		Short to Medium-Run	↓
Universities: incentives	Medium	Low		Medium-Run	↑
Universities: STEM Supply	Medium	Medium		Long-Run	↓
Exposure Policies	Medium	Low		Long-run	↓
Trade and competition	High	Medium		Medium-Run	↑

"Demand"

"Supply"

Source: Bloom, Van Reenen and Williams (2019, JEP)

Innovation Policies: R&D Grants

- **Academic**
  - See earlier lecture by Azoulay and Azoulay & Li (2022)
  - Examples in Health/NIH: Azoulay et al ’19; Jacob & Lefgren, ‘11

- **Private Sector**
  - Fairly large literature (though not as big as R&D tax credits)
  - Example: Green Energy (Howell, ’17 AER)
  - Interactions between tax credit & direct grants (Pless, 2022)

Innovation Policies: R&D Grants

- In contrast to horizontal policies such as tax, R&D grants can be more targeted
  - **Directed** at specific technologies; industries; geographical areas, etc.
- **Upsides:**
  - Can be target to where social benefits are highest – e.g. larger knowledge spillovers; climate change to tackle “double externality”, etc.
  - With general R&D tax credits firms focus on (marginal) **private** value projects
- **Downsides:**
  - Informational asymmetry over what projects are valuable (VCs better, so do “matched funding”? Lerner, 2022)
  - Administrative costs of deciding what & who to fund
  - Political economy risks: capture (Akcigit, Baslandze & Lotti, 2022); difficulty of closing down failing projects; big firms game system? (Criscuolo et al, 2019)
  - Deadweight? Crowd-out private sector (although similar issues with tax)

Identification Challenges/Benefits

- Unlike tax rules, grants are only awarded to specific “winners”, so more variation in who receives
- **But** highly selected - grants are consciously awarded to where agency thinks/claims they will do the most use. Estimating effects on later innov:
  – Bias **upwards** if successful firms more likely to get the funds
  – Bias **downwards** if money goes to compensate “losers”
- Comparing all winners vs. all losers unlikely to get around endogeneity biases. **Solution?:**
- Looking at “just winners” vs. “just losers” in a Regression Discontinuity Design type approach (e.g. Bronzini and Iachini, 2014, 2016 on Italian R&D program; Changes in funding rules generates nonlinearities, Einiö, 2014)
  – Howell (2017) on green energy …..

Howell (2017, AER)

- US Department of Energy green SBIR awards

- Admin data on applications, scores and future outcomes

- **Results:** Phase I award doubles chances of future VC. Also increases patenting and revenue
  - Stronger effects for financially constrained firms

Econometric model

- Regression Discontinuity Design (RDD) based on normalized rank of proposal *i* for competition topic *T* ($Rank_{iT} = 0$ for threshold)

Competition fixed effects

Treatment effect

Running variable

$$Y_{iT} = \alpha_T + \beta\,[1|Rank_{iT} > 0] + \gamma_1[Rank_{iT}|Rank_{iT} > 0] + \gamma_2[Rank_{iT}|Rank_{iT} < 0] + \varepsilon_{iT}$$

Positive effect on VC funding

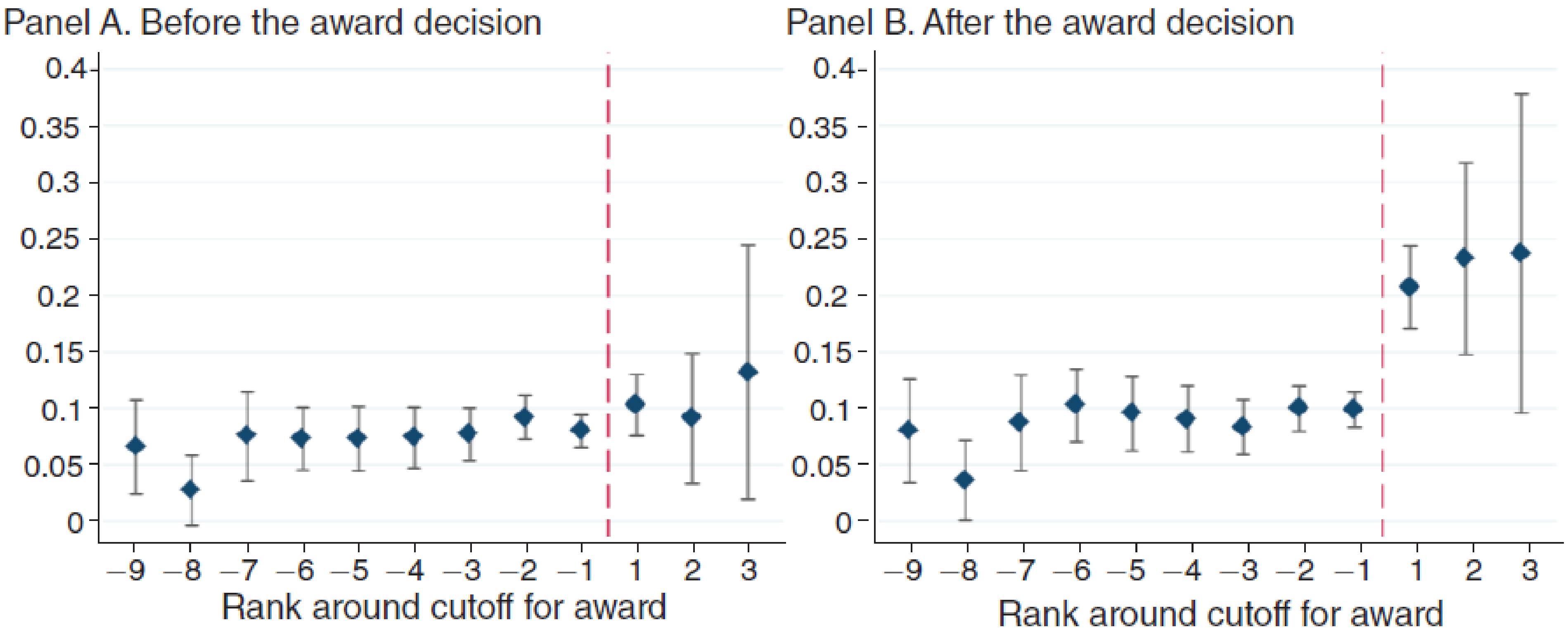

FIGURE 3. PROBABILITY OF VENTURE CAPITAL BEFORE AND AFTER GRANT BY RANK

Notes: This figure shows the fraction of applicants who received VC before and after the Phase 1 grant. Ninety-five percent confidence intervals shown.

Positive effect on innovation (cite-weighted patents)

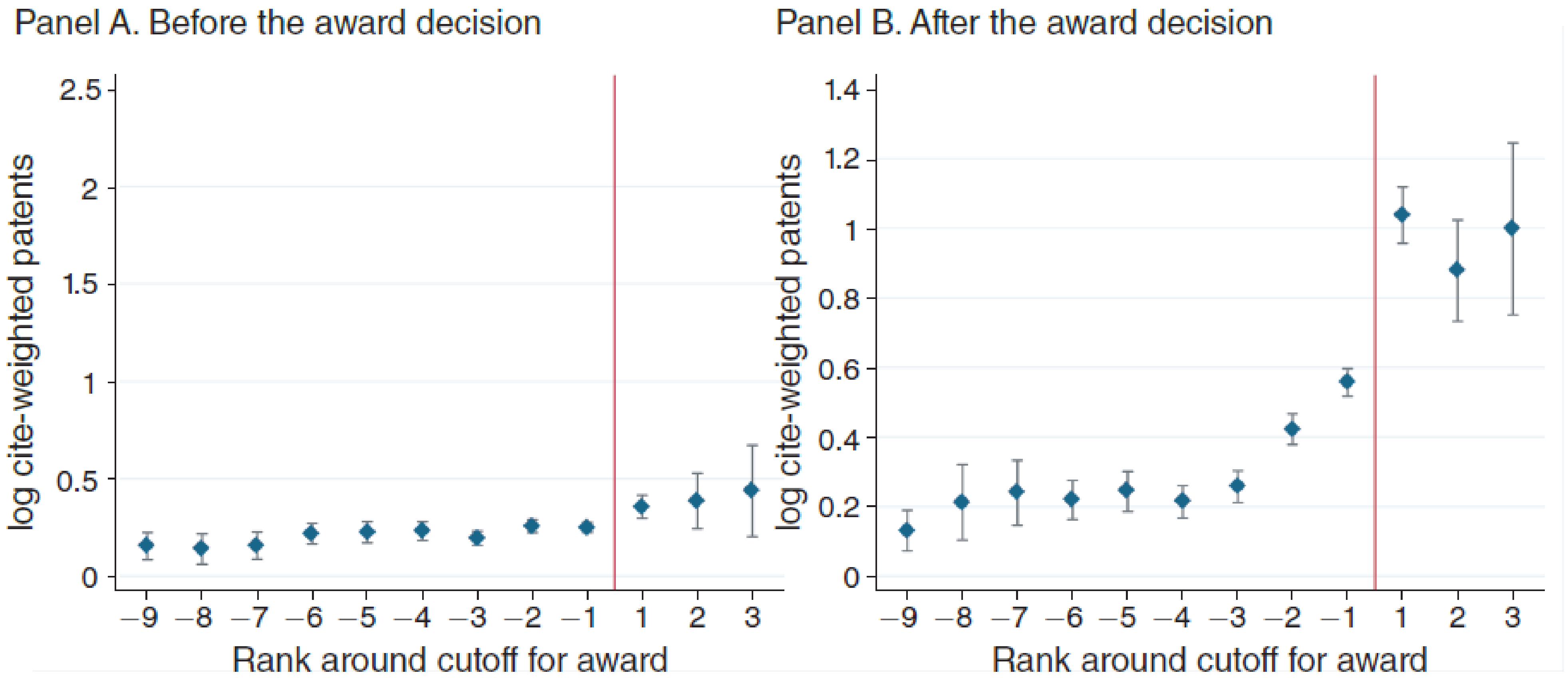

Figure 2. Cite-Weighted Patents before and after Phase 1 Grant by Rank

Notes: This figure shows $\ln(1 + Cites_i^{post})$ before and after the Phase 1 grant award decision, using the patent application date. DOE's rank is centered so $rank_{ic} > 0$ indicates a firm won an award. Ninety-five percent confidence intervals shown.

R&D Grants: Military shocks

- Many innovations from defense spillovers.
  - In US, 60% of all Federal R&D goes to Dept. of Defense (DoD): world's largest R&D supporting entity (6% of global R&D)
  - **Dual-use** aspect of frontier defense technology: large spillovers to private sector (e.g. GPS, cryptography, nuclear power, jet engines, Internet,..)
- US Dept. of Defense lauded as successful Mission-Oriented Industrial Policy. from case studies (e.g. Mazzucato and Semieniuk, 2017)
  - But Howell et al (2022) show that slowdown in US defense innovation even worse than rest of economy

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R&D Grants: Military shocks

- Moretti, Steinwender & Van Reenen (2022) use public R&D hikes induced by **<u>defense shocks</u>**:
  - Example: Post 9/11 ramp up in US military R&D focused more in some sectors (e.g. cyber-ICT, bio-pharma than others medical devices, transport)
  - 26 OECD countries by Industry panel data, 1987-2009
  - French firm level panel data, 1980-2015
  - Find 10% more public R&D stimulates ~5% more private sector R&D in long-run & higher TFP growth

OPENing up Military Innovation: Causal effects of Reforms to U.S. Defense Research

Sabrina Howell (NYU), Jason Rathje (US Air Force),
John Van Reenen (LSE and MIT) and Jun Wong (Chicago)

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Programme on Innovation and Diffusion

Conventional (centralized) vs. OPEN (decentralized) R&D Grants

- Conventional program took centralized top-down approach: tightly specified calls like:
  - *"Affordable, Durable, Electrically Conductive Coating or Material Solution for Silver Paint Replacement on Advanced Aircraft"*
- In response to declining military innovation, US Air Force (USAF) launched OPEN reforms to R&D procurement in their Small Business Innovation Research (SBIR) program
- OPEN Reform allowed firms more freedom to propose the innovations **they** thought USAF needed "unknown unknowns"
- Admin data on all applicants, grant scores and outcomes 1983-2021 to implement a sharp Regression Discontinuity Design

Findings from Howell, Rathje, Van Reenen & Wong (2022)

- New types of firms starting applying & winning: younger, smaller, based in VC hubs of Silicon Valley, Boston, etc.

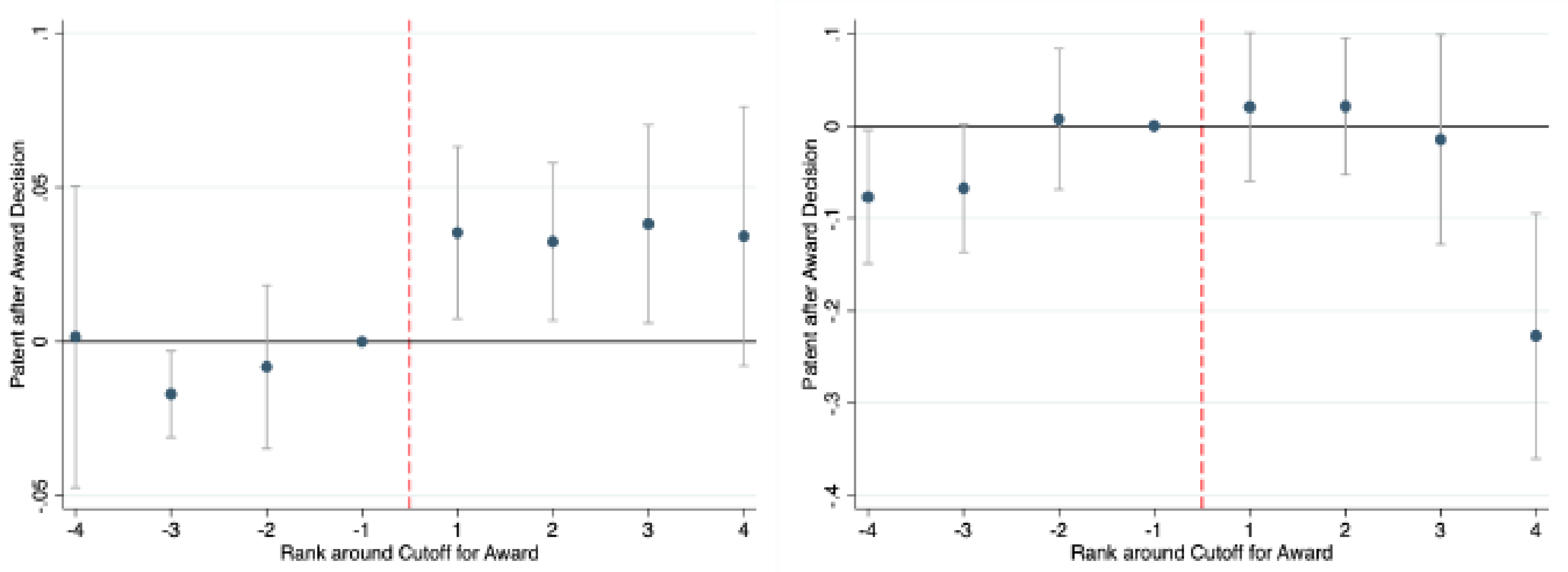
- <u>Large Positive causal</u> effects of OPEN program on:
  - VC funding
  - Defense Department Technology adoption
  - Innovation (quality-weighted patents)

- Conventional program had <u>no</u> causal effect on these & (unlike OPEN) only increased chances of winning another SBIR contract (implies lock-in by “SBIR mills”)

Big jump in innovation near threshold of winning for Open but not for Conventional

Figure 7: Probability of Patents by Rank Around Cutoff

(a) Open (b) Conventional (2017-19)

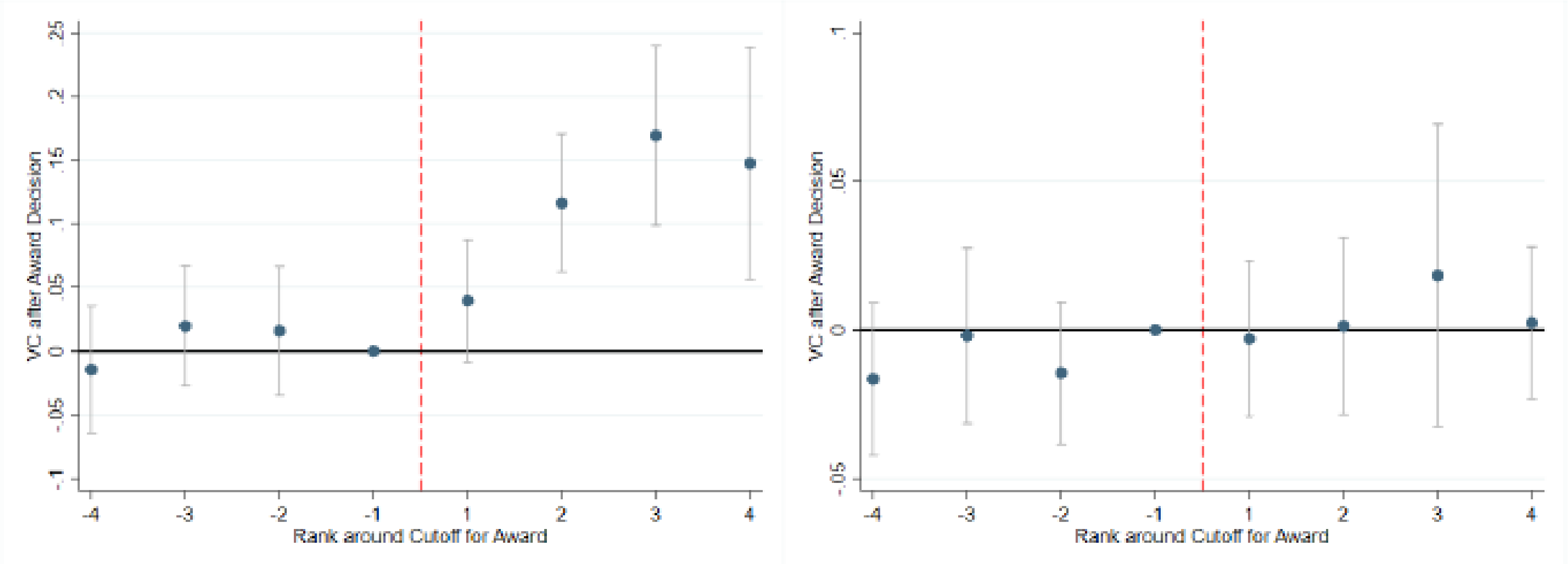


Note: These figures show the probability that an applicant firm had any ultimately granted patent applications within 24 months after the award decision. In both panels, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers. We plot the points and 95% confidence intervals from a regression of the outcome on a full complement of dummy variables representing each rank, as well as fixed effects for the topic. The omitted group is rank=-1.We include first applications from 2017-19.

Big jump in future VC funding near threshold of winning for Open but not for Conventional

Figure 5: Probability of Venture Capital by Rank Around Cutoff

(a) Open (b) Conventional (2017-19)



Note: These figures show the probability that an applicant firm raised venture capital investment (VC) within 24 months after the award decision. In both panels, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score among winners, while a rank of -1 indicates that the applicant had the highest score among losers. We plot the points and 95% confidence intervals from a regression of the outcome on a full complement of dummy variables representing each rank, as well as fixed effects for the topic. The omitted group is rank=-1. We include first applications from 2017-19.

Conclusions from Howell, Rathje, Van Reenen & Wong (2022)

- Direct R&D grants effective if not too tightly specified
  - Use a ML techniques on texts of Conventional proposals since 2003-2020: nonspecific proposals successful like Open
  - Compare other reforms which induced new entrants, but were still top-down

- Model of costs and benefits (calibrated with some moments from results and Bhattacharya, 2021, ECMA) shows large benefits for Open compared to conventional

R&D grants: Summary

- Direct R&D grants literature smaller than that on tax credits, but rapidly growing
- RDD and other credible identification strategies suggest that R&D subsidies can be effective in crowding in private R&D and stimulating innovation
- Several studies show larger effects for young/new firms (suggestive of financial constraints and/or capture by incumbents)
- Design matters: Tightly specified programs appear less successful
- But studies do not address GE issue that large programs may just induce higher price of R&D. What about supply policies?