NBER INNOVATION BOOT CAMP 2023

John Van Reenen,
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Lecture Structure *(3 one-hour lectures; July 17th 1-4pm)*

Lecture 1: Economic Framework(s) for thinking about Innovation Policies

Lecture 2: Evidence on "Demand-side" Innovation policies

Lecture 3: Evidence on "Supply-side" Innovation policies

A. KEY READINGS

(*) Akcigit, Ufuk and Stefanie Stantcheva (2022) "Taxation and Innovation: What do we know? in *Innovation and Public Policy* (Ben Jones and Austan Goolsbee, editors) Chicago: University of Chicago Press

(*) Bloom Nicholas, John Van Reenen and Mark Schankerman (2013) "Technology Spillovers and Product Market rivalry", *Econometrica* 81 (4) 1347–1393

(*) Bloom, Nicholas, John Van Reenen and Heidi Williams (2019), "A Toolkit of Policies to promote Innovation" *Journal of Economic Perspectives* 33(3) 163–184

(*) Dechezlepretre, Antoine Elias Einio, Ralf Martin, Kieu-Trang Nguyen and John Van Reenen (2023) "Do Fiscal Incentives increase innovation? An RD Design for R&D" CEP Discussion Paper 1413 forthcoming, *American Economic Journal: Policy*

(*) Kerr, Sari and William Kerr (2022) "Immigration Policy Levers for US Innovation and Start-Ups" in *Innovation and Public Policy* (Ben Jones and Austan Goolsbee, editors), Chicago: University of Chicago Press

Note: The recent volume *Innovation and Public Policy* (edited by Ben Jones and Austan Goolsbee) Chicago: University of Chicago Press https://press.uchicago.edu/ucp/books/book/chicago/I/bo138500594.html has a lot of other good survey chapters on various aspects of innovation policy

Innovation Policies: Introduction

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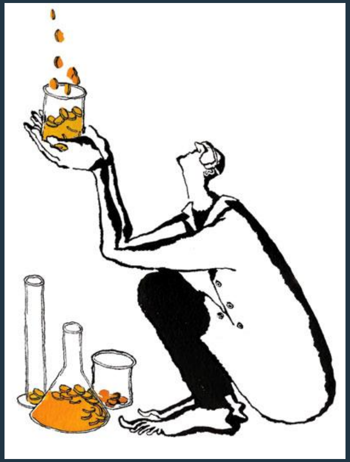
July 17th, 2023

John Van Reenen
Ronald Coase School Professor, LSE
Digital Fellow, MIT



poid Programme on Innovation and Diffusion

Innovation Policies: R&D Spillovers

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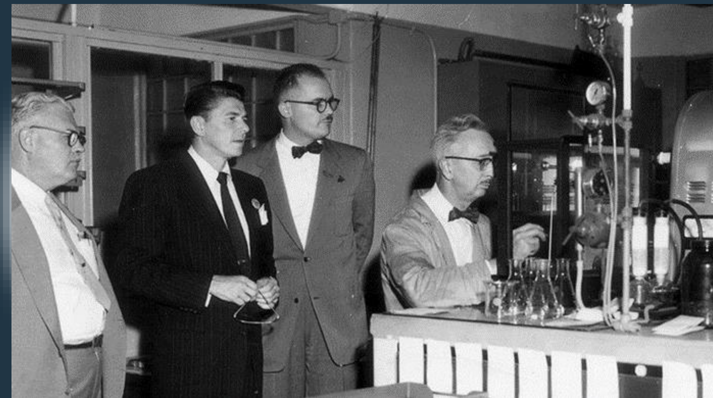

R&D Tax Credits

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General Taxation and Innovation Policies

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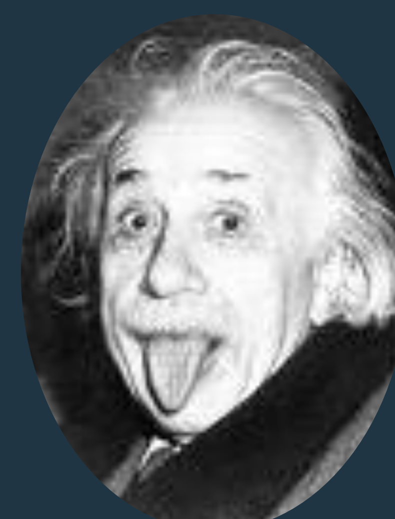

Direct R&D Subsidies

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Innovation and Human Capital Policy

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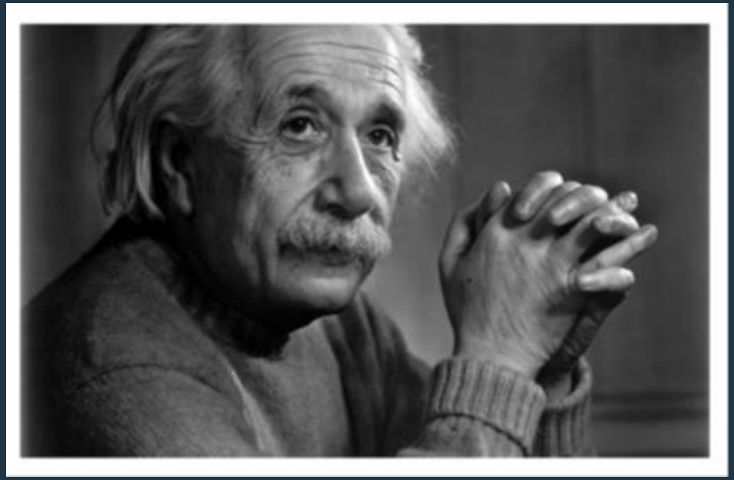

Programme on Innovation and Diffusion

Competition and Innovation:

NBER Innovation Boot Camp
July 21st 2022

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Innovation Policy: Lessons and Conclusions

NBER Innovation Boot Camp
July 21st 2022

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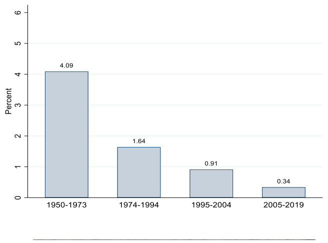
Lessons

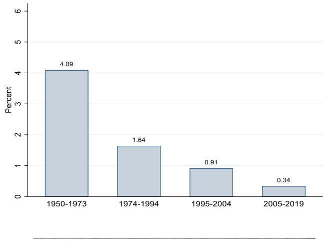
- Credibility Revolution in applied economics has strongly influenced modern empirical work in innovation policy, but poses some special challenges
  - Spillover effects intrinsic issue
  - GE effects critical as we focus on <u>growth</u>
- Despite these problems, significant progress has been made over policies which work better (or worse)

Threats and Opportunities (with examples!)



Threats	Examples
Long-run productivity Slowdown	Post Global Financial Crisis

Threats and Opportunities (with examples!)



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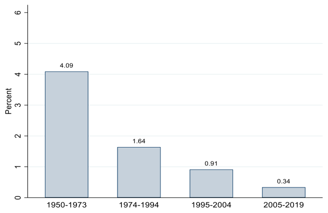

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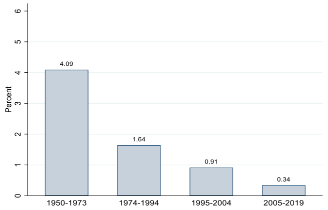

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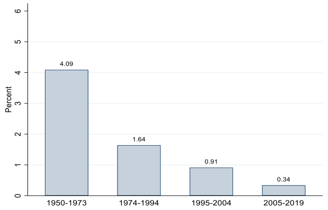

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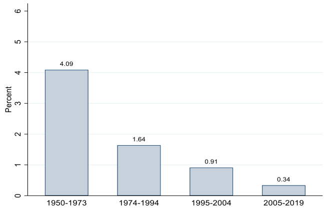

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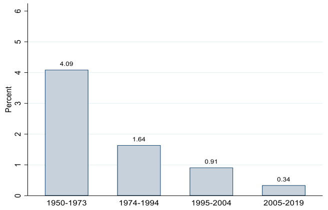

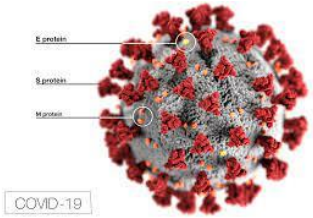

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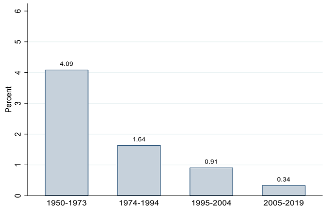

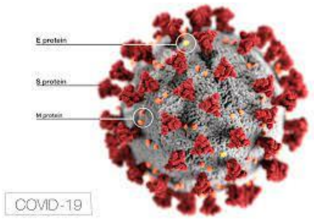

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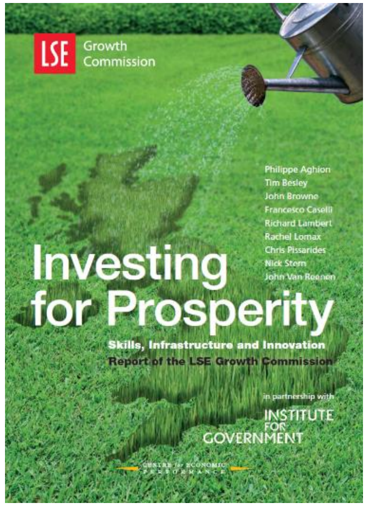
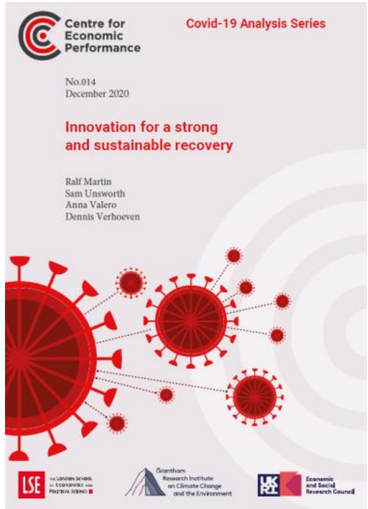
Health	COVID-19	Public-Private partnerships	Vaccines, EHR

A New Marshall for Growth

- Big threats, but also opportunities for creative policies, especially around innovation
- We know much about what can be achieved evidence: e.g.:
  - – *Structural* (**competition**, trade, skills, tax & subsidies; infrastructure, etc.)
  - – *Direct* (e.g. management information and training)
- Country-specific plans based on best evidence:
  - – Toolkits for innovation & management policy
- Bind together in a **mission**:
  - – Climate Change; Defense; Healthcare

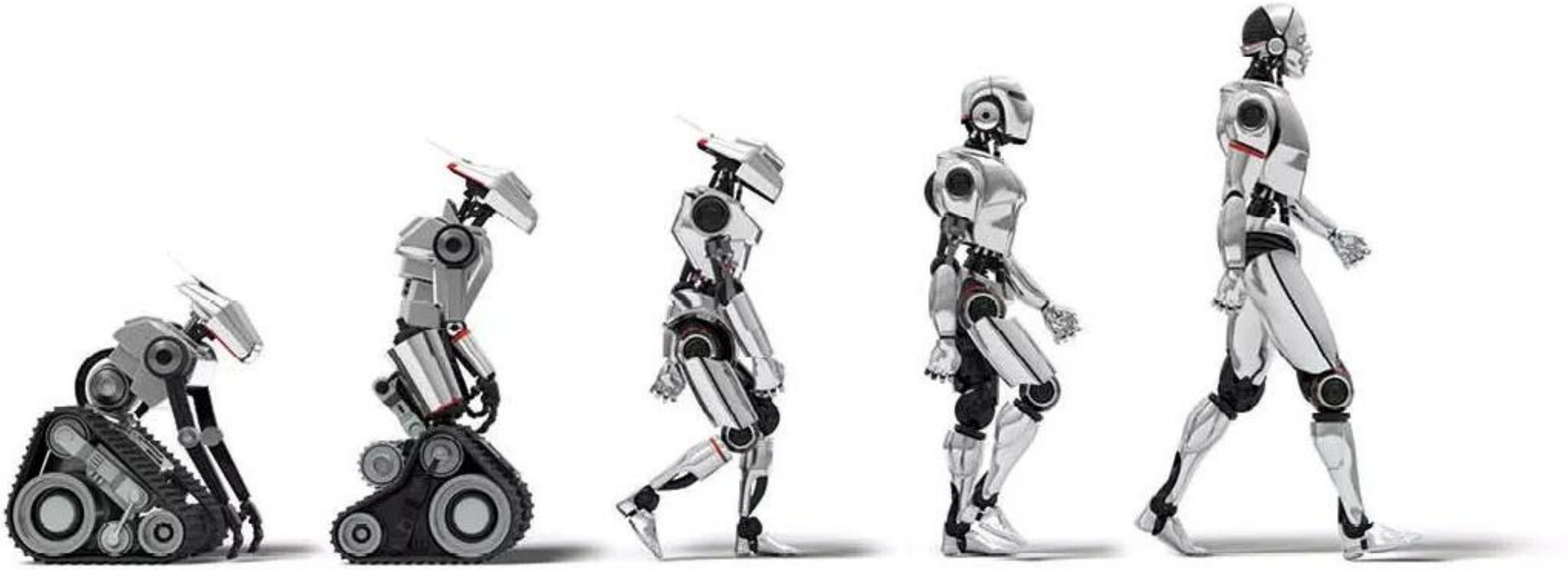




Major Challenge is Political rather than Economic

- Productivity challenge requires long-run policy plans
- Governments suffer Policy Attention Deficit Disorder (PADD)
- Lurch to populism has made this worse (e.g. Brexit and Trump)
- Importance of national & international institutions that can "lean in" against this tendency
  - Independent Central Banks; Competition Authorities, Fiscal Councils, Health regulators
  - Examples of infrastructure reforms in LSE Growth Commission
- And of course, NBER itself!

THANKS!



Introduction

- Relationship between innovation and competition is huge area with long history in economics

- Briefly review the theory and empirics

- Relate to recent debates on the role of Anti-trust (competition) policy
  - Major discussions happening over reforms, especially in digital markets

Forbes

Apple Becomes First Company Worth $3 Trillion—

Forbes, Jan 3rd 2022

https://www.forbes.com/sites/zacharysmith/2022/01/03/apple-becomes-1st-company-worth-3-trillion-greater-than-the-gdp-of-the-uk/?sh=2468cc8d5603

Forbes

Apple Becomes First Company Worth $3 Trillion—Greater Than The GDP Of The UK

Forbes, Jan 3rd 2022

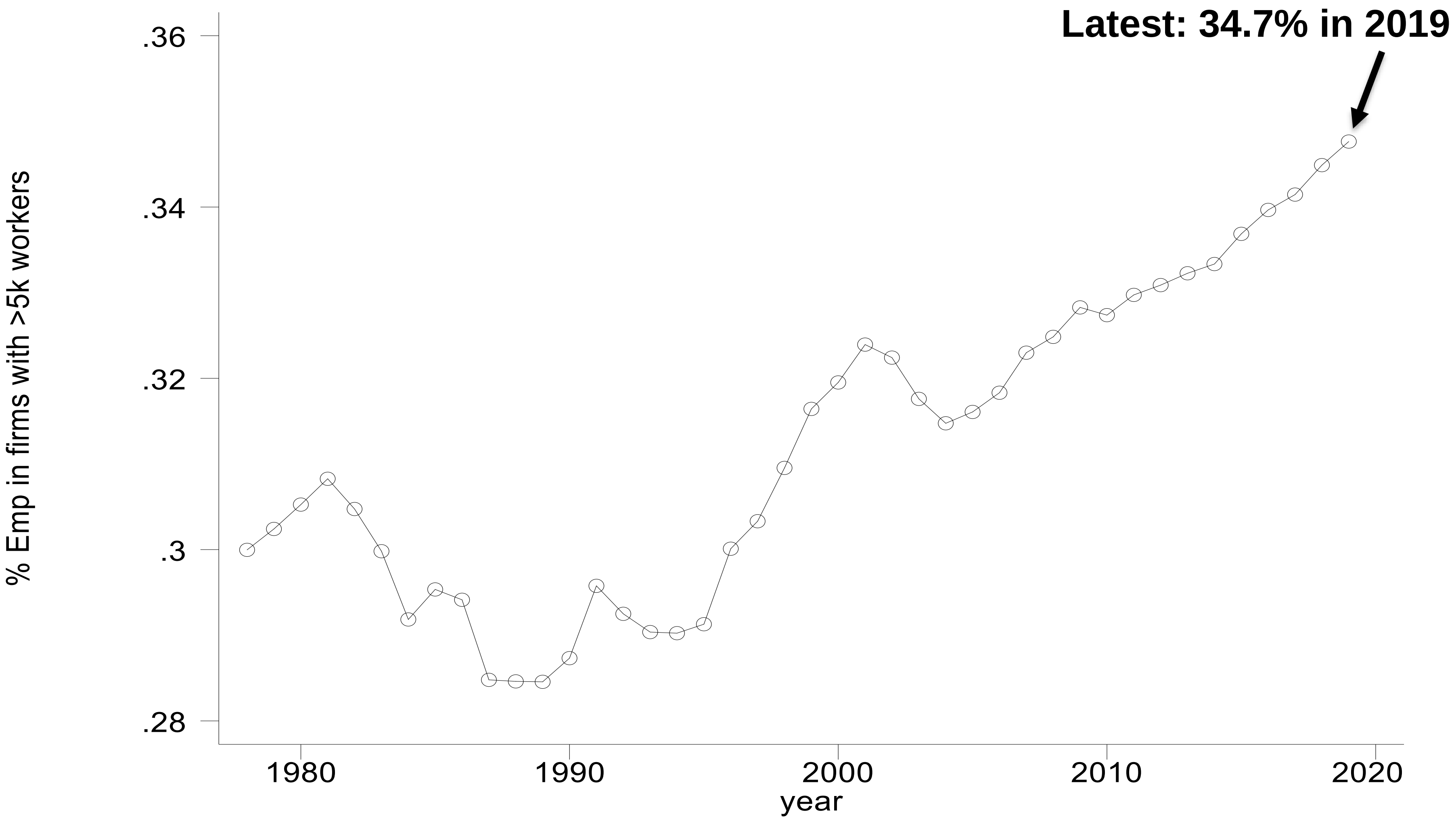
Ex-PM Johnson

https://www.forbes.com/sites/zacharysmith/2022/01/03/apple-becomes-1st-company-worth-3-trillion-greater-than-the-gdp-of-the-uk/?sh=2468cc8d5603

Market Valuation at start of 2022 (“GAFAMs”)

- ***Apple*** $3 Trillion
- ***Microsoft*** $2.53 Trillion
- ***Google/Alphabet*** $1.92 Trillion
- ***Amazon*** $1.69 Trillion
- ***Facebook/Meta*** $0.93 Trillion
- Growth has been supercharged by COVID’s push to online, but has been going on long before the Pandemic

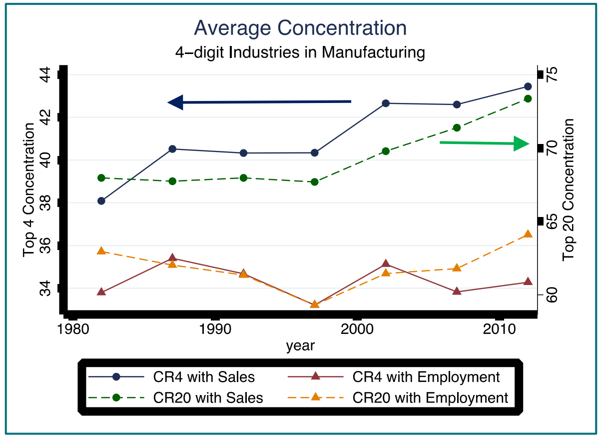
Since mid ’80s Big Firms getting bigger: % jobs in US firms with 5,000+ workers rose from ~28% in 1987 to ~35% in 2019



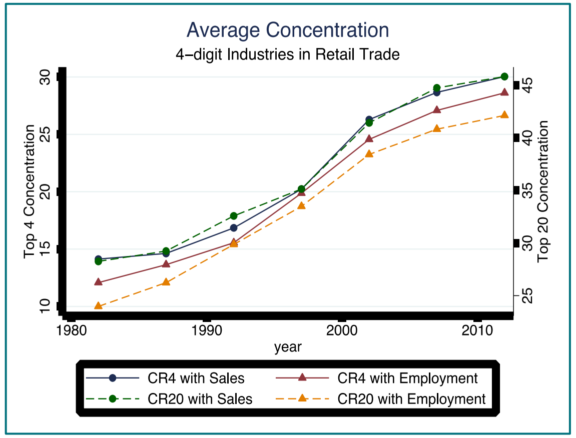
Source: US Business Dynamics Statistics (2021), https://www.census.gov/data/datasets/time-series/econ/bds/bds-datasets.html

Rising Sales Concentration in US SIC4 since 1982

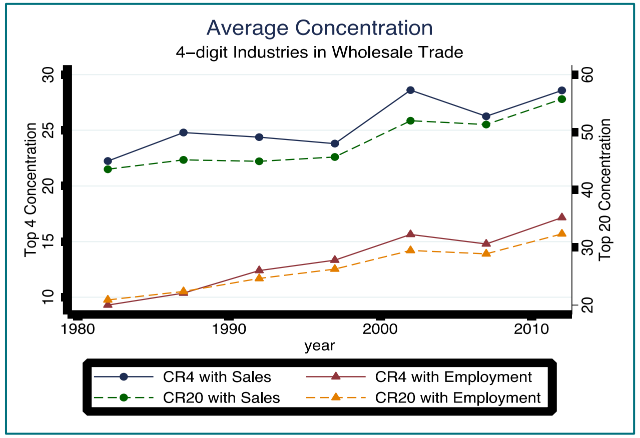
Manufacturing



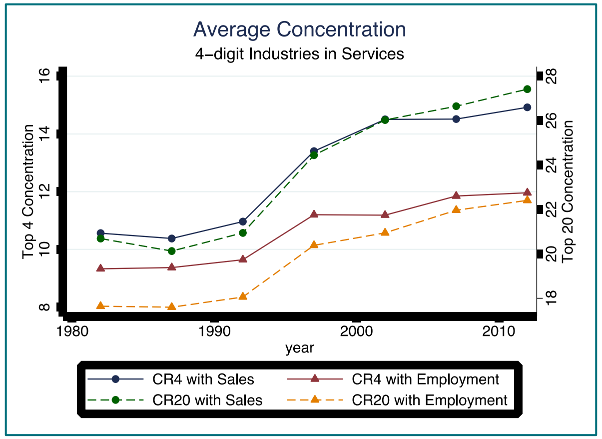
Retail Trade



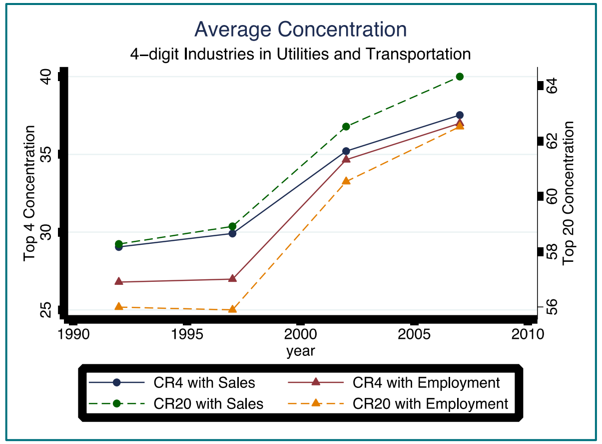
Wholesale Trade



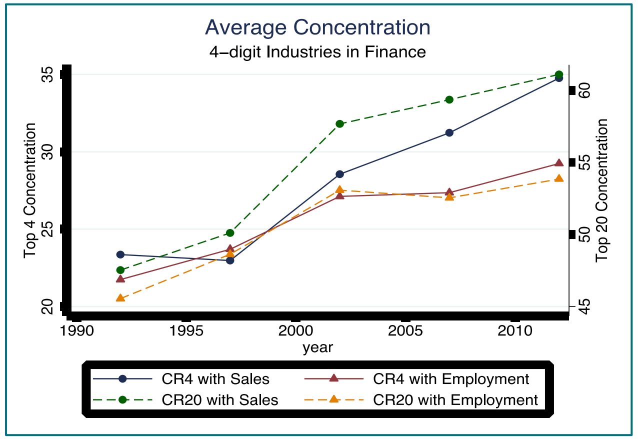
Services



Utilities + Transportation



Finance



Notes: Autor, Dorn, Katz, Patterson & Van Reenen (2020) from Economic Census; Weighted av. of concentration across the SIC-4's within each sector. 676 SIC4 industries underlying this.

Product Market Power

- Industrial Concentration is not the same as market power
  - Use better defined (narrower) anti trust markets (e.g. Benkard, Yurukoglu & Zhang, 2021)
  - Taking imports into account (e.g. Amiti & Heise, ’21)
  - Examine price-cost markups

Aggregate Price-Marginal Cost Markups in US publicly listed firms seem to have risen after 1980

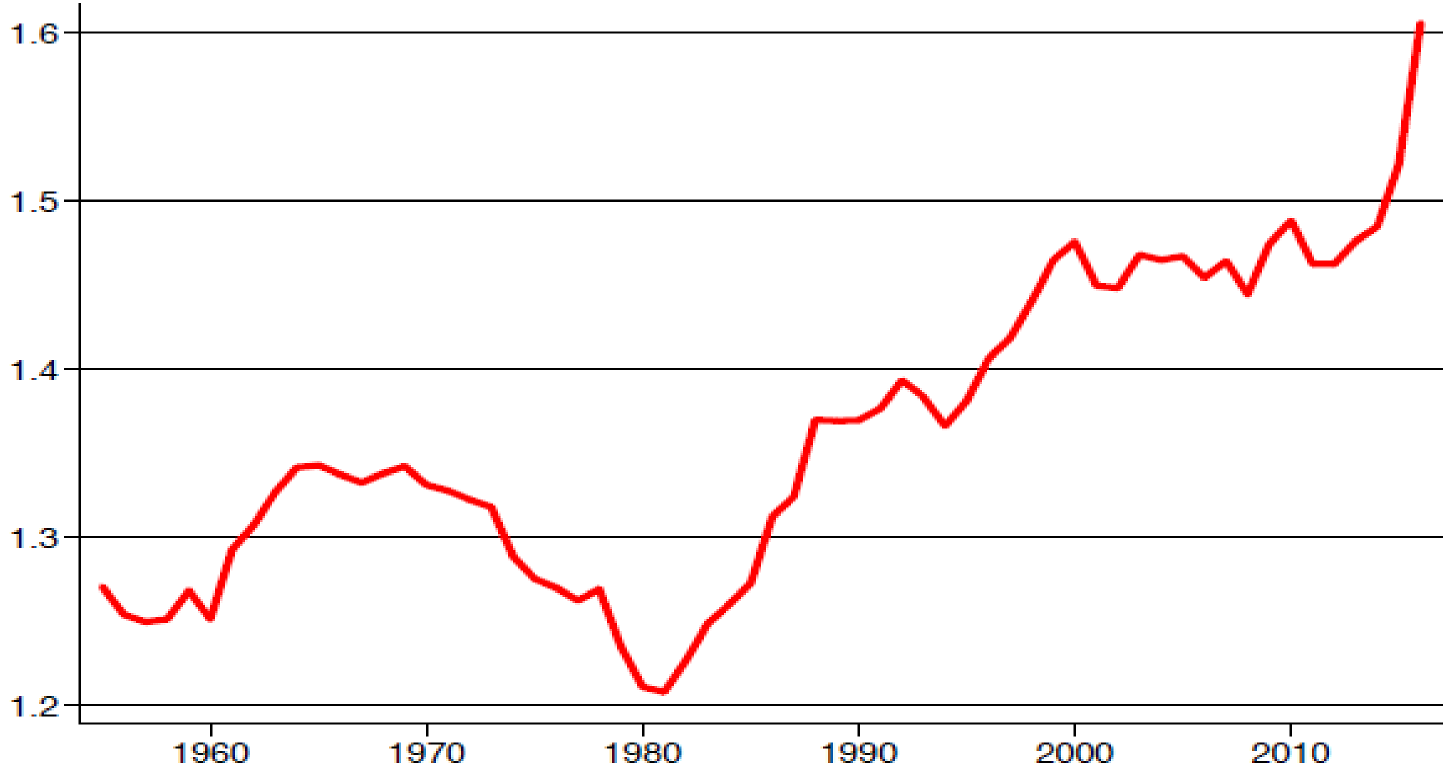
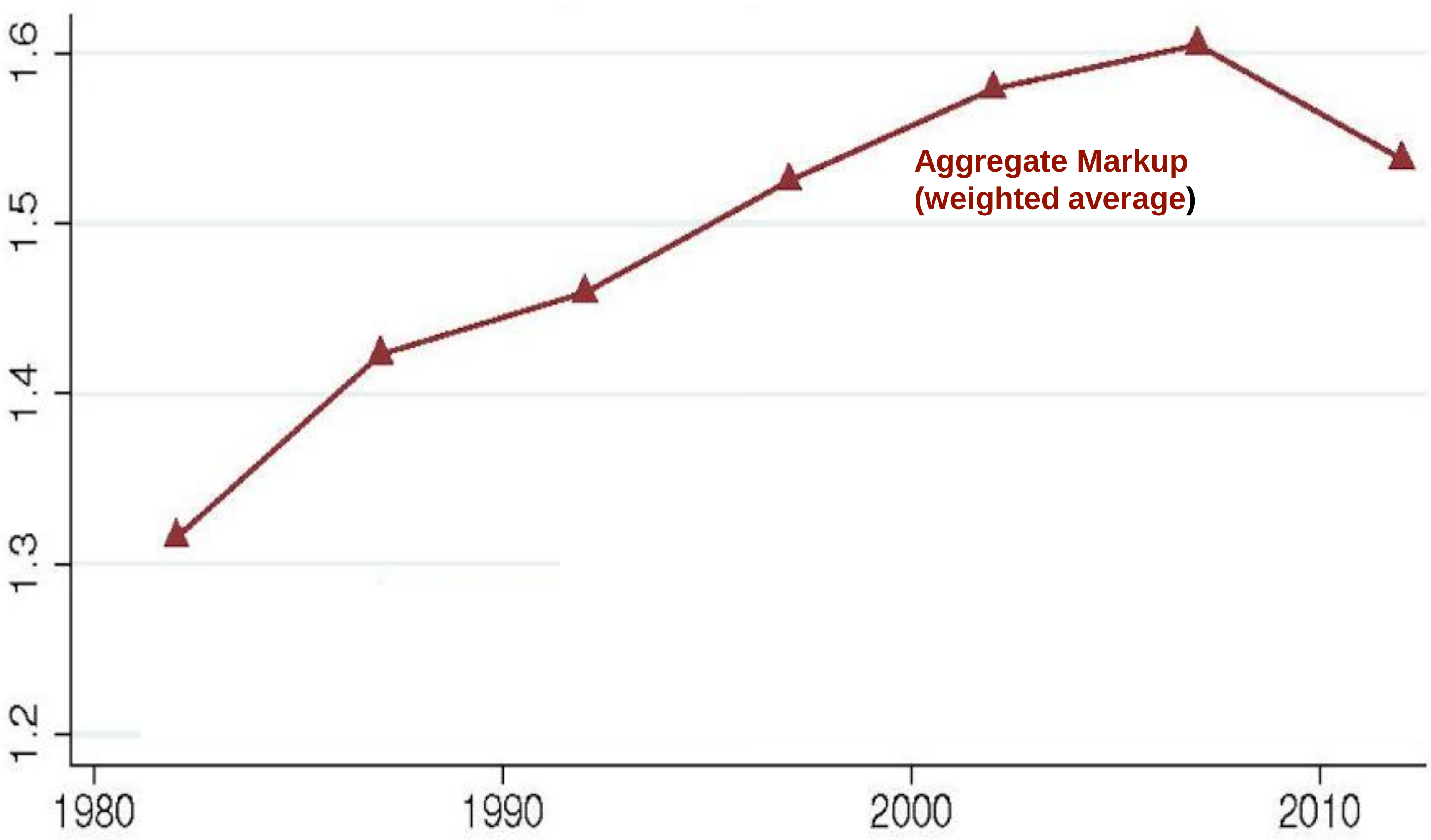


Figure 1: Average Markups for Conventional Production Function. Output elasticities θ_{st} from estimated PF1 are time-varying and sector-specific (2 digit). Average is sales weighted. Evolution 1955-2016.

Source: de Loecker, Eeckhout and Unger (2020) on Compustat

Aggregate size-weighted markup also rose in US Census Data

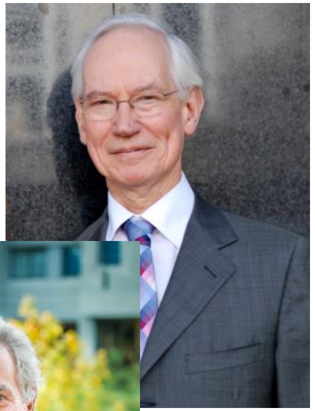


Notes: Accounting markup is defined as sales over total costs. Weight is the sales share of the establishment.
Source: Autor et al (2020) on Census of Manufactures

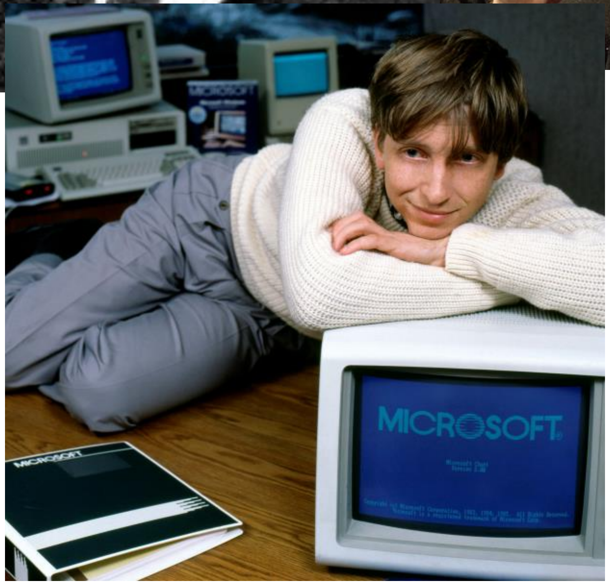
Questions

- If there has been an increase in product market power what (if any) if likely to be the effect on innovation?
- Competition agencies generally presume this will be negative (i.e. dynamic inefficiencies in addition to standard static inefficiencies)
  - But also idea of monopolists enjoying the “easy life” (Hicks)
- Or maybe the changes are due to innovation: growth of winner take all/most markets?

Competition and innovation



Theory

- **Schumpeter** (1943) challenged view that product market competition (PMC) was desirable:
  - On static grounds of better allocation/lower prices, PMC was good
  - But competition drives profits to zero, so an innovating firm would have no rents and therefore no financial incentive to do R&D
  - Hence, on dynamic grounds, some degree of market power desirable to incentivize innovation.
  - And since market economy aggregate growth due to new products and processes rather than better allocation, monopoly better

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  - Hence, on dynamic grounds, some degree of market power desirable to incentivize innovation.
  - And since market economy aggregate growth due to new products and processes rather than better allocation, monopoly better
- Patent system does this by granting temporary **ex post** monopoly power for innovation (in exchange for publication), but highly imperfect
- Other arguments such as importance of fixed costs, lower uncertainty and financial frictions also used to argue for benefits of having some **ex ante** market power. We focus on PMC incentives here.

Theory

- **Arrow** (1962) challenged main Schumpeterian argument
  - Monopolist firm earns a stream of rents, whereas competitive firm does not.
  - Which type of firm has greater incentive to invest in cost-reducing R&D? Compare after innovating profits to pre-innovation profits for both firms
  - If after innovating both firms earn same profits (e.g. a drastic innovation), potential entrant will do **more** R&D because her current profits are zero, whereas incumbent gets monopoly rents
  - More generally, the current stream of rents reduces incentive of monopolist to innovate
- This is the Arrow **replacement effect** and suggests competition spurs innovation

Theory

- Both Schumpeterian & Arrow effects generally at work in modern models

- Aghion et al (2005) “Inverted U”
  - At low level of competition, Arrow effect dominates whereas at high levels, Schumpeterian effects dominate
  - Strategic interaction in product market
  - “Neck & Neck”: PMC ↑ then innov ↑; “leader-follower”: PMC ↑ then innov ↓

- Gilbert and Newbury (1982): If non-stochastic innovation and non-drastic R&D, monopolist will do more R&D as sharing market reduces total industry rents (unless perfect collusion).

Empirics

- No clear consensus, but a tendency towards on average positive effects

- Cohen and Levin (1989) an early survey, more recently see Bryan & Williams (2021), Gilbert (2021)

- Example: Aghion et al (2005) “Inverted U” empirics
  - British publicly listed firms, cite-weighted patents as outcome
  - Competition measured by (inverse) Industry level Lerner Index

Estimated relationship at industry level: The “Inverted U” (Aghion et al, 2005)

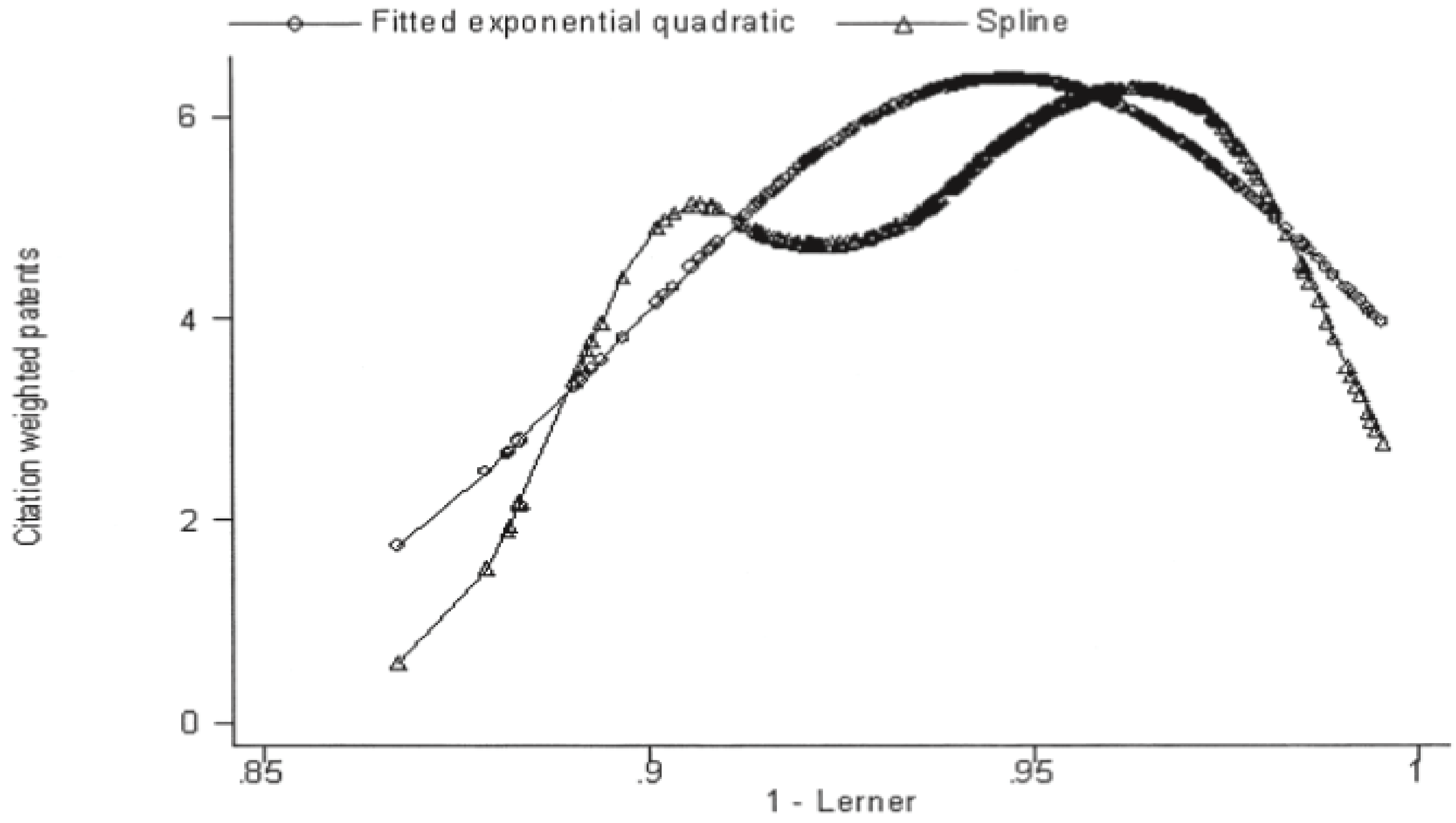


FIGURE II
Innovation and Competition: Exponential Quadratic and the Semiparametric Specifications with Year and Industry Effects

<u>Note:</u> A linear regression would give a clear positive slope .

Competition Policy Implications of Aghion et al (2005) Inverted U

- No “one size fits all” as depends on where industry is on the inverted U
- However, a linear regression would give a clear positive slope, so no Schumpeterian presumption of negative effects (consistent with general anti-trust agency view that competition good for dynamic innovation)
- For almost all real competition cases, most will be on left of inverted U: so more competition raises innovation, reinforcing static effects (Ex-Chief Economist of DG-COMP, Kuhn et al, 2012)

Some issues with Aghion et al (2005)

- Robustness of empirical relationship (highly aggregated: SIC2 industries)
- Measure of competition based on average profit to sales ratio (Inverse Lerner) which has different interpretations (e.g. could rise with competition)
- Many alternative theoretical interpretations
- How can PMC get shifted by **competition policy regimes**?
  - Paper is mainly on competition in general not competition policies (exception: MMC decisions as IV)
- For almost all real competition cases, most will be on left of inverted U: so more competition raises innovation, reinforcing static effects (Ex-Chief Economist of DG-COMP, Kuhn et al, 2012)

Some issues with Aghion et al (2005): Basic empirical relationship not robust (highly aggregated: SIC2 industries)

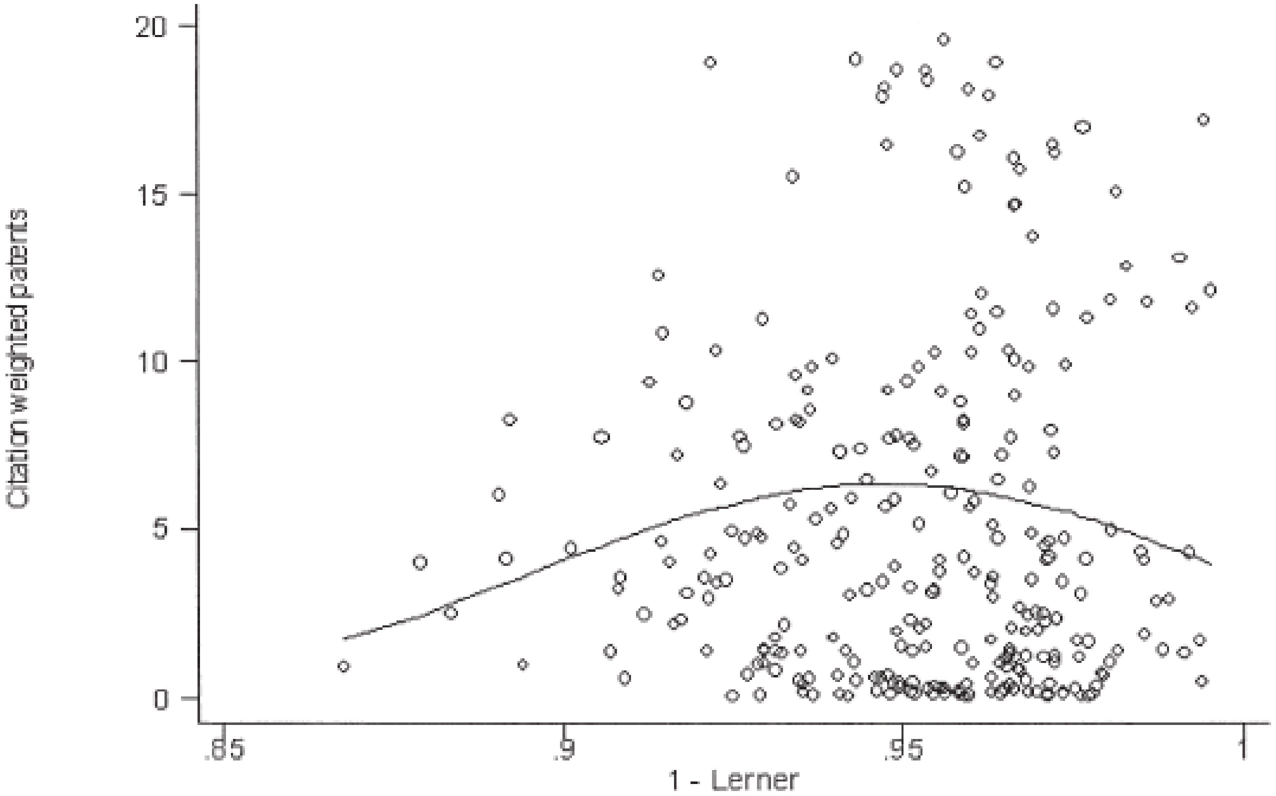


FIGURE I

Scatter Plot of Innovation on Competition

The figure plots a measure of competition on the x-axis against citation-weighted patents on the y-axis. Each point represents an industry-year. The scatter shows all data points that lie in between the tenth and ninetieth deciles in the citation-weighted patents distribution. The exponential quadratic curve that is overlaid is reported in column (2) of Table I.

Some issues with Aghion et al (2005)

- Robustness of empirical relationship (highly aggregated: SIC2 industries)

- Measure of competition based on average profit to sales ratio (Inverse Lerner) which has different interpretations
  - e.g. In 1960s, Demestz pointed out that competition reallocates to more efficient firms which will tend to *raise* industry profit-sales ratio

- Many alternative theoretical interpretations

- How can PMC get shifted by competition policy regimes?
  - Paper is mainly on competition in general not competition policies

Empirical Studies of Competition Policy Reforms

- Arguments that actions on Bell Labs, IBM in 1970s, Microsoft in 1990s (and maybe more recent actions on Google, Facebook, etc.) spur innovation
- Aghion et al (2005) uses IVs: EU Single Market Program; Monopoly & Monopoly Commission Decisions & Privatizations
- Watzinger, Fackler, Nagler & Schnitzer (2020): Government-mandated compulsory licensing at Bell Labs in the 1950s led to a substantial increase in forward citations to affected Bell patents
- Kang (2020) Found that actions against collusion actually decreased innovation (via low cash flows because prices fell)

Published 2016

Some Recent issues in Competition Policy

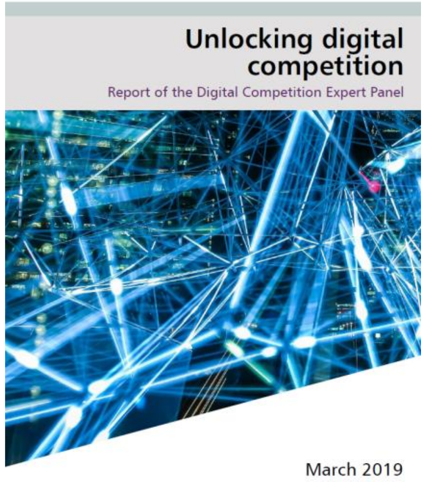
- Acceptance of market power as a reward for innovation, especially in high tech markets. Competition for the market more important than “in the market”

Some Recent issues in Competition Policy

- Acceptance of market power as a reward for innovation, especially in high tech markets. Competition for the market more important than "in the market"
- **But** must guard that rivals (e.g. potential entrants) are not disadvantaged by anti-competitive actions of powerful incumbents. Examples:
  - *Abuse of a dominant position:* Data as essential facility; degrading interoperability – e.g. Genakos et al, 2018 on Microsoft
  - *M&A:* incumbent acquires a start-up which could have developed into an independent platform competitor (e.g. *Facebook/Instagram; Facebook/WhatsApp; Google/Waze*; *SalesForce/Slack*, *GM/Cruise*, etc.)
  - Even worse, after merger the start-up's innovation might remain undeveloped (Cunningham et al, 2021, JPE "killer acquisitions" in pharma)

How to reform Competition Policy? (Tirole, 2020)

- Greater focus on **future** competition & innov, not just current market
  - Standard approach focuses on short-term, static effects
- Shift Burden of Proof in merger cases towards dominant incumbents when they want to take over potential platform startups
- *More ex ante* regulation: e.g. UK Competition & Market Authority’s Digital Market Unit; EU Digital Market Act
- Lower the Hart-Scott-Rodino thresholds for merger notification (Wollman, 2019; Barrios and Wollman, 2021)




EUROPEAN COMMISSION

Brussels, 15.12.2020
COM(2020) 842 final

2020/0374 (COD)

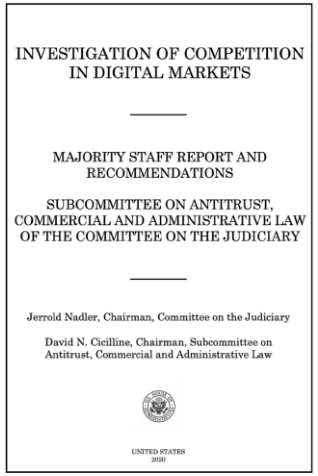
Proposal for a

REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL

on contestable and fair markets in the digital sector (Digital Markets Act)

(Text with EEA relevance)

{SEC(2020) 437 final} - {SWD(2020) 363 final} - {SWD(2020) 364 final}


INVESTIGATION OF COMPETITION IN DIGITAL MARKETS

MAJORITY STAFF REPORT AND RECOMMENDATIONS

SUBCOMMITTEE ON ANTITRUST, COMMERCIAL AND ADMINISTRATIVE LAW OF THE COMMITTEE ON THE JUDICIARY

Jerrold Nadler, Chairman, Committee on the Judiciary

David N. Cicilline, Chairman, Subcommittee on Antitrust, Commercial and Administrative Law

Trade Policy

- Reducing **Trade barriers** a key way that competition can be boosted
  - Increased import competition via reduced lower tariffs barriers, technology reducing transport costs, etc.
  - Expanding market size also increases incentives to innovate in wide class of models
  - Many other potential mechanisms (see Melitz & Redding, 2022) such as importing higher quality inputs, learning from exporting, etc.

Trade Policy: The China Shock

- **Example:** Rise of **China** a major exogenous shock to Western product markets, due to Deng Xiaoping's policy choices
  - Massive increase in Chinese imports, esp. after 2001 WTO Accession
  - Bloom, Draca & Van Reenen (2016) firm-level panel data in EU. IV from detailed industry changes (e.g. from MFA quotas). Found:
    - Big **fall** in jobs, especially for low-tech firms (reallocation effect)
    - Big ***increase*** in innovation (cite-weighted patents) within more exposed firms (as well as greater IT diffusion & TFP)

Trade Policy: China Shock

- Autor et al (2020) look at China shock in US. Also find jobs fall but a negative effect on innovation. Bloom et al (2021) show that using same IV as Autor (predicted growth of Chinese imports in other countries) still gives different result in EU

- “Inverted U” helps interpret the different results.
  - Competition initially weaker in EU than US pre-China, so on upward part of the Inverted U: higher competition from China shock increases innovation
  - US already had high competition, so on a downward part of the Inverted U: higher competition from China shock decreases innovation

Structural IO models of innovation and competition

- Recent empirical literature goes more deeply into specific sectors and explicitly models the R&D stage and the later price/quantity stage.
  - **Advantage** of the structural approach is that explicit counterfactuals can be modelled and welfare effects compared
  - **Disadvantage** is a narrower focus and more parametric assumptions

- Structural dynamic IO models much more technically challenging compared to more well developed static approaches (Pakes, 2021)

Some Examples of structural models

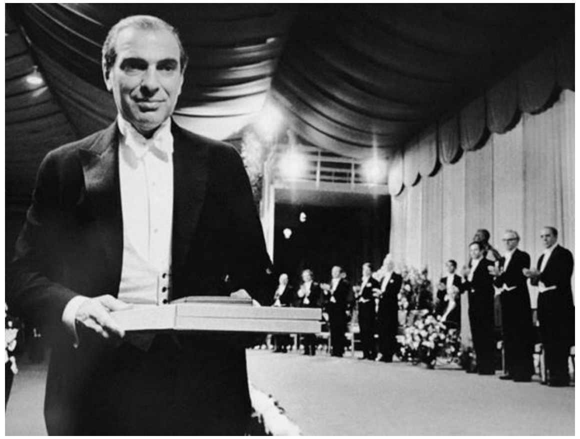
- **Goettler & Gordon** (2011, JPE) *PC Micro-processors* **Intel vs. AMD**
  - Full solution concept. More innov under monopoly but welfare lower

- **Hashmi & Van Biesebroeck** (2014, REStat) *Automobiles*
  - 2 step approach of Bajari et al (2007, “BBL”). Total innov higher with entry
- **Igami** (2017, JPE) *Hard-Disk Drives (HDD)* 1981-1998
  - 2 step approach + allows for many firms. Incumbents innovate less

- **Igami & Uetake** (2020, ReSTUD) *HDD* 1996-2016
  - Models dynamic merger policy. Innovation increases from monopoly to duopoly to triopoly
- **Bhattacharya** (2021, ECMA)
  - R&D procurement in *US Navy.* More competition would increase welfare
- **Yang** (2020, RAND) *System-on-a-Chip tech components for Smartphones*
- ***<u>Summary</u>**: My general sense is that increase in competition (from low comp) usually increases innovation, but much heterogeneity*

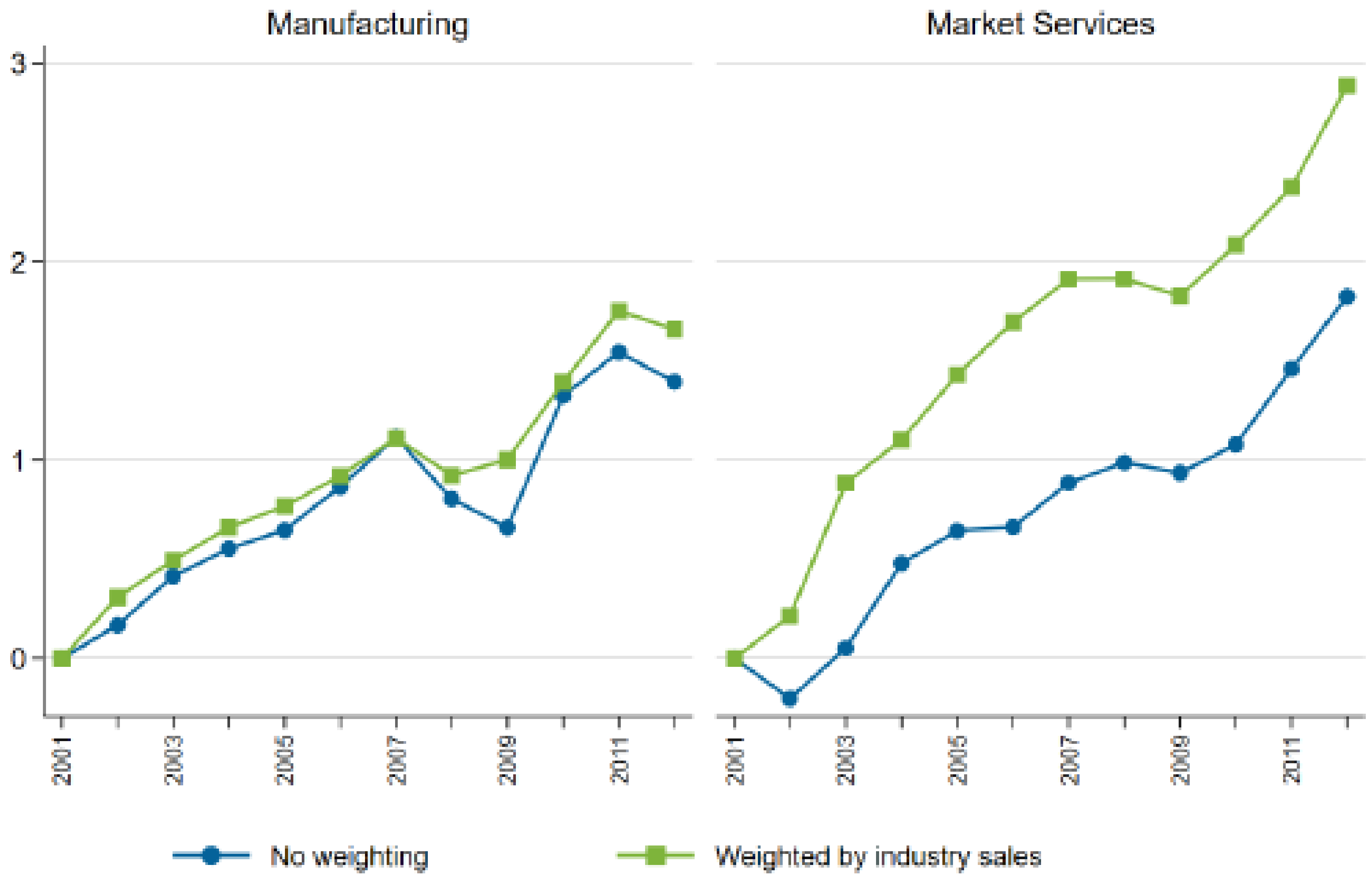
Conclusions

- Product market competition and Innovation an enormous theoretical and empirical area
  - Impact will depend on details of market and theoretical model
- My general sense from empirical literature is that competition tends to increase innovation: a bit more Arrow than Schumpeter?
- Reforming competition regime highly complex area, but hugely important, as weight of economy moves to high innovation areas and evidence of problems
- Modernisation happening and can be done on current economic principles of focusing on consumer harm



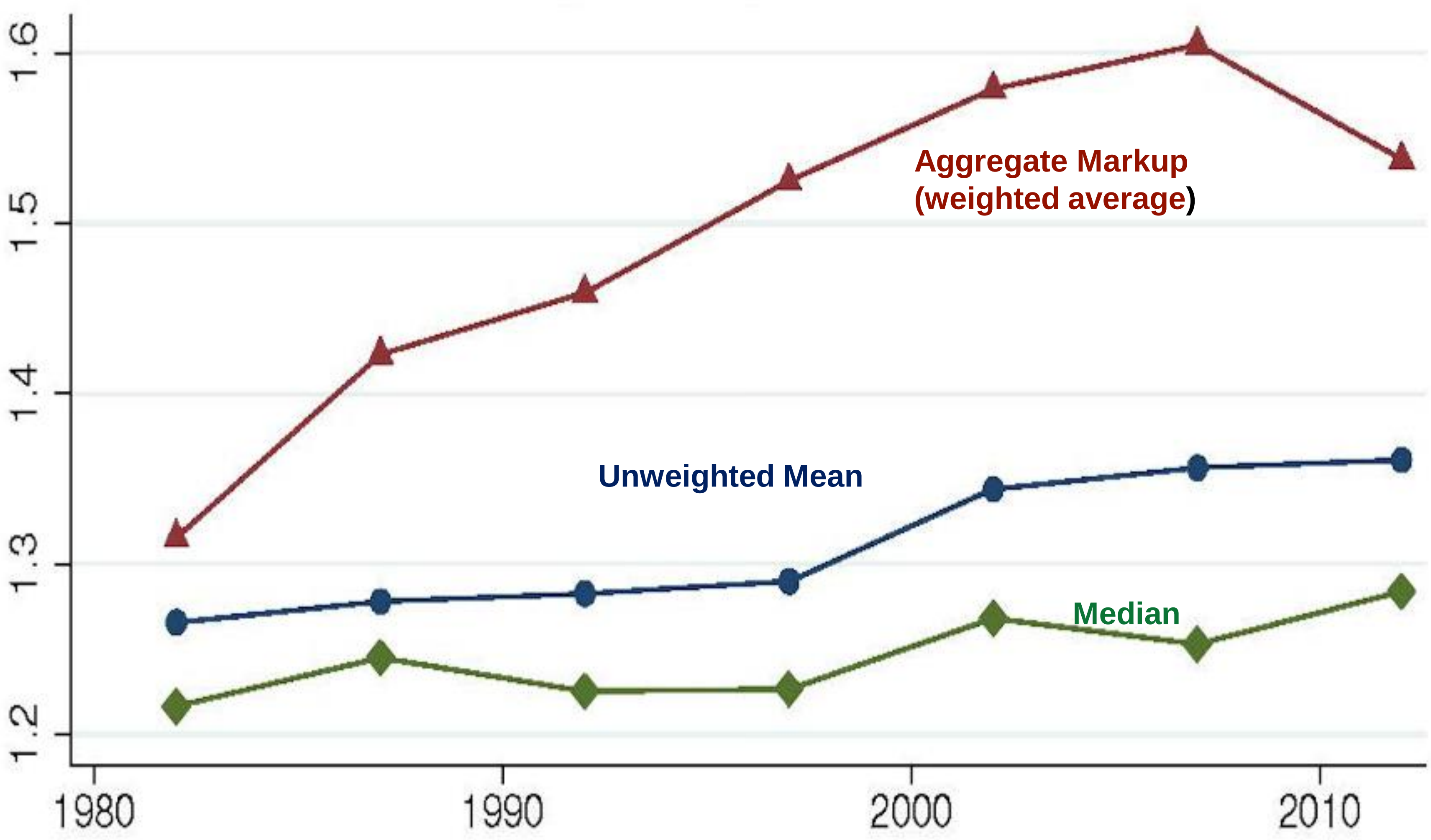
Back Up

Like US, Sales Concentration seems to have increased in Europe (country-industry Census micro data)



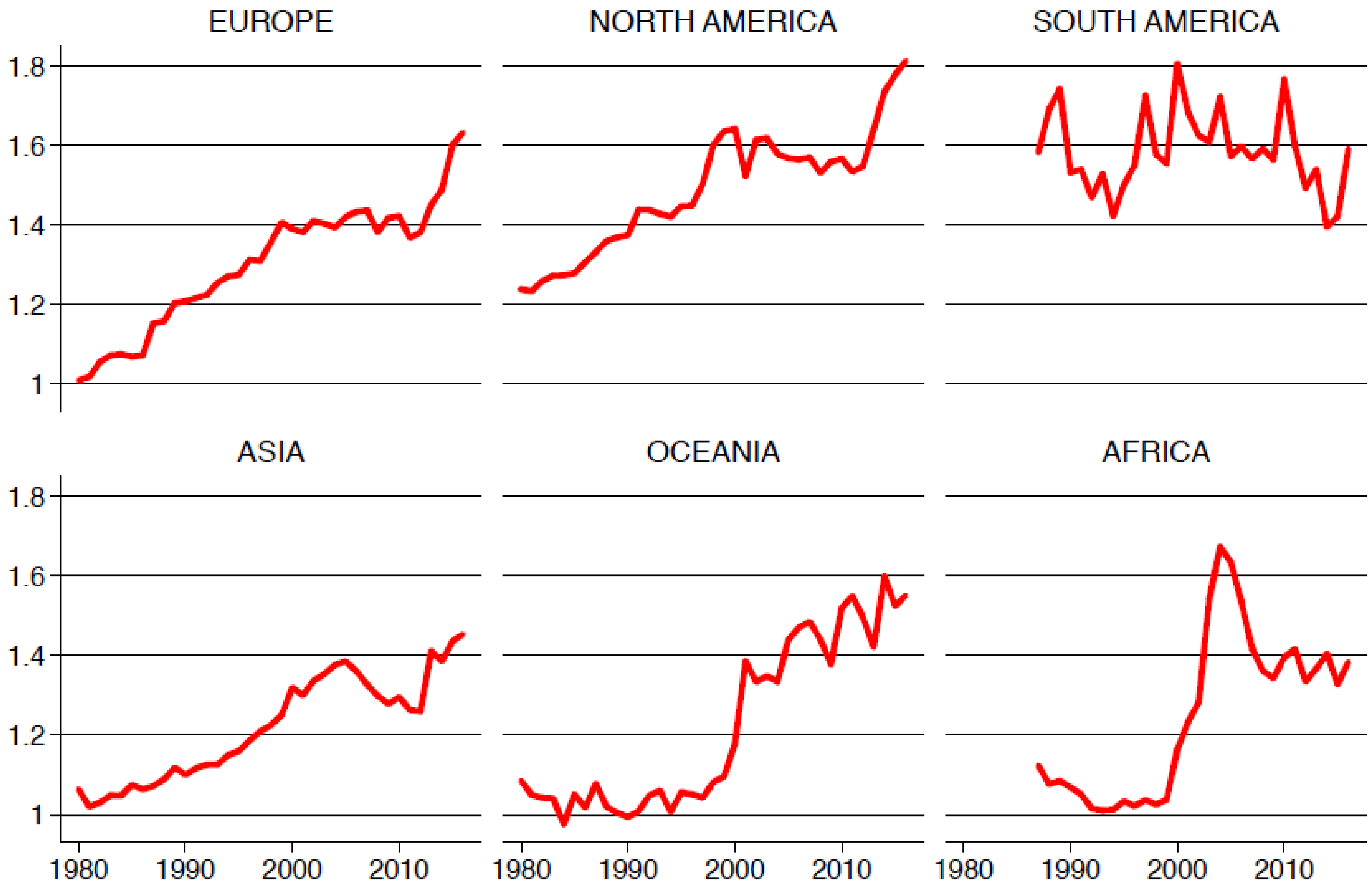
Source: OECD Multiprod; Bajgar et al (2019); **Notes:** Share of top 10% firms in industry gross output. Year effects from regressions with country-industry dummies and year dummies (AUT, BEL, DEU, DNK, FIN, FRA, HUN, NOR, PRT, SWE). Weights give more importance to larger industries https://www.oecd-ilibrary.org/docserver/2ff98246-

Aggregate US markup rises, but median does not (US Census Data)



Notes: Accounting markup is defined as sales over total costs. Weight is the sales share of the establishment. **Source:** Autor et al (2020) on Census of Manufactures

Price-Cost Markups rising around the world (listed firms)



Source: Eeckhout and de Loecker (2018) using Worldscope

Killer Acquisitions?

- Benefits to startup firm to exit to acquisition?
  - Incentivizes entry and VC funding
  - Big firm brings complementary benefits (technologies, financing, marketing to help startup develop)
- But startup could still develop via IPO or be sold to another nondominant firm
- Kamepalli, Rajan, and Zingales (2020): consumers won't adopt products if they worry that incumbents will acquire & remove products in "kill zone".
  - VC investments in areas related to firms acquired by Google & Facebook fall after acquisition, but investment up in areas when nondominant firm acquires

Why is human capital policy attractive to boost innovation?

- **Demand Side innovation Policies**
  - Fiscal incentives (e.g. R&D tax credits)
  - Direct subsidies to firms (e.g. SBIR)
  - Seem effective in micro studies. But if supply side inelastic, main effect is to increase R&D price rather than volume (Romer, 2001)

- **Supply side innovation policy** (survey in Van Reenen, 2022)
- Increase quantity of R&D workers - direct boost to innovation
  - Supply reduces R&D price - indirect boost via GE effect
  - But (i) leakage” concern & (ii) slower than subsidy

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	↑
Gr Inn Challenge					

"Demand"

"Supply"

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

Innovation Policy: The "Lightbulb" Table

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Types of Human Capital Policy

- **Increase supply of STEM qualified people**
- **Expand Universities**
  - General
  - Effect via supply of grads and postgrads
  - National Labs (Jaffe and Lerner, 1990)
  - Academic incentives (Lach & Schankerman, 2008; Hvide and Jones, 2018)
- Immigration
- “Lost Einsteins and Marie Curies”

Universities: General Effects

- Positive impact of university entry/expansion on GDP per capita
  - Valero and Van Reenen (2019), 50 years of sub-national data across 100 countries

- Effects of universities on innovation (usually positive)
  - Jaffe (1989): US state-level spending on university research associated with more local corporate patenting
  - Acs et al (1992) using innov surveys
  - Belenzon and Schankerman (2013), Hausman (2018) on patenting

Some Issues with university studies

- **Endogeneity** of university presence/expansion
  - Furman & MacGarvie (2007) use Morrill Acts (land grant college funds) to IV for university location looking at impact on corporate pharma R&D labs 1927-46

- Even if causal impact of universities on innovation, is the **mechanism** through graduate supply? Alternatives:
  - Faculty research/activity
  - Institution building (Valero & Van Reenen, 2019)
  - Demand (Andrews, 2018)

Is the university impact on innovation (partially) through graduate supply? More direct evidence

- Bianchi & Giorcelli (2020)
  - Enrolment requirements changed for STEM majors in Italy
  - Subsequent innovation increased, especially in bio-medical & ICT
  - But some leakage into other sectors (like finance)
- Increase in STEM-focused colleges and long-term innovation (patenting measures)
  - Toivanen & Vaananen (2016), founding of technical schools in 1960s led to supply increase of engineers in Finland. Had effects on 2nd generation (Aghion et al, 2023)
  - Carneiro, Liu & Salvanes (2018), university expansion in Norway in 1970s led to STEM supply boost

Types of Human Capital Policy

- Increase supply of STEM qualified people
- Expand Universities
- **Immigration**
- “Lost Einsteins”

Immigration (“Buy rather than Make”)

- **Kerr & Kerr (2022):** Immigrants are 14% of US workforce but 25% of patents; 42% of STEM doctorates, 1/3 Nobel Prizes

- Relaxing immigration an attractive policy because:
  - Quickly increases STEM workforce
  - Foreign country pays for (at least) some of training

- Note that zero sum from a world perspective. “Brain Drain” vs. “Brain Gain” ethical issues.

Empirical Findings on immigration and innovation

- Generally, studies find positive effect on innovation of immigrants themselves and from spillovers to natives
  - Hunt & Gauthier-Loiselle (2010) state panel 1940-2000; Kerr & Lincoln (2010) on H1(B) policy changes
  - Bernstein, Diamond, McQuade & Pousada (2021):
    - Infutor data/USPTO to get SSN based measure of immigrant status
    - Immigrants 10% of pop, 16% of inventors & ~30% of ag. innovation
    - Use premature inventor deaths to identify spillovers (30% of ag. innov immigrants)
  - Moser and San (2019); Doran and Yoon (2018) 1920s quota IV
  - Moser, Voena & Waldinger (2014): Jewish scientists fleeing Nazis

Empirical Findings on immigration and innovation

- Generally, find positive effect on innovation of immigrants themselves and from spillovers to natives
- Exceptions: Doran et al (2015) on H1(B) lotteries (zero effect); Borjas & Doran (2015) on US mathematicians after fall of Communism
- Problem with pro-immigration policy is socio-political (Tabellini, 2020)

Types of Human Capital Policy

- Increase supply of STEM qualified people
- Expand Universities
  - General
  - Effect via supply of grads and postgrads
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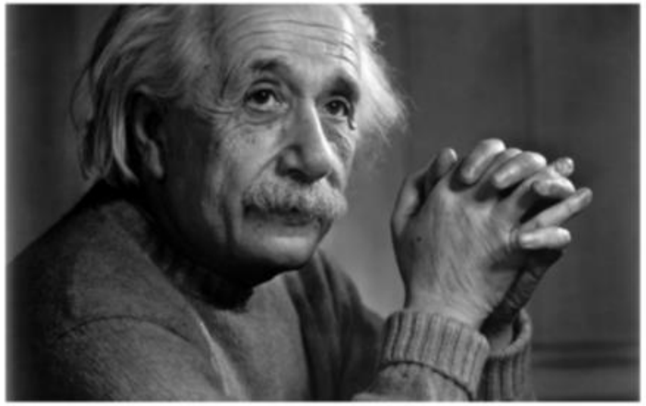
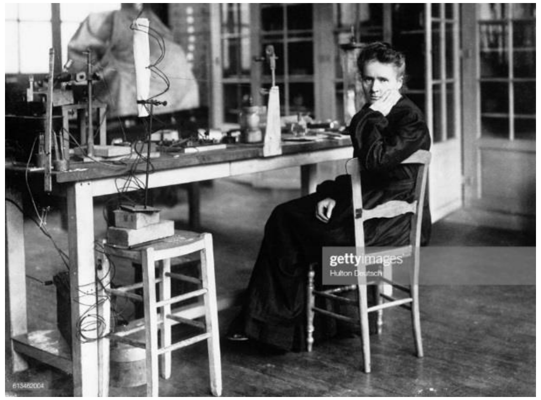
  - Academic incentives
- Immigration
- **“Lost Einsteins”**

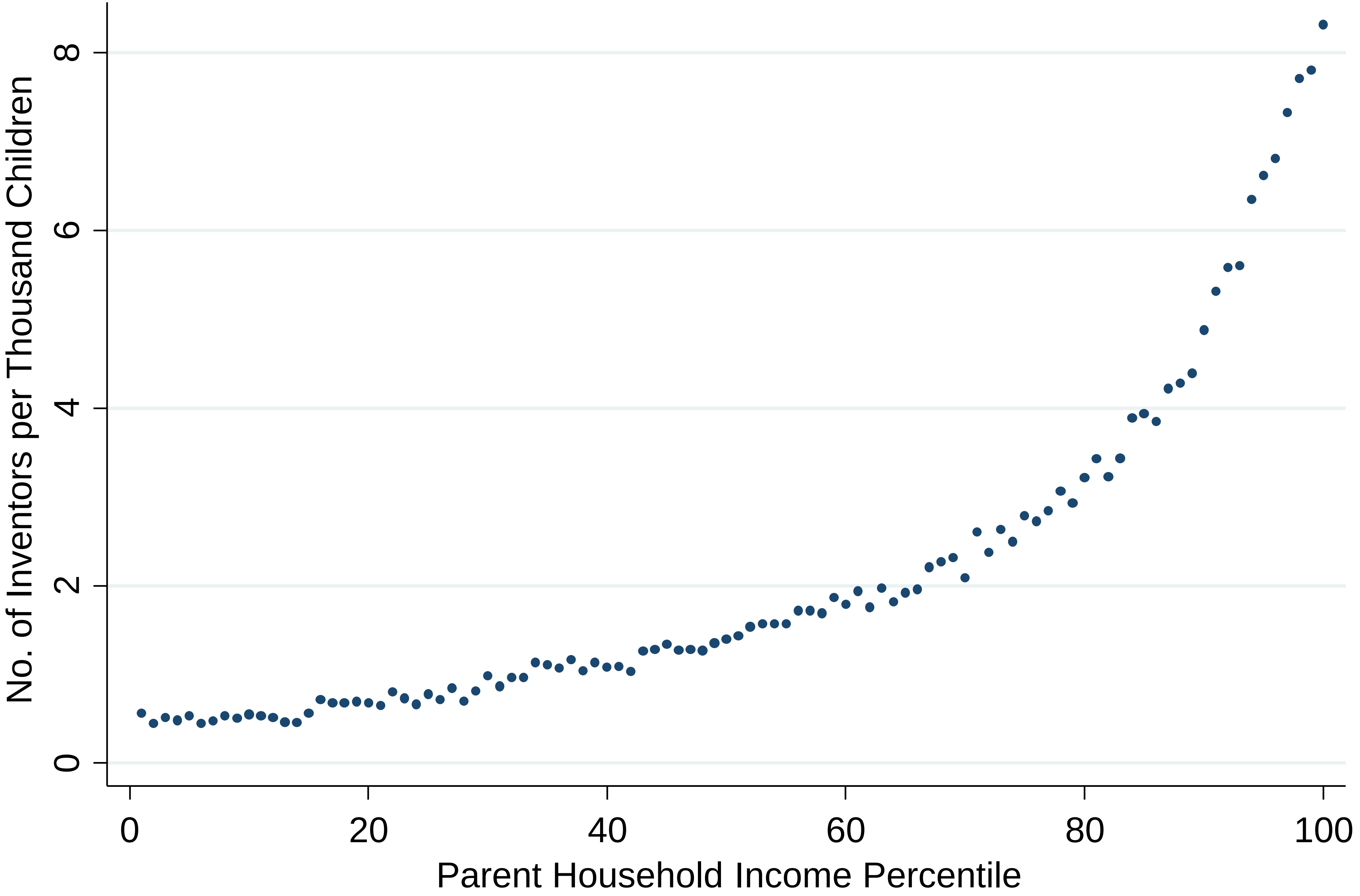
“Lost Einsteins and Marie Curies”

- **Quality** of inventor pool could be improved as well as quantity
- Bell, Chetty, Jaravel, Petkova & Van Reenen (2019, QJE) match US patent applicants & grants 1996-2014 to de-identified tax records
- Kids from low-income families, minorities and women under-represented in the inventor pool
- Vast majority of this is not due to lower ability, but rather lack of opportunity/exposure to innovation

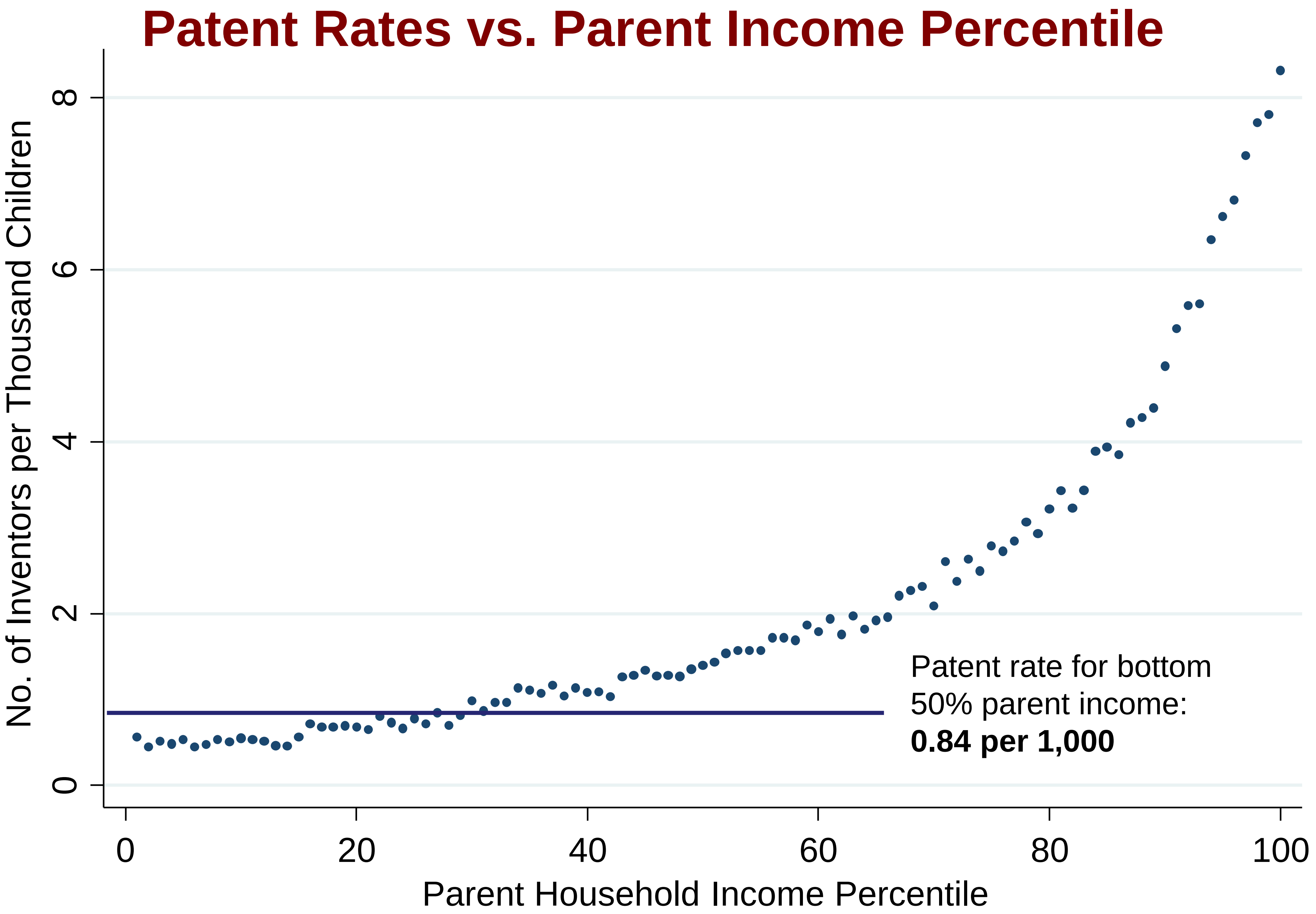




Patent Rates vs. Parent Income Percentile



Notes: Sample of children is 1980-84 birth cohorts. Parent Income is mean household income from 1996-2000.



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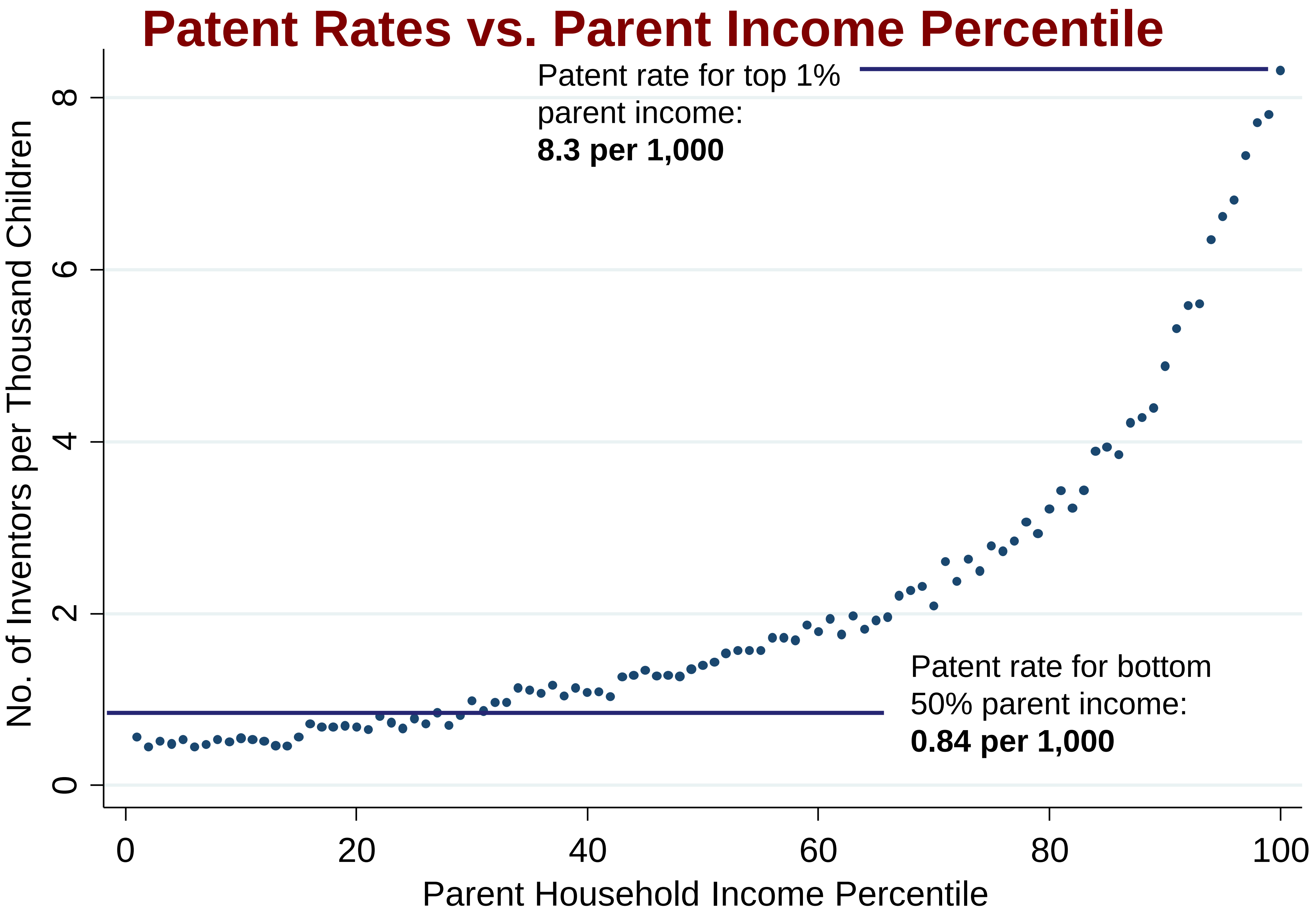

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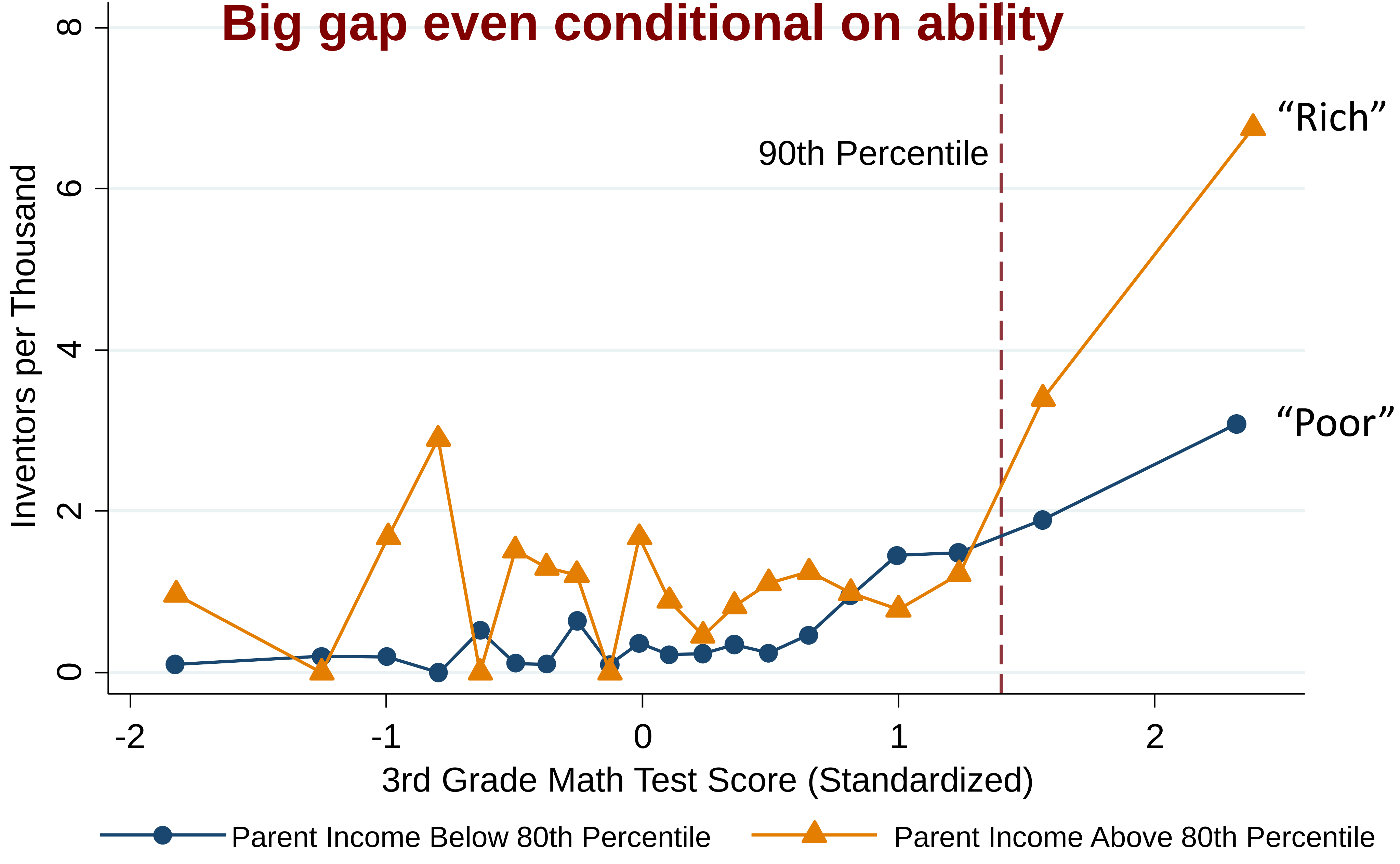
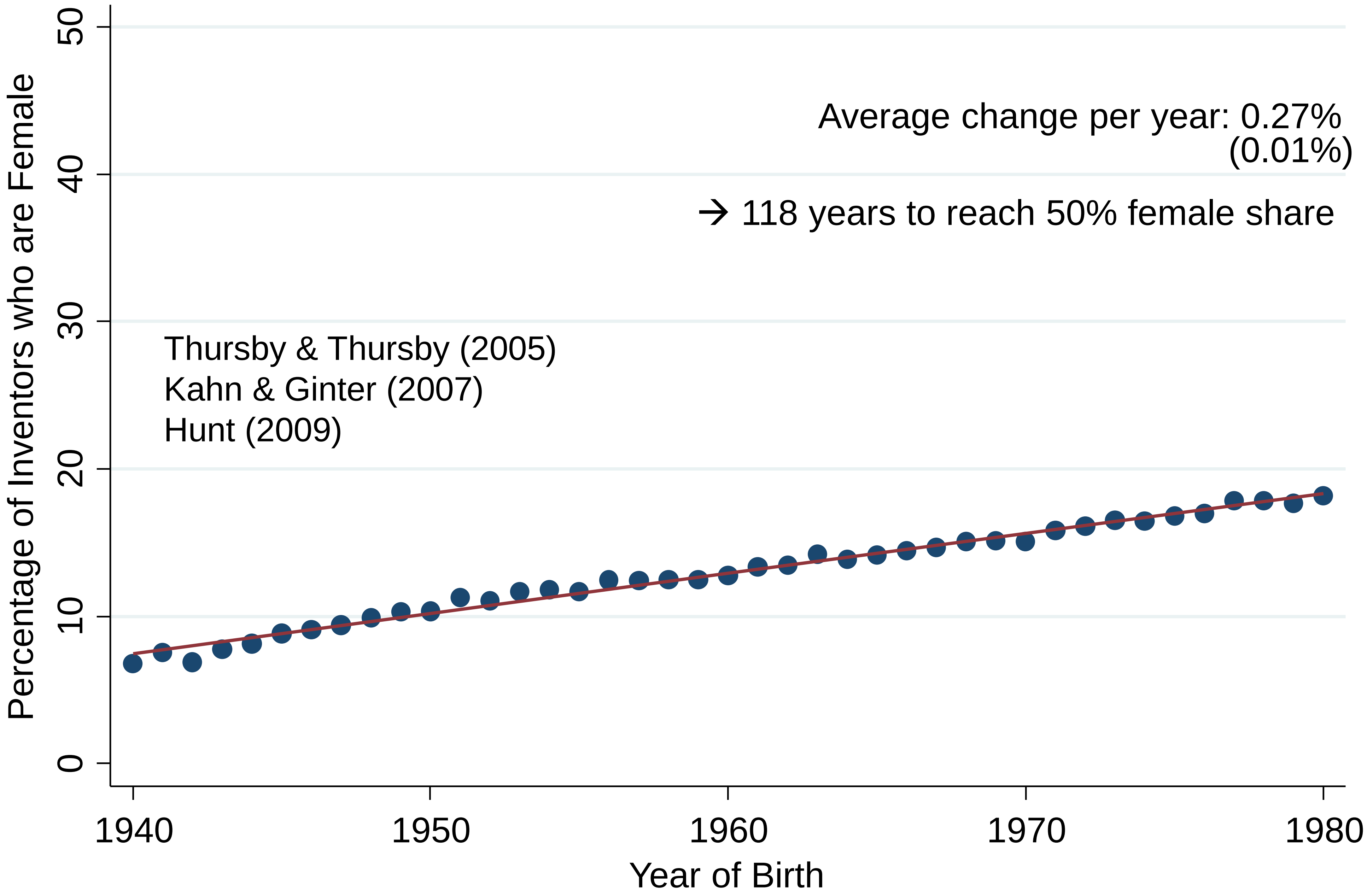
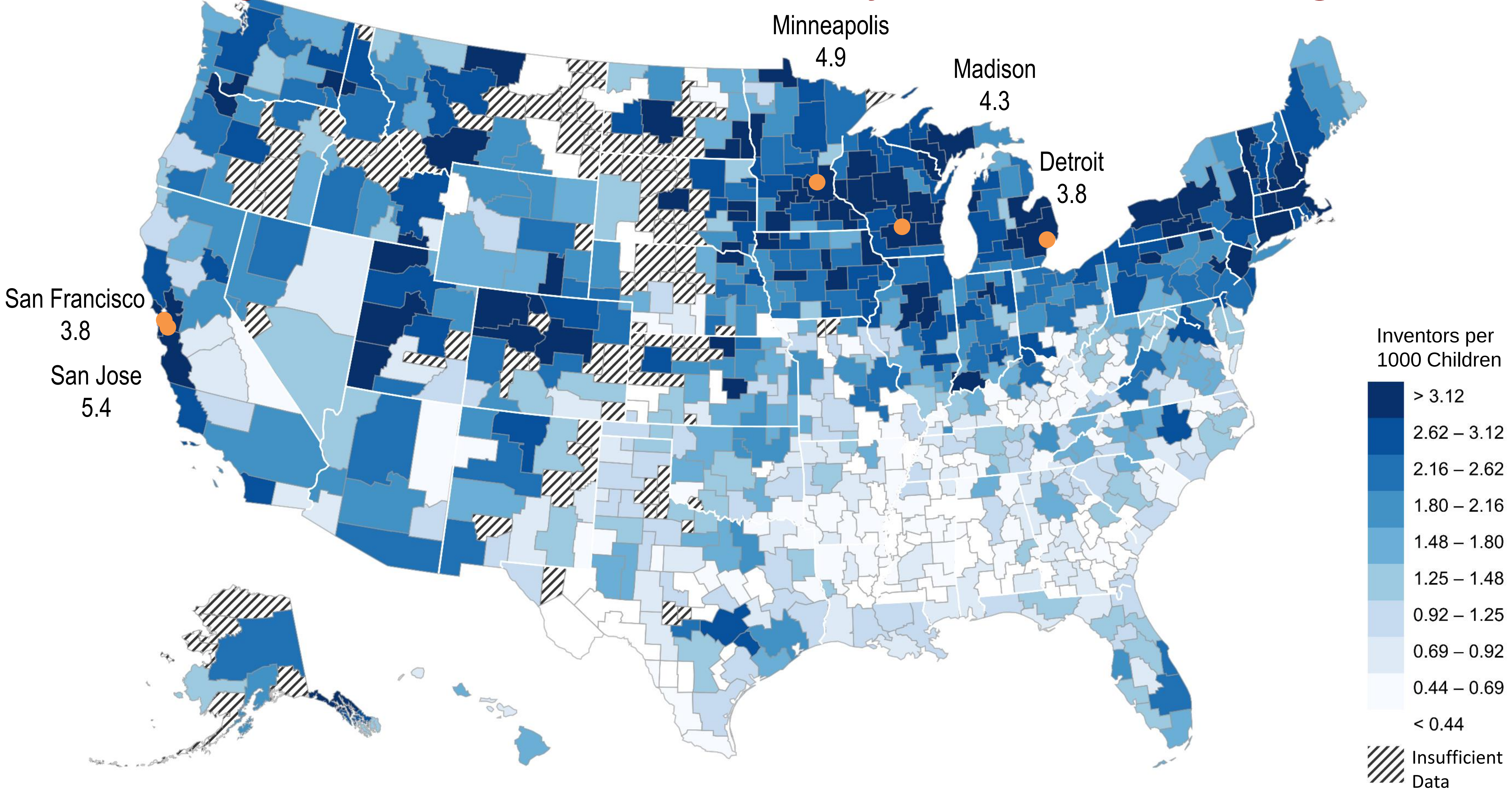
Patent Rates vs. 3rd Grade Math Test Scores by Parental Income: Big gap even conditional on ability



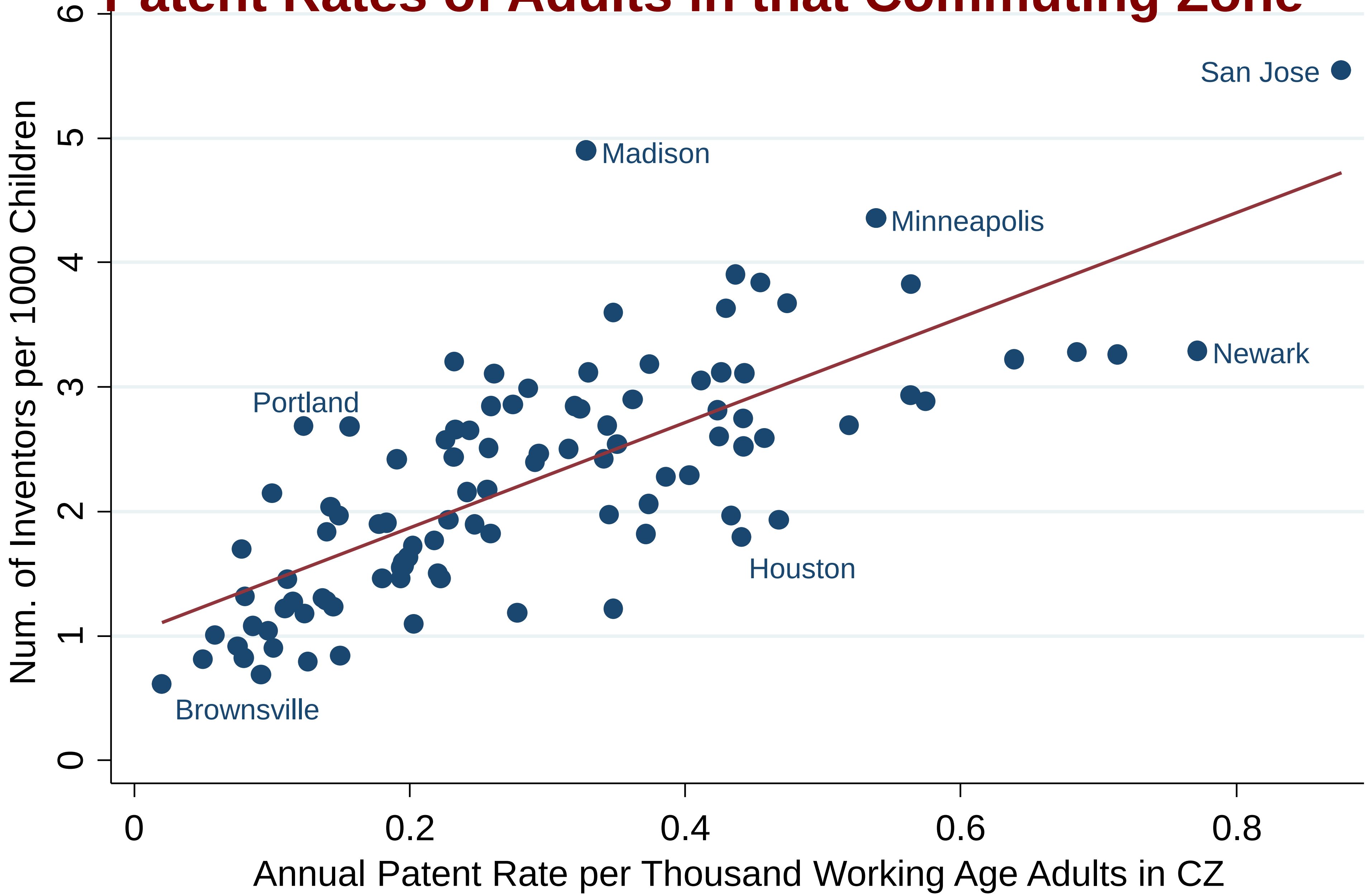
Gender: Percentage of Female Inventors by Birth Cohort



The Origins of Inventors: Patent Rates by Childhood Commuting Zone



Patent Rates of Children who Grow up in a Commuting Zone vs. Patent Rates of Adults in that Commuting Zone



Identification of the causal impact of place-based exposure

- **Timing and Fixed effects:** Regress adult outcomes on childhood exposure, including current destination place effects

- Use the sharp discontinuity by **technology class**.
  - Idea is that growing up in area that specializes in software (vs. medical devices) relatively more likely to innovate in software (vs. medical devices)

- **Movers design**: compare families where kids moved at early vs. later age

Lost Einstein Policies

- Regulatory Reforms in patent offices; Clinical trials, etc.
- Mentorship/internship programs
- Anti-Discrimination policies
- **Education policies**

Within School tracking for Gifted and Talented ("G&T")

- **Card and Giuliana (2016)** study large urban US School District with in-school tracking program
- 4th and 5th graders. If a G&T pupil, school has to have a separate "Gifted/High Achievers" class. But, since few G&T most seats are simply high achievers
- Since lots of between school segregation many high achievers are Black & Hispanics
- Rank RD Design shows large positive effects on Math & English for minorities (0.5sd). Persist until at least 6th grade
- Diff-In-Diffs on cohort shows no negative effects on kids who don't get selected into GHA class
- Not better teachers or quality peers, but teacher expectations

Within School tracking

- **Cohodes (2010)** looks at similar in-school tracking in Boston Public School System
- 3rd graders in Advanced Work Class. Half are minorities
- Fuzzy RDD finds college enrolment 15 pp higher, with gains mainly from minority students (65% increase in college enrolment on 4 year course)

Summary on examples of exposure programs in Card & Giuliano (2016) and Cohodes (2020)

- Not simply a Gifted and Talented program (where low income and minority kids often don’t quality). These have ambiguous findings (e.g. Bui et al, 2014)

- Rather, both papers a broader within (not between) school tracking policy to create exposure

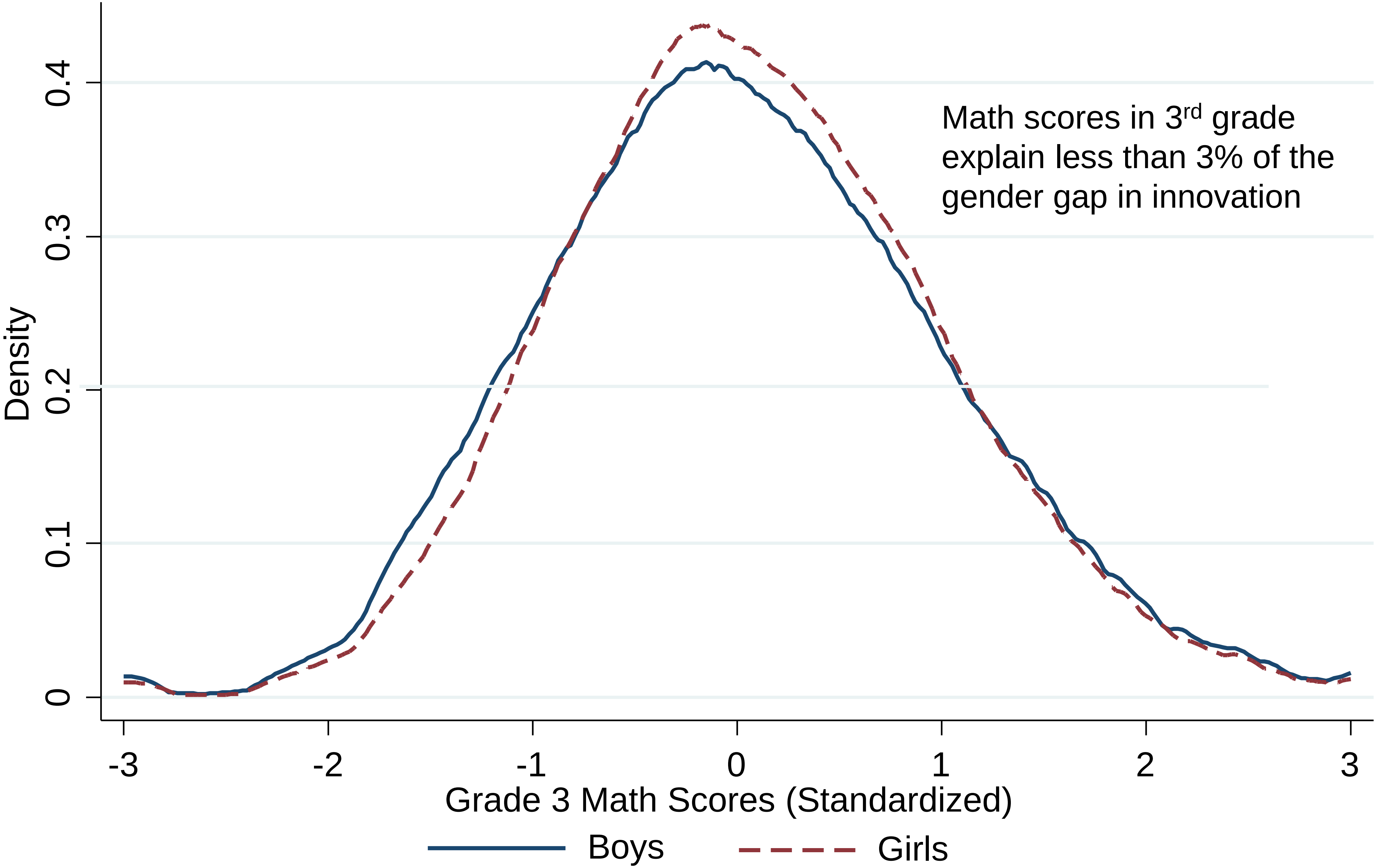
Conclusions on Human Capital Policies for innovation

- Human capital policy acts on supply side, so more attractive than “demand side” tax/subsidy policies
  - Lower risk of increasing equilibrium costs (and inequality)
  - And some evidence of successful interventions

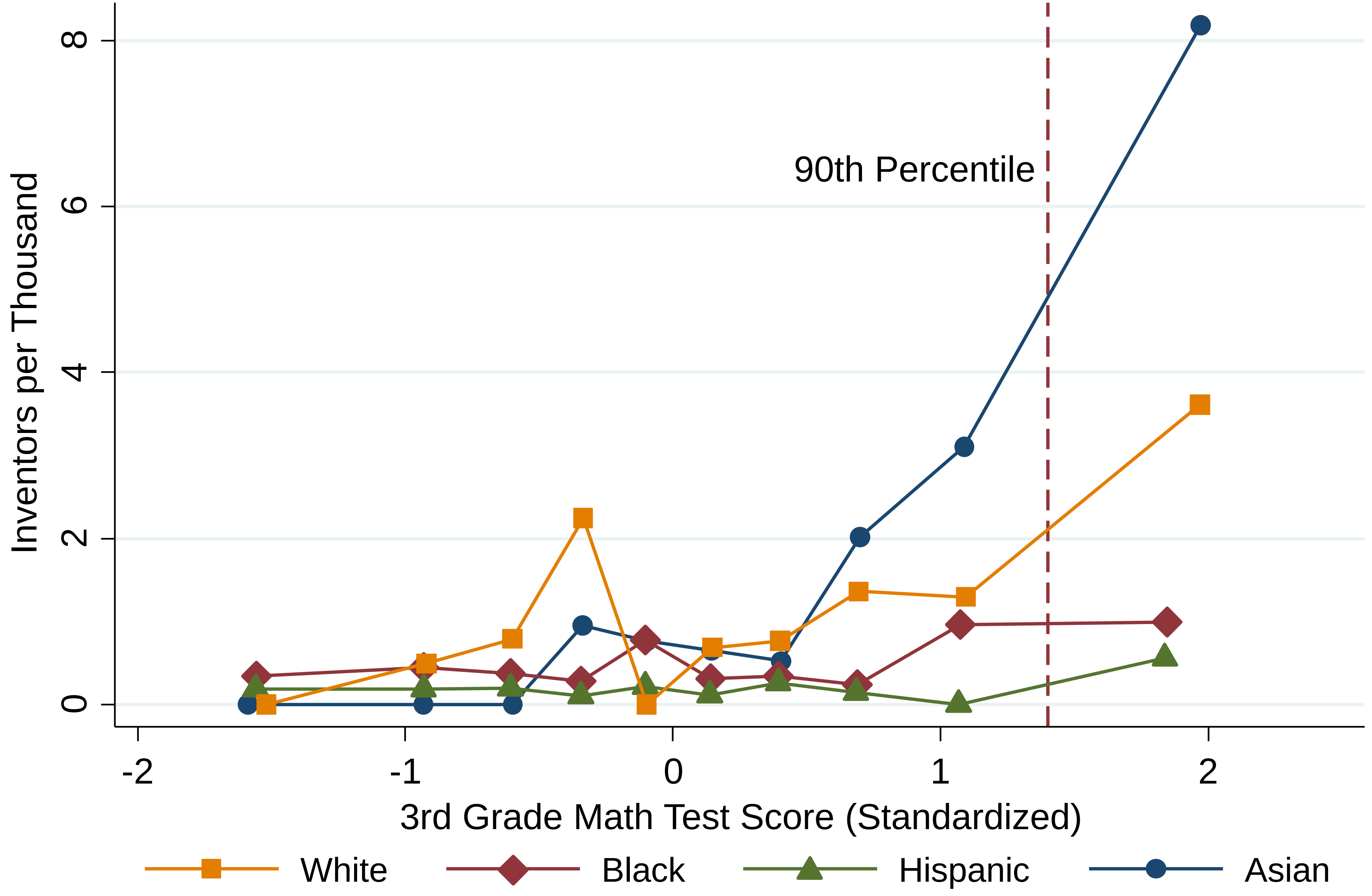
- But some limitations:
  - Less of an empirical literature than demand side policies
  - Policies will take longer to have an effect
  - Leakage issues (although less of a problem for US than for other countries)

Back Up

Distribution of Math Test Scores in 3rd Grade for Boys vs. Girls



Patent Rates vs. 3rd Grade Math Test Scores by Race and Ethnicity



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"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 (2019); Jacob & Lefgren (2011)

- **Private Sector**
  - – Fairly large literature (though not as big as R&D tax credits)
  - – Example: Green Energy (Howell, 2017)
  - – 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

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  - 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 Small Business Innovation Research 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

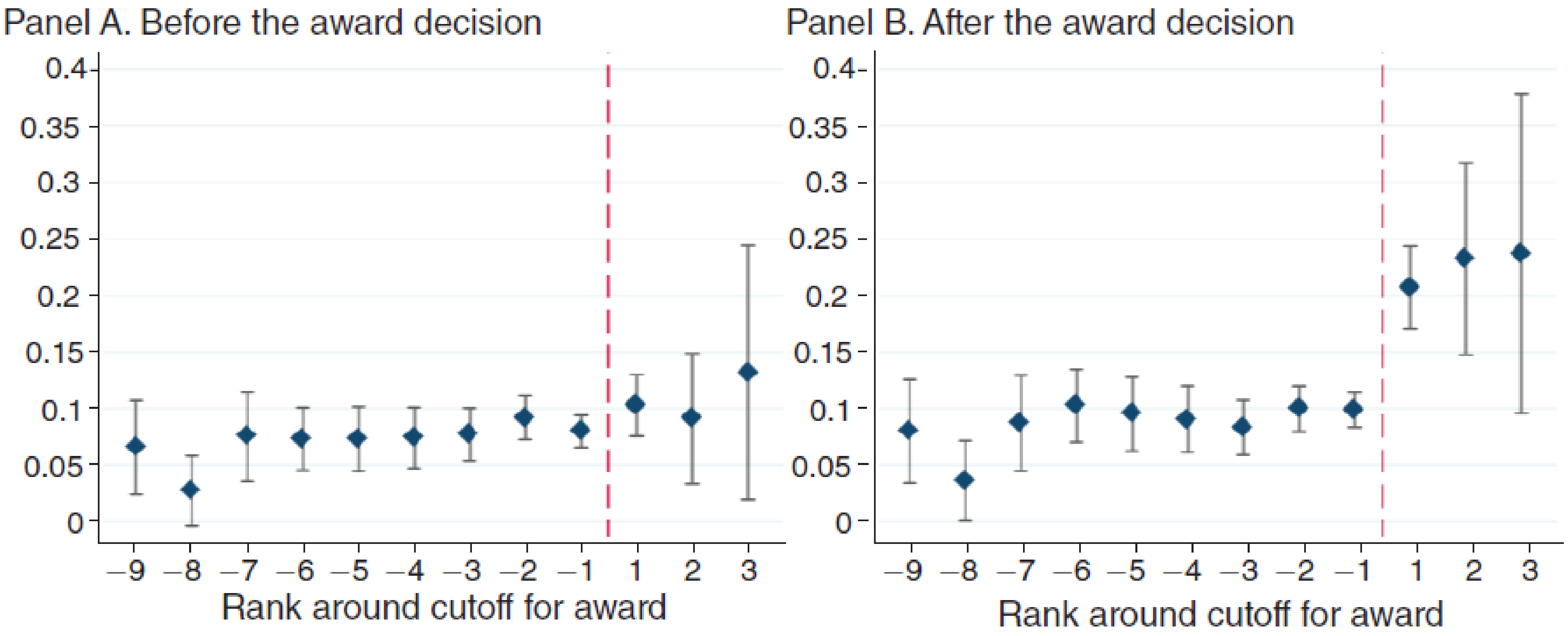


FIGURE 3. PROBABILITY OF VENTURE CAPITAL BEFORE AND AFTER GRANT BY RANK

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)

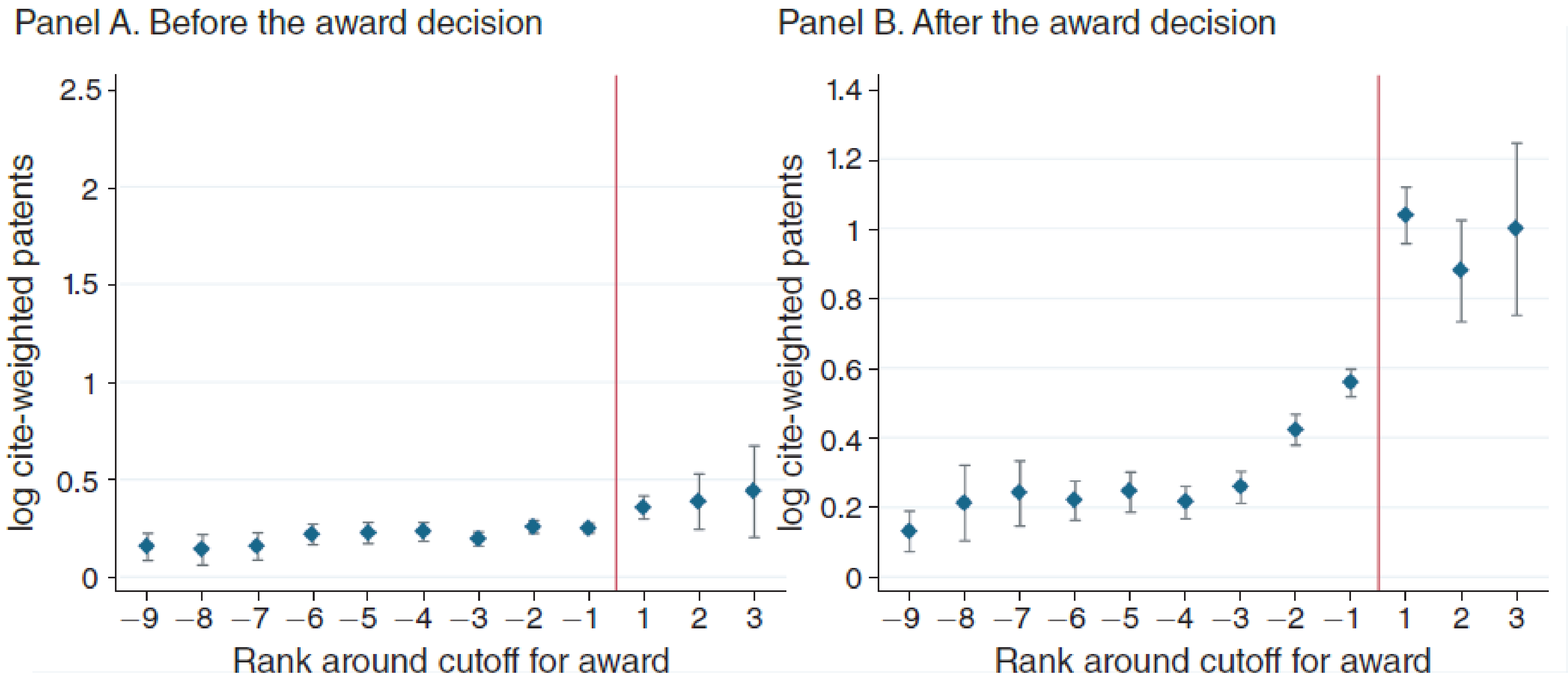


FIGURE 2. CITE-WEIGHTED PATENTS BEFORE AND AFTER PHASE 1 GRANT BY RANK

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

R&D Grants: Military shocks

- Moretti, Steinwender & Van Reenen (2023) 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

- But what methods of direct R&D funding (defense or otherwise) are most effective?

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)

LSE THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

poid 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 (2023)

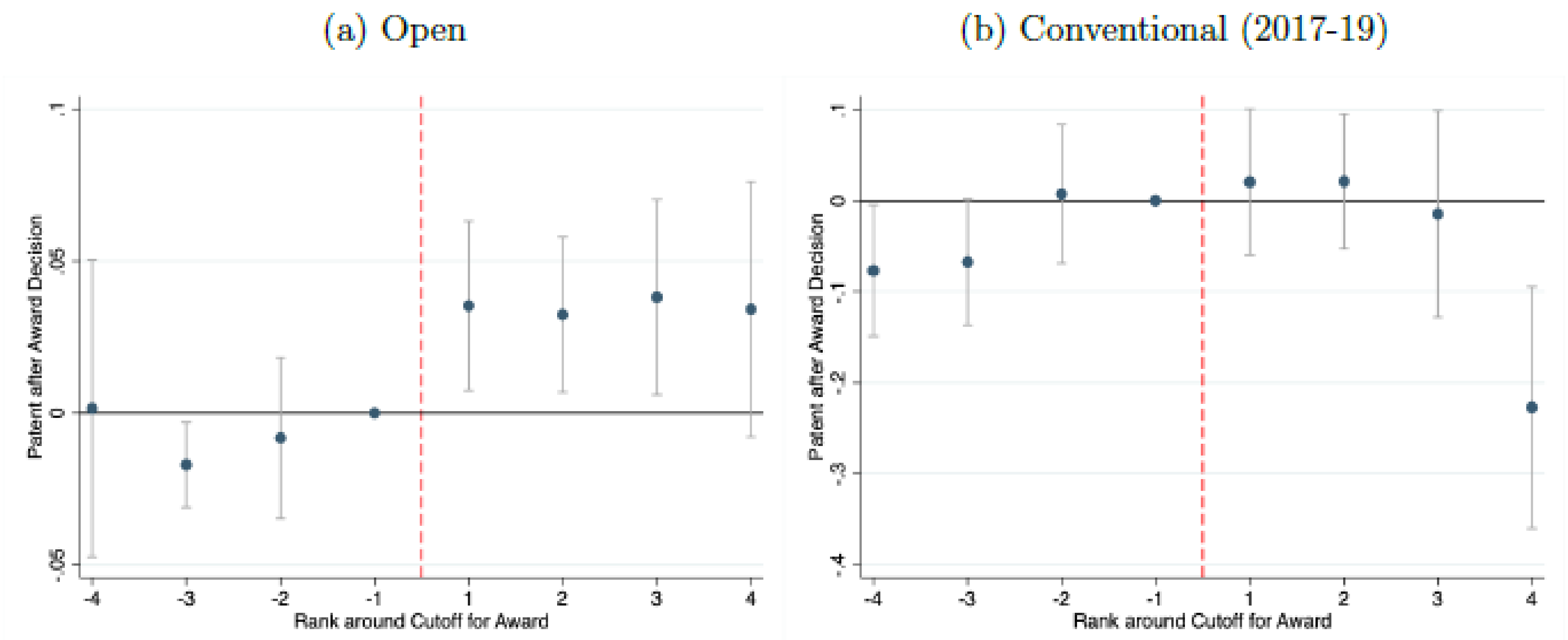
- New types of firms starting applying & winning: younger, smaller, based in VC hubs of Silicon Valley, Boston, etc.

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

- Conventional program had no 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 Awards but not for Conventional

Figure 7: Probability of Patents by Rank Around Cutoff

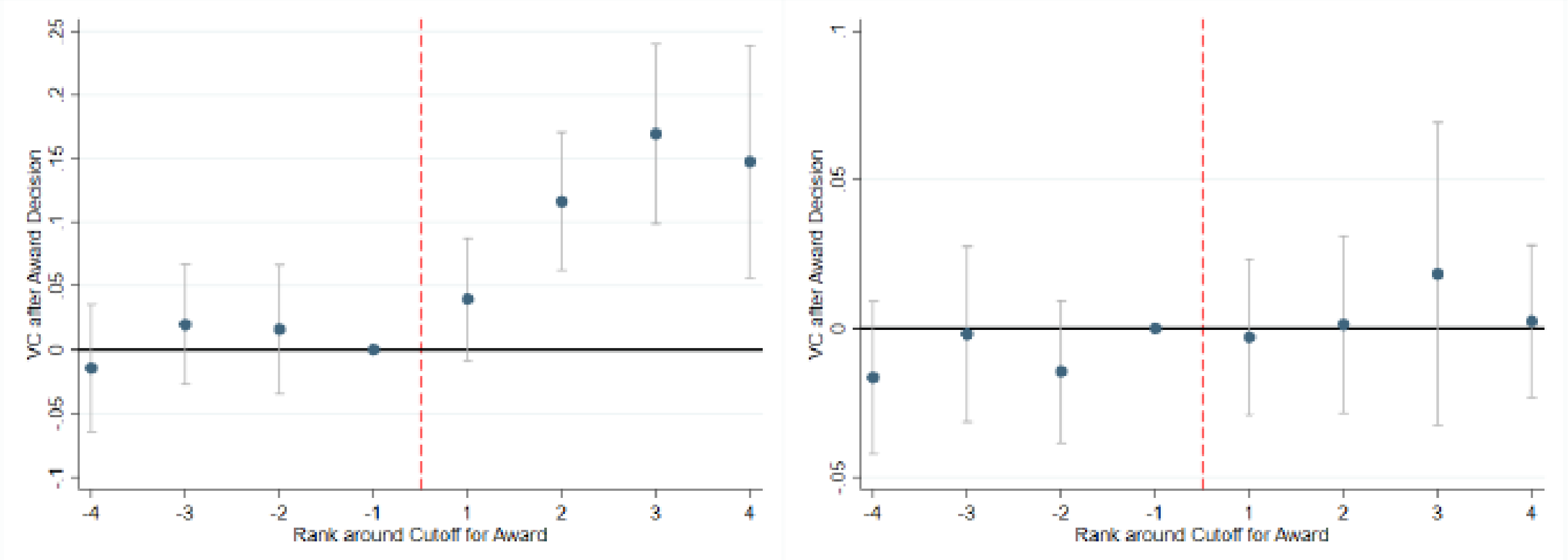


Note: These figures show the probability that an applicant firm had any ultimately granted patent applications within 24 months after the award decision. In both panels, the x-axis shows the applicant's rank around the cutoff for an award. A rank of 1 indicates that the applicant had the lowest score 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
  - Less specific proposals <u>more</u> successful (like Open)
  - Compare other reforms which induced new entrants, but were still top-down
    - Zero treatment effects (unlike open)

- 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, very centralized R&D 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?

General taxation & Innovation: Issues

- Higher taxes reduce returns to income from successful innovation, so the obvious effect of tax is to **reduce** innovation incentives
- So, questions include:
  - By how *much* is innovation reduced? “lone genius” model would suggest that there is little effect
  - To what extent do we identify an *aggregate* change or rather a **shifting** of location of innovation across units
    - e.g. does increase in state taxes just shift activity within the US without affected economywide innovation?
- Recent work has focused on <u>individual inventors</u> (as measured by patents) and the incentives they face

Some reasons to think aggregate innovation-tax elasticity might be small in magnitude

- Bell et al (2019, JEEA) model choice of inventor career:

1. A fall in tax rates induces more **marginal** inventors and R&D projects. Since these are lower quality, the aggregate effect is small (Jaimovich and Rebelo, 2017, JPE)
   - “forecastable” innovation

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   – "forecastable" innovation
2. Since innovation is uncertain, it is like buying lottery ticket. For an individual with concave utility, a difference between a $1m and $5m lottery win is not great, so tax impact is small (cf. optimal tax literature)
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2. Since innovation is uncertain, it is like buying lottery ticket. For an individual with concave utility, a difference between a $1m and $5m lottery win is not great, so tax impact is small (cf. optimal tax literature)
   - "unforecastable" innovation
3. Decision to become an inventor depends on information and early motivation/exposure (e.g. evidence in Bell et al, 2019, QJE)

Akcigit, Grigsby, Nicholas and Stantcheva (2022, AGNS in QJE)

- USPTO 1920-2000 (estimate 1940-00): Disambiguate inventor names (Lai et al, 2014). From address know which in state inventors live
- Calculate state-specific Marginal Tax Rates (MTR) for corporations and for individuals
  - For innovators focus on the 90^{th} percentile of income distribution compared to average (e.g. use Bakija, 2006, tax-sim model)
- Estimate at state (“macro”) and individual (“micro) level of the effect of taxes (lagged 3 years) on:
  - Inventor counts (including cross-state mobility); Patent counts; Patent quality (citations)

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- Estimate at state (“macro”) and individual (“micro) level of the effect of taxes (lagged 3 years) on:
  - Inventor counts (including cross-state mobility); Patent counts; Patent quality (citations)
- **Key Result:** lower general taxes encourage significantly more innovation

States that increase taxes had lower slower growth in innovation

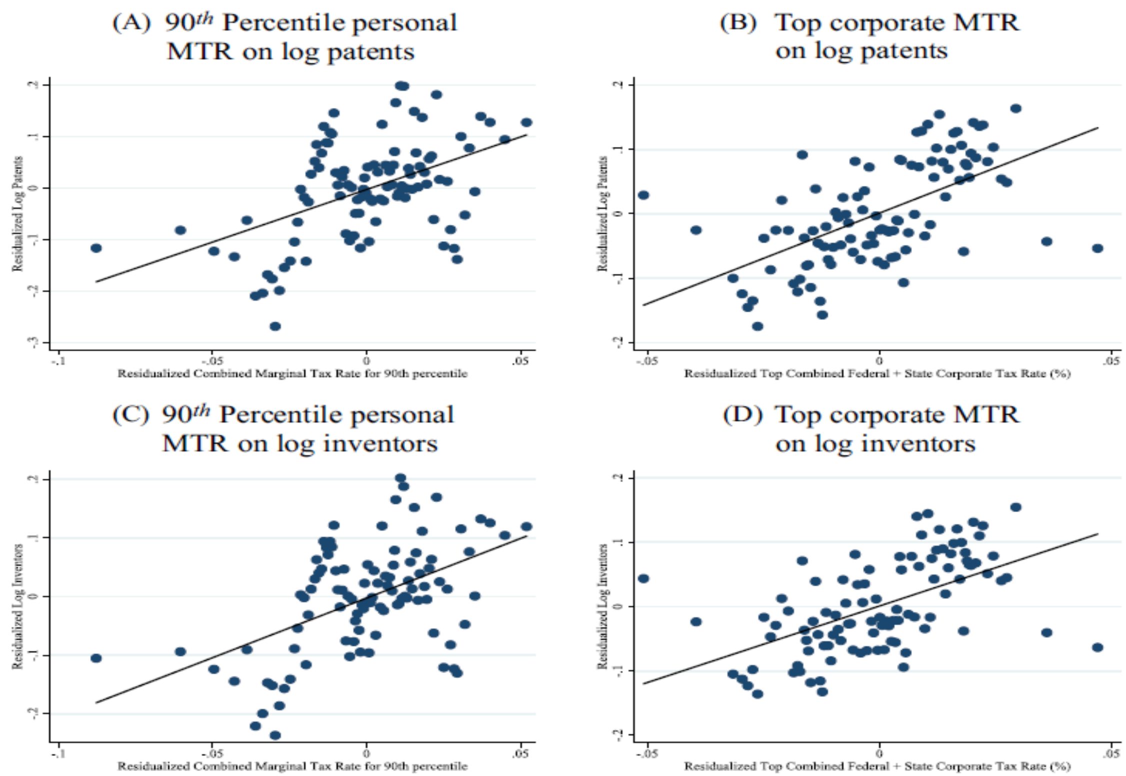

FIGURE I

Binned Scatters

This figure plots binned scatter plots for the effect of taxes at the state level. The top row shows the effect on log patents, and the bottom row shows log inventors. The leftmost column shows the relationship between innovation and the marginal tax rates (MTRs) for the 90th percentile earners, and the rightmost column shows the effect of top corporate MTRs. All tax rates include both federal and state taxes. Both the horizontal and vertical axes are residualized against state and year fixed effects, as well as lagged population density, personal income per capita, and R&D tax credits. Panels A and C also residualize against the lagged corporate tax rate, while Panels B and D residualize against 90th percentile personal income MTR. All mainland U.S. states except Louisiana are included over the period 1940–2000.

Identification concern: other factors change when states change tax burden

- Detailed fixed effects
  - For inventor-level regressions can control for individual fixed effects
- Compare top tax rate (relevant for inventors) vs. median personal tax. Then can include state by time dummies.
- Gruber-Saez (2002) synthetic IV. Tax burden of firm or individual is a mix of state and federal taxes. Use just the changing federal rules to instrument tax burden, keeping state rules fixed.
- Event studies…

Event studies around large tax reforms (synthetic cohort approach)

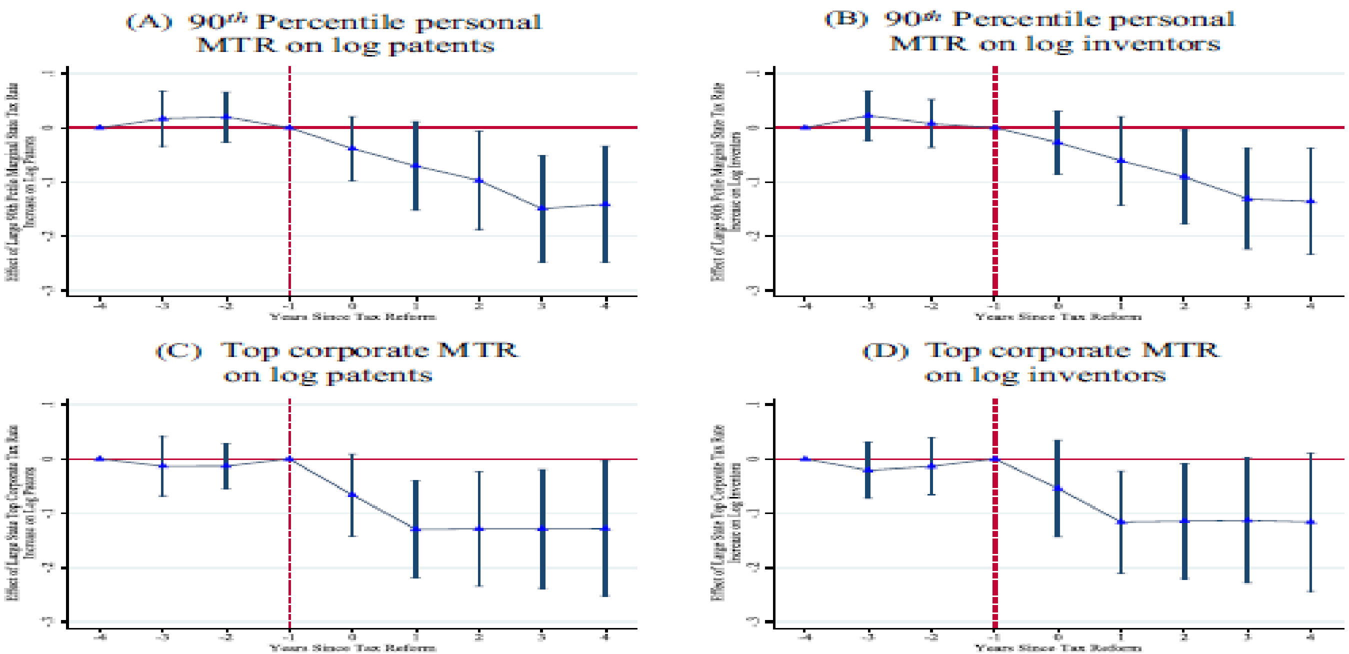

FIGURE III

State-Level Event Studies around Large Tax Reforms

This figure reports estimates of γ_l from equation (9), based on event study regressions around large tax reforms. A large tax reform is defined as being in the top 10% of state tax changes in the period 1940–2000 that does not have another large reform within four years before or after the focal reform. Panels A and B consider state tax reforms affecting the personal tax rate for the 90th percentile earner, while Panels C and D consider large reforms to the top statutory corporate tax rate. We generate a synthetic control state for each reform following Abadie, Diamond, and Hainmueller (2010) by matching on prereform outcomes (patents or inventors), population density, and personal income/capita averaged over the four years before the reform. Only states that do not themselves have a large reform in the event window are eligible to be included in the synthetic control. See Section IV.C for details. All regressions include reform $\times$ treatment state fixed effects and relative-year fixed effects and are unweighted. Bars represent 95% confidence intervals using standard errors clustered at the reform level.

Elasticity of state innovation (Y) with respect to net-of-income personal tax rate (τ^p), $\varepsilon_{Y,p}$

$$\varepsilon_{Y,p} := \frac{dlog(Y)}{dlog(1-\boldsymbol{\tau^p})} =$$

Share of innovation by **corporate** inventors

$$\gamma_Y^c \varepsilon_{Y,p}^c + (1-\gamma_Y^c)\varepsilon_{Y,p}^p + \gamma_Y^d \eta_p^d + \left(1-\gamma_Y^d\right)\eta_p^o$$

Elasticity of **corp. inventors** innovation wrt personal tax

NB: Analogous expressions for elasticities wrt corporate tax rates

Elasticity of state innovation (*Y*) with respect to net-of-income personal tax rate (τ^p), $\varepsilon_{Y,p}$

$$\varepsilon_{Y,p} := \frac{dlog(Y)}{dlog(1-\boldsymbol{\tau}^{\boldsymbol{p}})} =$$

Share of innovation by
corporate inventors

Share of innovation by
Non-corp. inventors

$$\gamma_Y^c \varepsilon_{Y,p}^c + (1-\gamma_Y^c)\varepsilon_{Y,p}^p + \gamma_Y^d \eta_p^d + (1-\gamma_Y^d)\eta_p^o$$

Elasticity of **corp. inventors**
innovation wrt personal tax

Elasticity of **non-corp.** inventors
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Share of innovation by **corporate** inventors

Share of innovation by **Non-corp.** inventors

Share of innovation by **out of state** inventors

$$\gamma_Y^c \varepsilon_{Y,p}^c + (1-\gamma_Y^c)\varepsilon_{Y,p}^p + \overbrace{\gamma_Y^d \eta_p^d + (1-\gamma_Y^d)\eta_p^o}^{\textbf{Mobility effects}}$$

Elasticity of **corp. inventors** innovation wrt personal tax

Elasticity of **non-corp.** inventors innovation wrt personal tax

Elasticity of **out-state** inventors mobility wrt personal tax

Elasticity of state innovation (Y) with respect to net-of-income personal tax rate (τ^p), $\varepsilon_{Y,p}$

$$\varepsilon_{Y,p} := \frac{dlog(Y)}{dlog(1-\boldsymbol{\tau^p})} =$$

Mobility effects

Share of innovation by **corporate** inventors

Share of innovation by **Non-corp.** inventors

Share of innovation by **in-state** inventors

Share of innovation by **out of state** inventors

$$\gamma_Y^c \varepsilon_{Y,p}^c + (1-\gamma_Y^c)\varepsilon_{Y,p}^p + \underbrace{\gamma_Y^d \eta_p^d + (1-\gamma_Y^d)\eta_p^o}_{\text{Mobility effects}}$$

Elasticity of **corp. inventors** innovation wrt personal tax

Elasticity of **in-state** inventor mobility innovation wrt personal tax

Elasticity of **non-corp.** inventors innovation wrt personal tax

Elasticity of **out-state** inventors mobility wrt personal tax

AGNS Results

- **Elasticity of patents (citations) to:**
  - Personal net of tax rate is 0.8 (1.0)
  - Corporate net of tax rate is 0.49 (0.46)
    - Corporate taxes do not affect noncorporate ("garage) inventors, but do reduce proportion of inventors working for firms
- **Location choice** is affected: inventors significantly less likely to move to high tax state (but corporate taxes only affect location choices of corporate inventors)
  - Thus, taxes affect mobility. Corporate tax is likely all location choice, whereas personal taxes affect both mobility and aggregate
- No effect of tax on **patent quality** (as measured by citations)

Issue I: Why should personal tax rate matter for corporate inventors?

- Inventors working in firms do not own the IP from innovations they help produce, so why should they be affected by personal tax rates?
- This would not matter with standard competitive models of the labor market, but if the firm shares innovation rents with workers, then personal tax will matter
  - This seems to be true in Van Reenen (1996) and Kline et al (2019) rent-sharing from innovation evidence
  - Exact imperfect competition model still controversial. Does this represent bargaining over surplus or monopsony (wage posting)?

Issue II: Identification

1. How well is **extensive** margin captured? When include inventor fixed effects, this conditions on people who are inventors at some point in their lives.
   - What about those who could have invented, but did not? (this is key to "Lost Einstein" work in Bell et al, 2019a,b)

2. Where are inventors in the income distribution? They use the top 10% in citation distribution for the top inventors (assume these are at p90 in income distribution) and use p50 for the rest
   - Just using p90 seems very crude – could do much better using inventor income distribution
   - Even bottom 90% of citations do better than p50 worker

Issue III: Firm Incentives

- Link to existing firm R&D tax credit literature vague
- R&D tax credits are “controlled for”, but not integrated into the analysis (e.g. higher corp tax rate makes them *less* valuable)
- Major US firms operate across many states (and indeed countries). Within such a multi-state firm, why would a corporate tax cut in one state generate more incentives to do more **innovation** in that state?
  - Indeed, logic of R&D tax credit says the opposite (state R&D credits *less* valuable when statutory rate cut)

Policy implications

- Risk of beggar-thy-neighbor tax policies since much of effects are re-location, so zero-sum game.

- **Note:**
  - AGNS find that tax elasticities are lower when state has more innovation in their field

- Implies that building up amenities/research infrastructure may be a better way of reducing risk of “brain drain” than just cutting taxes

Conclusions

- Standard approach is to focus on **firms** and how their R&D incentives are influenced by changes in corporate tax rates and base (including R&D tax credits)
  - Can be done in a sophisticated way via details of tax code and tax-adjusted user cost

- Alternative approach to focus on how **individual** incentives are shaped by personal (and corporate) tax rates
  - Can use tax-sim models to do this, but less clear theoretically why these should matter

- AGNS do find some evidence for effects of top taxes on innovation: best empirical evidence so far

Back Up

Summary of AGNS

	Individual Level		*State level*		*Relocation*	
	Individual income tax	*Corporate income tax*	*Individual income tax*	*Corporate income tax*	*Individual income tax*	*Corporate income tax*
Individuals (garage)	-ve	0	-ve	-ve	+ve 0.72	+ **0.6**
Individuals (corporations)	-ve	-ve	-ve	-ve	0	+ve 1.25
All individuals	0.8	0.49	0.8-1.8	1.3-2.8		
Corp share		0.6				

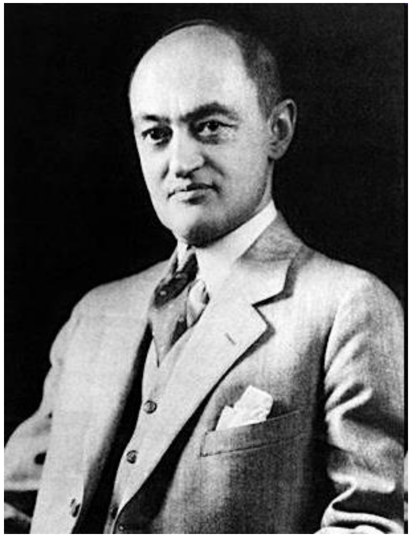
Note: Numbers are elasticities wrt net of tax income; -ve means a significantly negative coefficient, etc.

Issue IV: Aggregate effects

- Economy-wide effects hard to cleanly identify
  - AGNS conclusion comes from comparing state-level elasticities to aggregates of individual level, but unclear how to do correct aggregation
- Moretti and Wilson (2017) also find much relocation of star scientists from state-specific personal & corporate taxes
- Akcigit, Baslandze and Stantcheva (2016) look at international mobility of inventors 1977-2003 in EPO, USPTO, PTC
  - Use citations to stratify inventors in top 1%, top 1-5%, 5-10%, etc. Then construct counter-factual income in different countries
  - Elasticity of number of domestic (foreign) superstars to net of tax rate is 0.03 (1.00)

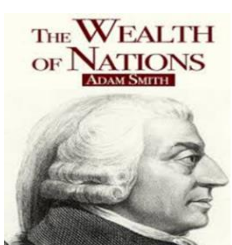
“On the one hand, taxation is an essential attribute of commercial society . . . on the other hand, it is almost inevitably . . . an injury to the productive process.”

Joseph Schumpeter, *Capitalism, Socialism, and Democracy* (1942)



Although probably his most famous quote was:

- "*Early in life I had three ambitions. I wanted to be the greatest* ***economist*** *in the world, the best* ***horseman*** *in all of Austria, and the greatest* ***lover*** *in all of in Vienna.*"



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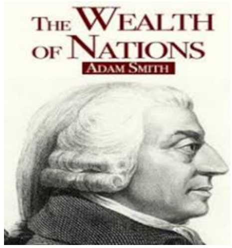
- "Those who knew *Schumpeter as an Economist, Lover or a Horseman presumed his skills were in the other two fields*"

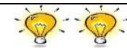
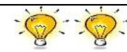
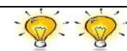


Introduction

- The impact of taxation on innovation is a broad question

- **Narrow:** Specific taxes around innovation (**R&D tax credit**, patent and innovation boxes, etc.). Start here.
- **Wider**: what is impact of general personal and corporate tax systems on innovation? e.g. Akcigit, Grigsby, Nicholas & Stantcheva (2022). Next lecture.
- **Very wide**: Many policies can be seen as implicit taxes or subsidies on innovation incentives. Example:-
  - Some regulations like an implicit tax: see Garicano et al., 2016 and Aghion et al., 2023 on size-dependent regulations. If larger firms face bigger tax burdens this is like an implicit tax on growth and innovation

Innovation Policy: The “Lightbulb” Table

(1)	(2)	(3)	(4)	(5)	(6)
Policy	**Quality of evidence**	**Conclusiveness of evidence**	**Benefit - Cost**	**Time frame:**	**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	↑

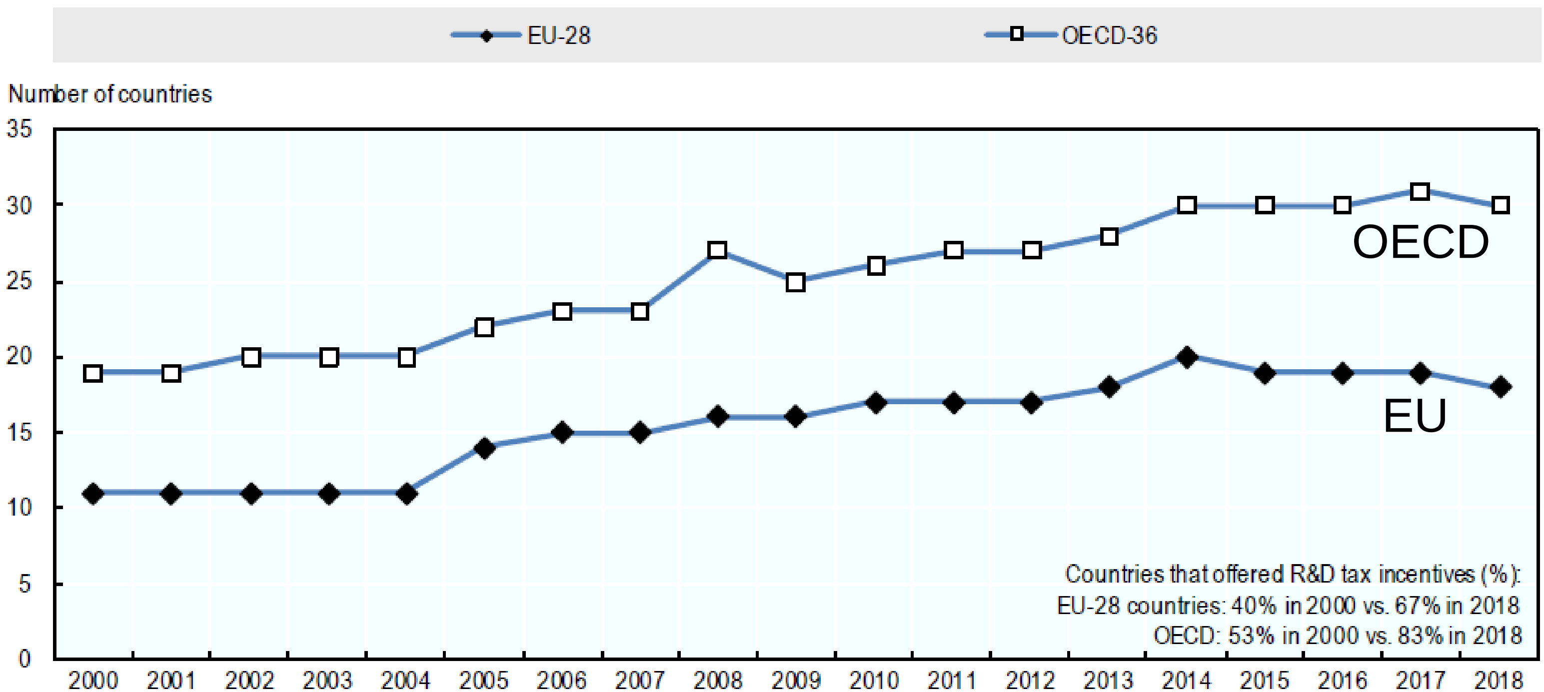
Source: Bloom, Van Reenen and Williams (2019, JEP)

R&D Tax credits

- A way of supporting R&D through the tax code
- Basic idea is to change the tax system to make R&D more attractive than other forms of spending
- Increasingly popular all over the world
  - There has been a general a shift from direct support via R&D grant policies to indirect support via tax system

- **Background facts**
  - Reagan introduced first “Research and Experimentation” tax credit in 1981
  - OECD (2021): 34/42 countries have tax credits (up from 20 in 2000)
  - Has been a general switch away from direct support via grants to indirect support through tax system

Increase in use of R&D tax incentives in OECD
83% of countries in 2018 compared to 40% in 2000



Note: EU-28 excludes Malta as no sufficiently detailed information is available on R&D tax relief provisions.
Source: OECD R&D Tax Incentives Database, http://oe.cd/rdtax, March 2019.

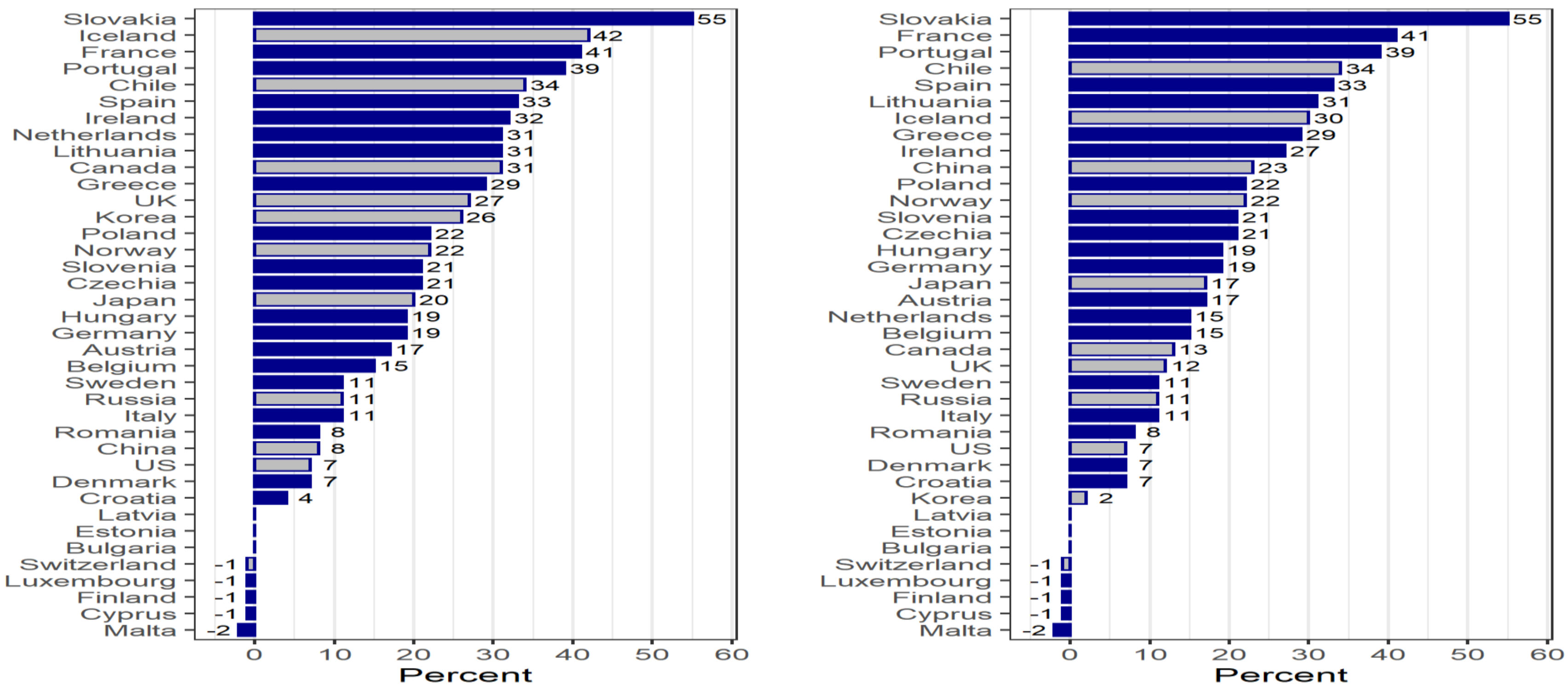
- In 2016 OECD countries granted $45bn R&D tax relief 46% of all gov support in form of tax relief (up from 36% in 2006)

Generally, R&D tax credits are more generous to Small & Medium Sized Enterprises (SMEs)

Figure 1: Implied tax subsidy rates on R&D expenditure in different countries in 2020

Panel A: SMEs

Panel B: Large enterprises



Source: OECD R&D Tax Incentives Database. https://stats.oecd.org/Index.aspx?DataSetCode=RDSUB
Notes: Shown are implied tax subsidy rates for Small and medium size enterprises (SMEs, (Panel A) and Large enterprises (Panel B) in different countries in 2020. The bars of EU countries are blue, those of non-EU countries gray. This is the “profitable scenario”. For a detailed methodology behind calculations see https://stats.oecd.org/Index.aspx?DataSetCode=RDSUB#. Countries with no notable bar (i.e. Latvia, Estonia, and Bulgaria) have an implied tax subsidy rate of 0%. Countries are ordered by level of tax subsidy rate (descending order). A corresponding graph showing the values for both firm types in 2007 as a comparison can be found in the Appendix.

R&D Tax credits: Advantages

- Performed by private sector: probably more efficient than government labs

- No need for government to explicitly *choose* projects so economizes on bureaucracy and information

- Mitigates risk of political capture by single firm/industry

R&D Tax credits: Disadvantages

- **Blunt:** not well targeted at high externality R&D “near market” rather than basic R&D (e.g. universities)
- Firms may **re-label** exiting activities to obtain tax break
- Limited use for new/SMEs as low/zero tax liabilities
  - Can overcome with refundable credits and carry-forward provisions help (but discounting limits usefulness)
- Perverse incentives due to **design features**
  - Example of moving “base” in US 1980s R&E credit
- As with other R&D demand side policies:
  - R&D narrowly defined: some innovation costs not classified as R&D (e.g. service firms)
  - Deadweight cost if not targeting marginal investments

Questions about R&D tax credits

- **Do Fiscal incentives increase *R&D?***
  - Elasticity of R&D with respect to user cost >1
  - See Hall (2022) and Blandinieres et al (2020) meta-study

- **Do Fiscal incentives increase *Innovation*?**
  - Important because of re-labelling concern (e.g. Chen et al, 2021 on China)
  - Dechezlepretre et al (2023) using Regression Discontinuity Design. Change in SME R&D thresholds (discuss later)

Simplified tax-adjusted user cost of R&D capital (Hall & Jorgensen, 1984)

Discounted value of tax credits and depreciation allowances

interest rate

Inflation rate

$$\rho_{it} = \left(\frac{1 - D_{it}}{1 - \tau_{it}} \right) \left(i_t + \delta - \frac{\Delta p_t}{p_{t-1}} \right)$$

Statutory corporate tax rate

R&D capital depreciation rate

- R&D is a form of intangible capital, so if R&D treated like other capital $D_{it} = 0$ and higher corporate tax discourages R&D
- If R&D just treated as an expense $D_{it} = \tau_{it}$ & tax system neutral (so favored relative to other forms of capital)

What are effects of tax credits? Alternative Designs

1. Federal tax credit generates substantial heterogeneity in firm level R&D user cost

2. Cross country variation in R&D tax credits

3. State-specific tax credits

4. Use non-linear design of tax credits to generate Regression Discontinuity Design (RDD)

What are effects of tax credits? Alternative Designs

1. **Federal tax credit generates substantial heterogeneity in firm level R&D user cost**
   – Firm's history (e.g. via "base" for incremental credit) matters, as does it's corporate tax eligibility, etc.

Constant fiddling around with the design of the R&D tax credit (1981-2013, Rao, 2016)

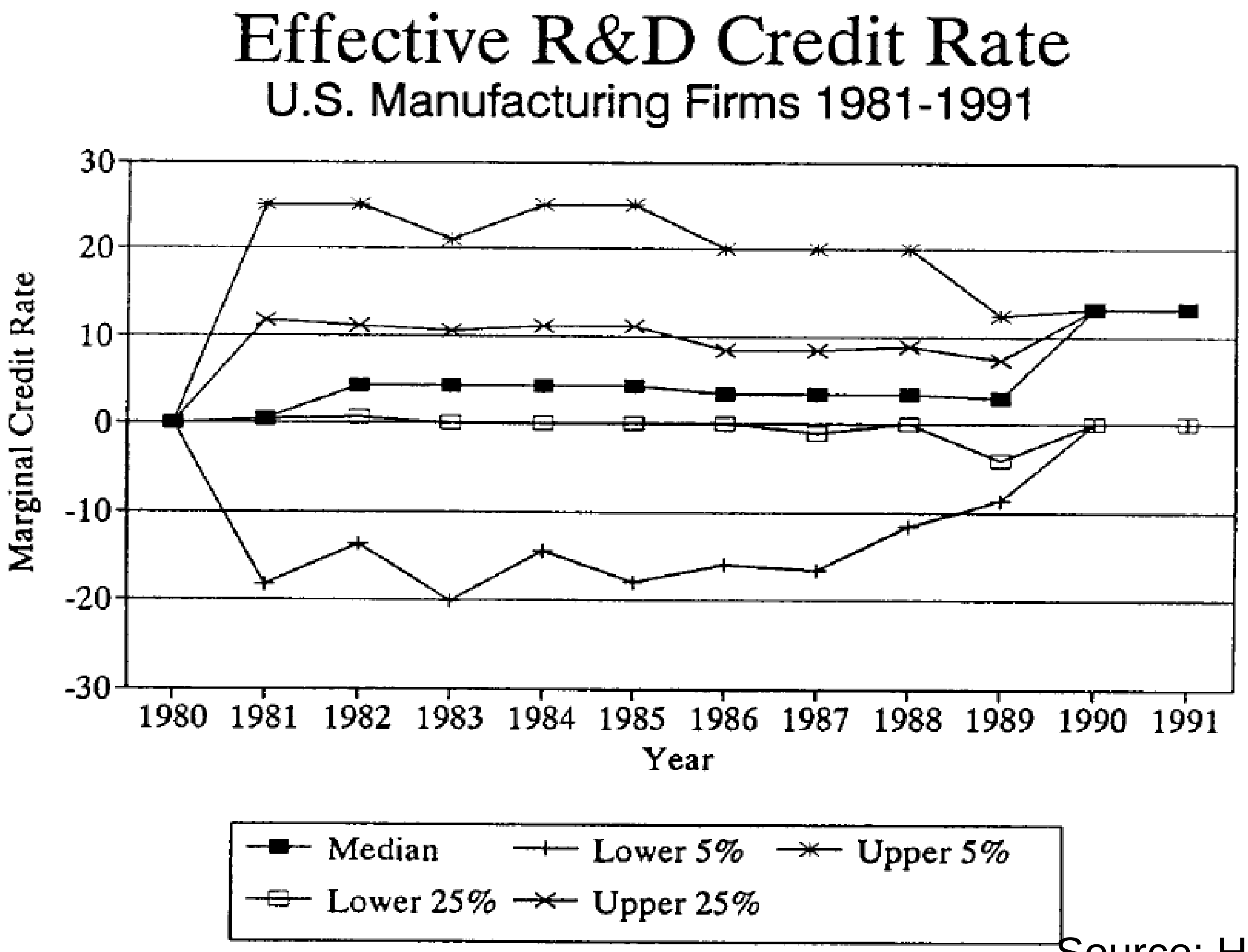
Table 1: Legislative History of the Federal Research and Experimentation Tax Credit, 1981-2013

	Credit Rate*	Corporate Tax Rate	Definition of Base	Qualified Research Expenditures	Sec. 174 deduction**	Foreign Allocation Rules	Carryback/Carryforward
July 1981 to Dec 1981	25%	48%	Maximum of previous 3-year average or 50% or current year	Excluded: research performed outside US; humanities and soc. science research; research funded by others	None	100% deduction against domestic income	3 years/15 years
Jan 1982 to Dec 1985	Same	46%	Same	Same	Same	Same	Same
Jan 1986 to Dec 1986	20%	34%	Same	Definition narrowed to technological research. Excluded leasing	Same	Same	Same
Jan 1987 to Dec 1987	Same	Same	Same	Same	Same	50% deduction against domestic income; 50% allocation	Same
Jan 1988 to Apr 1988	Same	Same	Same	Same	Same	64% deduction against domestic income; 36% allocation	Same
May 1988 to Dec 1988	Same	Same	Same	Same	Same	30% deduction against domestic income; 70% allocation	Same
Jan 1989 to Dec 1989	Same	Same	Same	Same	-50% credit	64% deduction against domestic income; 36% allocation	Same
Jan 1990 to Dec 1991	Same	Same	1984-1988 R&D to sales ratio times current sales (max of 16%); 3% of current sales for startups	Same	-100% credit	Same	Same
Jan 1992 to Dec 1993	Same	Same	Startup rules modified	Same	Same	Same	Same
Jan 1994 to June 1995	Same	35%	Same	Same	Same	50% deduction against domestic income; 50% allocation	Same
July 1995 to June 1996	0%	Same	None	-	-	Same	Same
July 1996 to June 1999	20%	Same	1984-1988 R&D to sales ratio times current sales (max of 16%); 3% of current sales for startups	Same as before lapse	-100% credit	50% deduction against domestic income; 50% allocation	Same
July 1999 to June 2004	Same	Same	Also includes research undertaken in Puerto Rico and U.S. posessions.	Same	Same	Same	Same
July 2004 to Dec 2005	Same	Same	Same	Same	Same	Same	Same
Jan 2006 to Dec 2007	Same	Same	Same	Transition rules altered slightly and alternative credits modified as outlined on next sheet.	Same	Same	Same
Jan 2008 to Dec 2013	Same	Same	Same	Same	Same	Same	Same

* In all years the firm can apply the credit rate to 50% of current QREs if the base amount is less than 50% of current QREs.

** Section 174 of the IRC provides an immediate deduction for most research and experimentation expenditures. Taxpayers can also elect to amortize these expenditures over 60 months, but in practice most firms immediately expense R&D. However, the IRC does not define what qualifies as R&D expenditures. Treasury regulations have generally interpreted them to mean "R&D costs in the experimental or laboratory sense."

Cross firm Heterogeneity of the effective R&D tax credit rate (Federal Only)



Source: Hall (1993)

An Empirical Model of R&D

R&D knowledge stock, *G*, perpetual inventory method**:**

$$G_t = R_t + (1-\delta)G_{t-1}$$

Production function: *Y = AF(L,K,G); K* = non-R&D capital, *L* = non-R&D labor. If CES, First Order Condition:

$$\ln G = a - \sigma \ln \rho + \mu \ln Y$$

σ = elasticity of substitution; μ = returns to scale (μ = 1 if Constant Returns To Scale). **In steady state:**

$$R = \delta G$$

$$\ln R = \ln G + \ln \delta$$

Empirical Models of R&D, R

Implies typical firm level empirical model (firm *i* at time *t*)

$$\ln R_{it} = \beta \ln \rho_{it} + \alpha' x_{it} + \mathrm{u}_{it}$$

$$\beta = -\sigma; \alpha' x_{it} = a + ln\delta + \mu lnY_{it}$$

- **Model is static:** adjustment costs mean that investment model is more complex (a policy correspondence). Path of *R* depends on expectations of fundamentals & shocks.
  – Common (ad hoc) empirical approach: add fixed effects, time dummies, lags of dependent variable & distributed lag of R&D user cost
- Standard econometric issues of dynamic panel data models

Basic empirical firm model

$$\ln R_{it} = \alpha \ln R_{it-1} + \beta_1 \ln \rho_{it} + \gamma' x_{it} + \eta_i + \tau_t + e_{it}$$

- Short run elasticity: $\frac{\partial lnR}{\partial ln\rho} = \beta_1$
- Long run elasticity: $\frac{\partial lnR}{\partial ln\rho} = \frac{\beta_1}{1-\alpha}$

Endogeneity issue with basic empirical model

$$\ln R_{it} = \alpha \ln R_{it-1} + \beta_1 \ln \rho_{it} + \gamma ' x_{it} + \eta_i + \tau_t + e_{it}$$

- User cost (ρ) will in general be correlated with error term.
  - e.g. a positive shock raising R&D incentives will affect the base, incremental credit & incentives

- Many elements that are exogenous (e.g. interest rates, tax rate) do not usually vary across firms and so are collinear with time dummies

Results using firm-level approach

- Surveys in Hall & Van Reenen (2000), Hall (2022)

- **Hall (1992)**
  - Uses Compustat firms and dynamic panel data approaches (e.g. Arellano & Bond, 1992 - use lagged characteristics as IVs)
  - Issues of serial correlation and weak instruments
- **Rao (2016)**
  - Use IRS data with actual tax credit receipt
  - Construct synthetic instruments (Gruber and Saez, 2002): simulate federal changes holding firm characteristics at lagged values

- Find long-run elasticity of around unity or greater

General Equilibrium (GE) Issues

- GE effects. If demand curve inelastic then price effects rather than quantity effects
  - Goolsbee (1998): Federal R&D subsidies just drive up scientist wages. Hard to identify (US time series)
- Policy Solutions?
  - In long-run more people switch into R&D;
  - Even in short-run, international mobility of R&D workers in short-run
- **Alternative empirical approach:** Exploit cross country panel data which controls for country GE effects

What are the effects of R&D tax credits?

1. Federal tax credit generates substantial heterogeneity in firm level R&D user cost

2. **Cross country variation in R&D tax credits**

3. State-specific tax credits

4. Use non-linear design of tax credits to generate Regression Discontinuity Design (RDD)

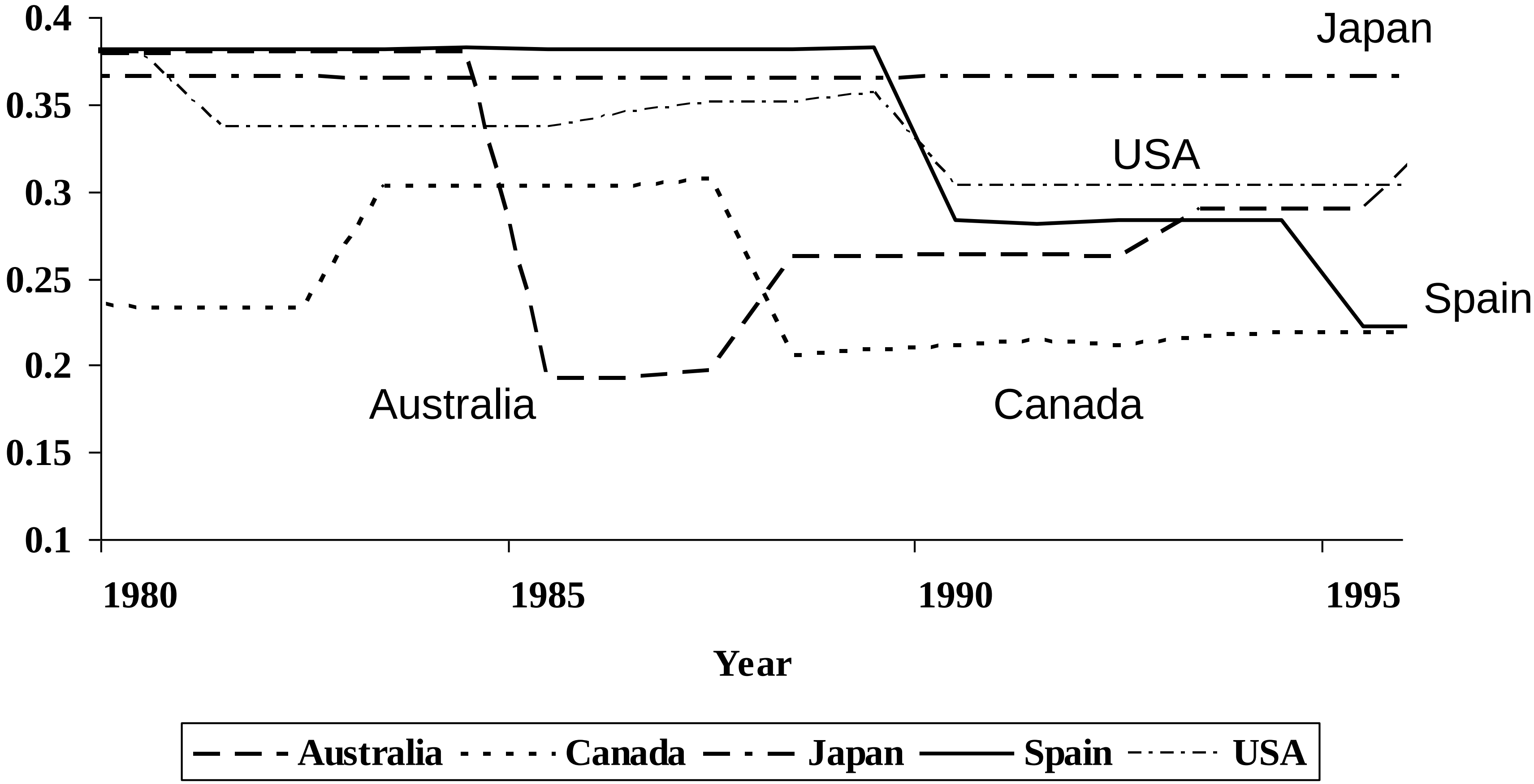
International variation in tax-adjusted user cost of R&D

- Many different R&D tax regimes generates much variation in use cost over countries & over time

- UK introduces tax credit in 2001, Australia 1985 150% super deduction, France changes (almost) every year

- Bloom, Griffith & Van Reenen (BGVR, 2002) look at OECD countries 1979-1997 & use tax rules in all nations to construct user cost (see over)

Examples of Cross country Heterogeneity of the effective R&D tax credit rate



Source: Bloom, Griffith & Van Reenen (2002)

International variation

$$\ln R_{it} = \alpha \ln R_{it-1} + \beta_1 \ln \rho_{it} + \gamma \ln GDP_{it} + \eta_i + \tau_t + e_{it}$$

- Estimate same basic equation, but *i* now country not firm
- Focus on tax price & use this to IV total R&D user cost
- BGVR find long-run elasticity of ~1 & short-run ~0.15. Interpret this as indicating substantial adjustment costs for R&D
- OECD (2013), Appelt et al (2019) find similar using more countries

What are the effects of R&D tax credits?

1. Federal tax credit generates substantial heterogeneity in firm level R&D user cost

2. Cross country variation in R&D tax credits

3. **State-specific tax credits generate additional variation**

4. Use non-linear design of tax credits to generate Regression Discontinuity Design (RDD).

Problems with Cross-country approach

- Many other factors varying in a year that are country-specific and could be correlated with user cost

- Wilson (2009) uses US state-specific variation
  – Many states have a more generous R&D tax credit that Federal government (like Minimum Wage)
  – Use this to construct state-specific user cost and estimate using a state-level panel

Wilson (2009) findings

- Wilson finds similar long-run elasticity to BGVR
  - Argues that this is mainly due to cross-state relocation, i.e. aggregate US R&D stays the same, but "tax competition" effects the location of activity

- **Problem**: Uses geographical proximity to define competitors. But unlikely to be appropriate (e.g. California vs. Massachusetts rather than California vs. Nevada)

- Issue of endogeneity of state policy (Chang, 2018, instruments with Federal changes)

What are the effects of R&D tax credits?

1. Federal tax credit generates substantial heterogeneity in firm level R&D user cost

2. Cross country variation in R&D tax credits

3. State-specific tax credits generate additional variation

4. Use non-linear design of tax credits to generate Regression Discontinuity Design (RDD). Dechezlepretre et al (2022)

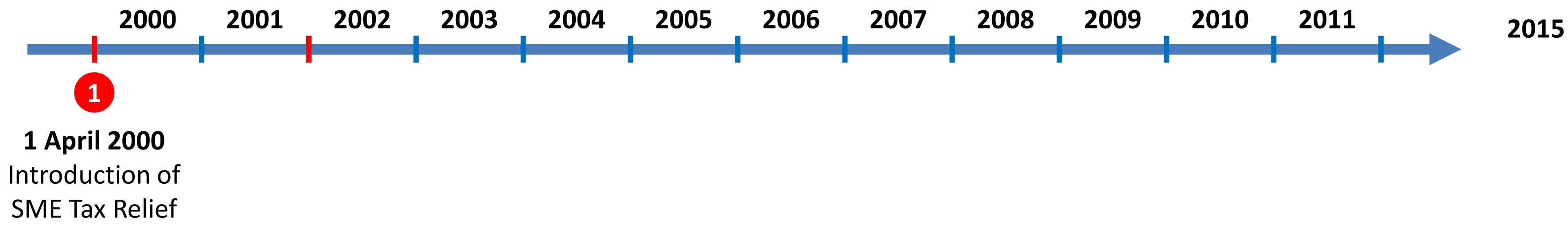
Do tax incentives for research increase firm innovation? An RD Design for R&D

Antoine Dechezleprêtre (OECD)
Elias Einiö (VATT)
Ralf Martin (Imperial College)
Kieu-Trang Nguyen (Northwestern)
John Van Reenen (LSE, MIT)

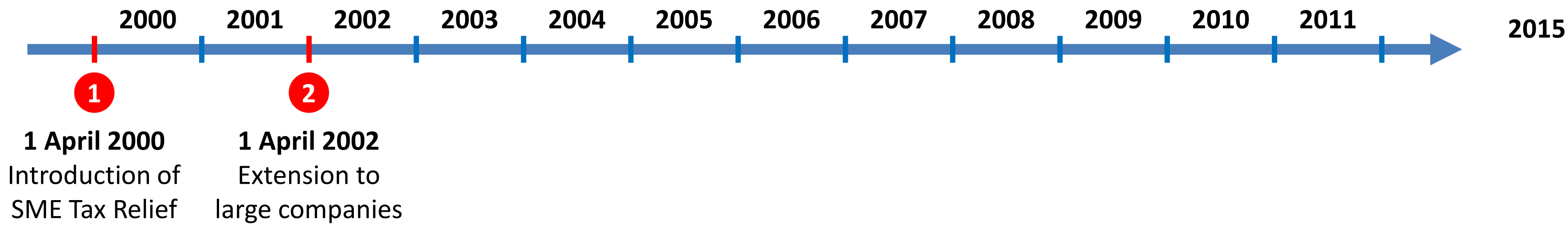
What does paper do?

- Use administrative tax data & firm accounts in UK to evaluate impact of R&D Tax Relief Scheme on:
  - Firm R&D **and** patenting (as well as jobs, productivity, etc.)
  - Effects on the subsidized firm itself **and** technology **spillovers** to other firms
- Exploit **discontinuity** in generosity of R&D tax relief at new (lower) asset eligibility thresholds for Small & Medium Enterprises (SME) in 2008.
  - SME eligibility determined by pre-2008 assets so can implement a **Regression Discontinuity Design** (RDD)
- **An RDD for R&D!**

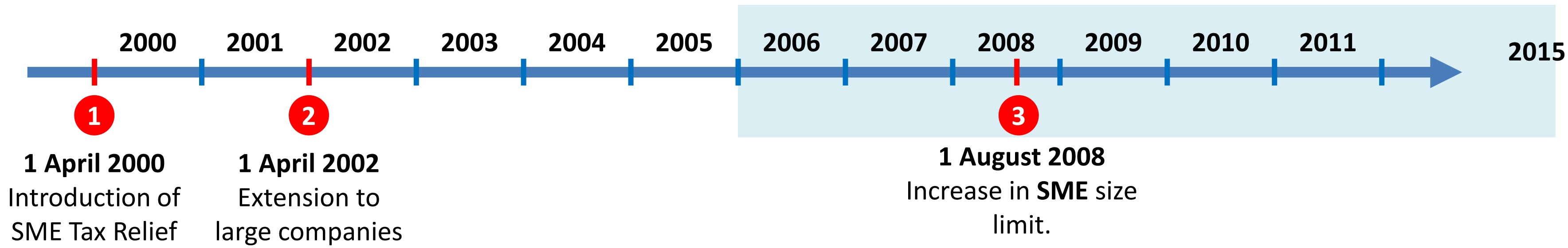
UK R&D Tax Relief Scheme – major changes



UK R&D Tax Relief Scheme – major changes



UK R&D Tax Relief Scheme – major changes



- In 2008, UK doubled size limits for SME eligibility, only for the R&D Tax Relief scheme (**no other policies at new thresholds**)
- Part of criteria to be small depended on assets/capital
  - **2007**: **Assets** ≤ €43m
  - **2008**: **Assets** ≤ €86m
- Must meet SME criteria for at 2 consecutive years to qualify, so Discontinuity uses 2007 data.

Data

- **IRS/HMRC Datalab CT600** panel of firm tax returns (including R&D expenditure) for all firms
- **BVD FAME/ORBIS**: Financial accounts of all incorporated UK firms - assets, industry, location, 3.1m firms between 2006-11
- **PATSTAT**: All patents applications to every patent office (EPO, USPTO, etc.) Use patent “family”, but also consider quality weights (e.g. citations, grants, countries)

Regression Discontinuity Design

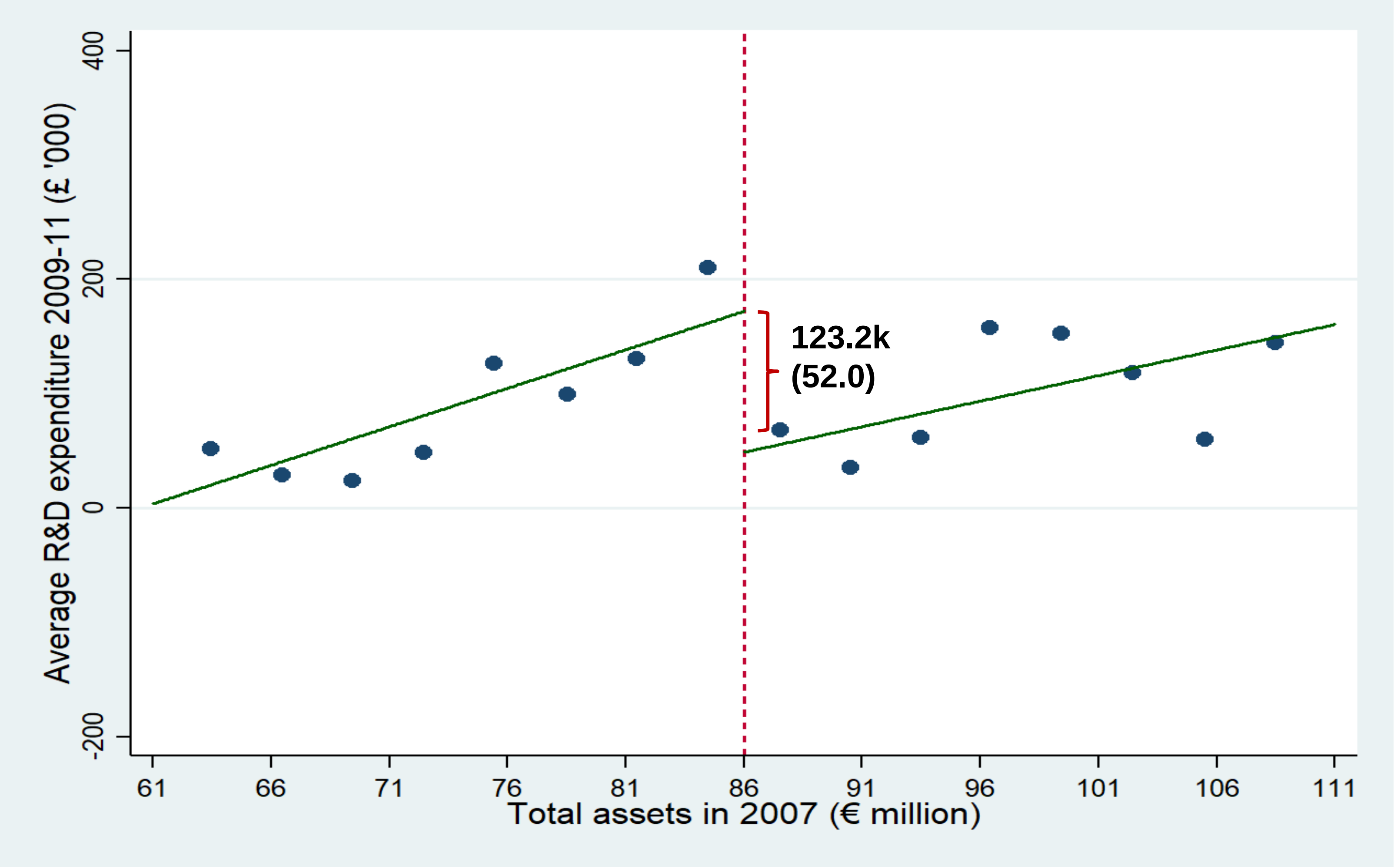
<u>**Outcomes for firm *i* in year *t***</u>

$$Y_{i,t} = \alpha_{1,t} + \beta_t^R E_{i,2007} + f_{1,t}\left(z_{i,2007}\right) + \varepsilon_{1i,t}$$

- $Y_{i,t}$ outcomes are R&D spend, Patents, Productivity, etc. through 2015

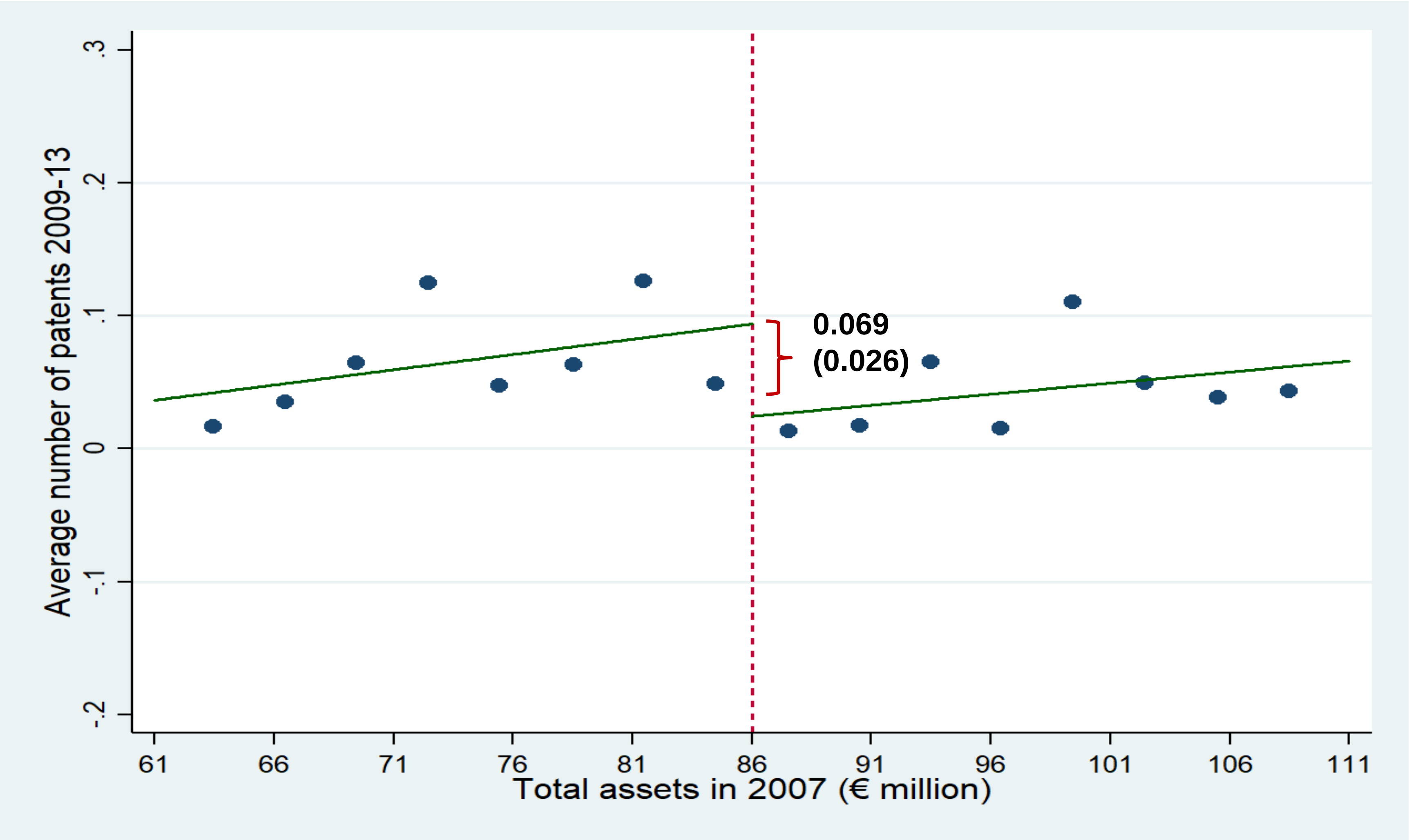
- $E_{i,2007} = I\left(z_{i,07} \leq \bar{z}\right)$: dummy = 1 if firm i's total assets (z) in 2007 is below €86m & zero otherwise
  - Total assets in 2007 as the running variable

Discontinuity in R&D



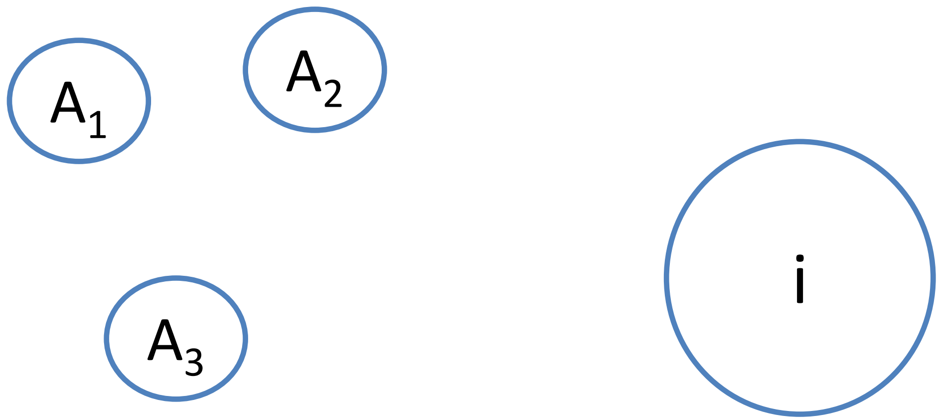
Notes: 5,888 obs. Assets from FAME based on SME threshold (€86m). R&D from CT600. Sample of firms with €25m above & below the threshold. 368 obs per €3m bin.

Discontinuity on patenting



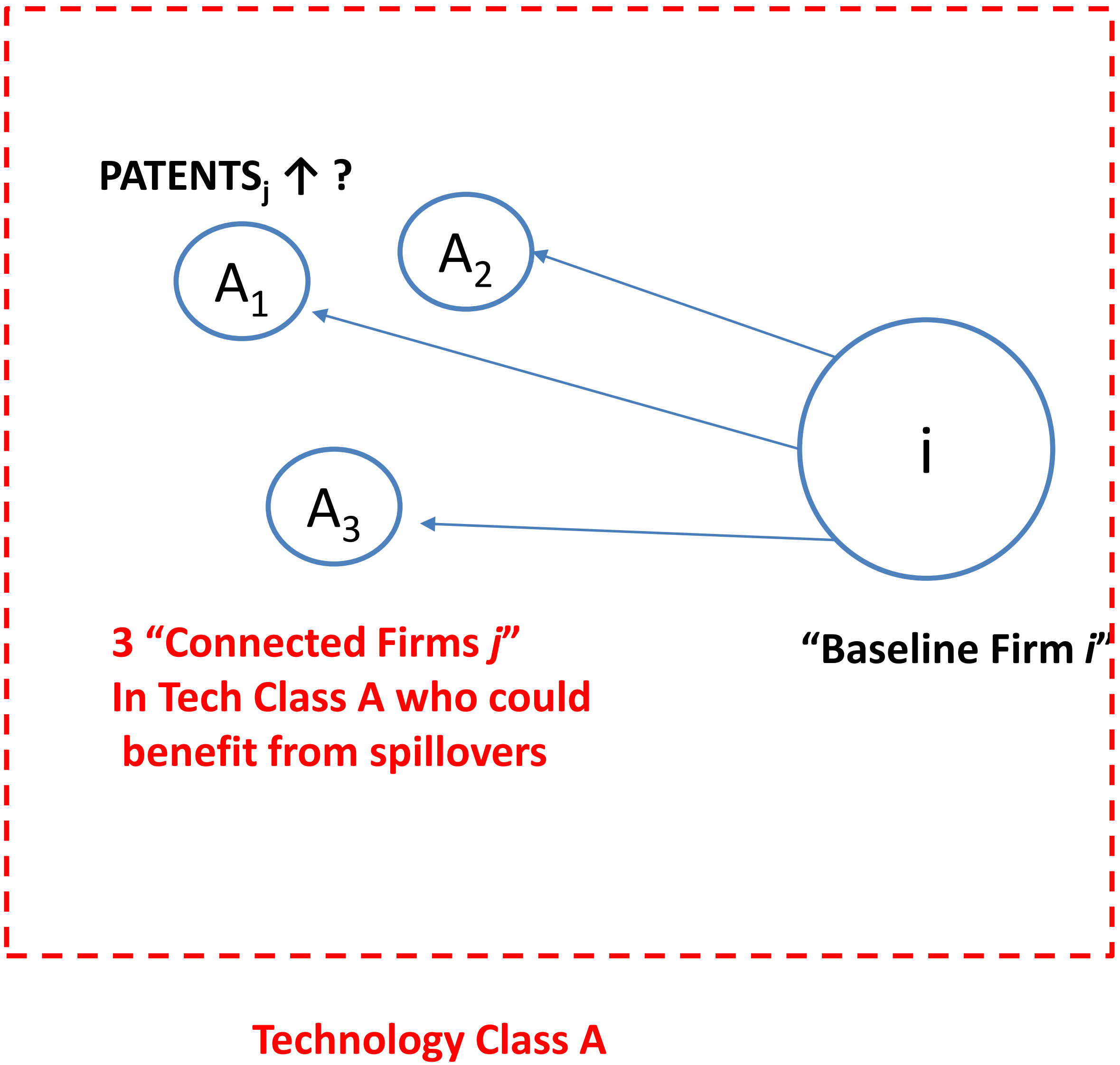
Notes: 5,888 observations. Assets from FAME based on SME assets threshold (€86m) definition. R&D is from CT600. Sample of firms with €25m above & below the threshold. Outcome is average number of patents filed between 2009 and 2013.

So far: R&D tax credit boosts R&D & patents in firm *i*



"Baseline Firm *i*"
(affected by R&D credit
$R\&D_i \uparrow$; $PATENTS_i \uparrow$)

Spillovers: R&D tax credit boosts R&D in firm *i*, which may also increase innovation in other firms



Spillovers: Peer effect RD Design

- Consider dyad of 2 firms {*i*,*j*} If firm *i* is below new assets threshold, did innovation rise in “connected” firm *j*?
- Connection = Same 3 digit technology class (& above median Jaffe, 1986, distance metric). Use firm population for this.

$$PAT_{j,09-13} = \alpha_5 + \boxed{\theta E_{i,2007} + f_5\left(z_{i,2007}\right)} + \mu E_{j,2007} + g_5\left(z_{j,2007}\right) + \varepsilon_{5ij}.$$

Spillover: Shifted exogenously by firm *i* being near threshold

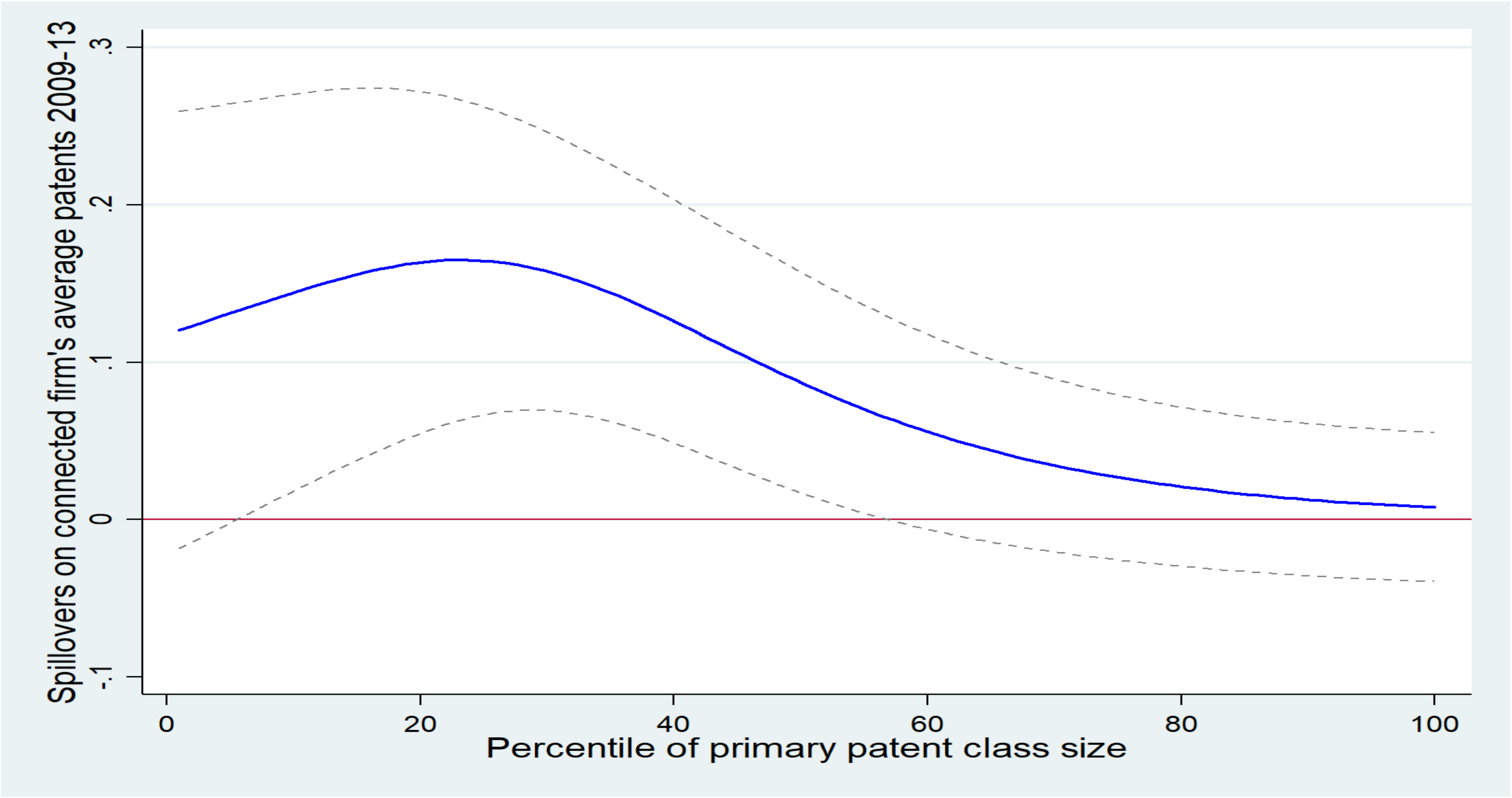
Own: If firm *j* is also near the threshold – very few

Issues with Spillover analysis

- If large numbers of peer firms, magnitude of coefficient likely to be smaller & hard to identify.
  - For example, firm *i*'s R&D less likely to be shifting the technology frontier if there are many firms in same class

- So, allow spillover treatment effect θ to vary with number of neighbors (size of technology class)

Tax policy induces <u>spillovers</u>: patenting by technologically close firms (stronger in smaller technology classes)

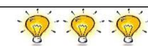
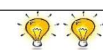
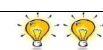


Source: Dechezlepretre et al (2023); **Notes:** Semi-parametric estimates of spillover coefficient on technologically-connected firm's patents as a function of # peers in technology class (percentiles on X-axis). Uses Gaussian kernel function of the X-axis variable and a bandwidth of 20%. For example, there are 200 firms in 40th percentile technology class.

Summary of Dechezleprêtre et al (2023) findings

- For firms around the threshold, policy approximately:
  - Doubled R&D 2009-11
  - Increase (quality adjusted) patents by 60% (by 2015)
- These larger effects than elsewhere in literature
  - likely because the treated firms are smaller than most of existing literature & more likely to be financially constrained (Arrow, 1962)
- RD Design shows positive **technology spillovers** (peer effects in small technology classes for close neighbors)
- **Issues**
  - LATE, so how to generalize?

Innovation Policy: The "Lightbulb" Table

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

"Demand"

"Supply"

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

Patent Boxes

- Rather than subsidize R&D these grant tax relief on income from patents (& other IP)
- Patent boxes do not cover nonpatentable R&D and not in direct control of firm
- Intangible income can be shifted within multinationals
  - Shift innovation costs to high tax country (e.g. US) and take royalties in low tax country (e.g. Ireland)
  - Patent boxes lower tax burden on intangibles - an attempt to keep/attract tax revenue (e.g. Cyprus, Liechtenstein & Malta latest to introduce)
- Sometimes justified as a way of incentivizing R&D, but unlikely as location of R&D and patent income can be very different

Patent Boxes

- Hall (2022)
  - 22 countries have some kind of Patent Box
  - Almost all in Western Europe (plus Israel, India, Japan and Turkey)
  - Literature suggests location and transfer respond to lower taxes on patent income, but effect is modest
- Gaessler, Hall and Harhoff (2021) through 2016 (17 countries with patent box for at least 2 years)
  - Higher corp tax reduces amount of patents located in a country (like Akcigit et al, 2022 in US)
  - But no effect on patented invention or R&D
- Essentially a form of (harmful) tax competition rather than innovation policy

Summary on innovation-specific tax policies

- R&D tax credits
  - Long-run (absolute) elasticity of greater than unity
  - Smaller short-run elasticity
  - Recent evidence that impacts innovation too
  - Probably best studied of all innovation policies and suggests that it is a successful policy

- Patent Box, by contrast, shows no effect on innovation, but some tax-shifting

Thanks!

Back Up

Policies towards diffusion

1. Adoption of specific technologies (e.g. Broadband)

2. Information provision (e.g. Small Business services)

3. Technology transfer (e.g. FDI support or export credits)

4. University-business linkages (Technology Licensing Offices, 1980 Bayh-Dole Act)

TABLE 4—ROBUSTNESS OF ESTIMATES TO UNRESTRICTED CURVATURE

Technology	Invention year ($\underline{v}_\tau$)	Percentage H_0 not rejected*	Correlation between Estimated adoption lags
Steam- and motorships	1788	65	.99
Railways - Passengers	1825	67	.89
Railways - Freight	1825	62	.97
Cars	1885	75	.82
Trucks	1885	81	.81
Aviation - Passengers	1903	66	.93
Aviation - Freight	1903	77	.83
Telegraph	1835	59	.95
Telephone	1876	80	.94
Cellphones	1973	67	.70
PCs	1973	59	.41
Internet users	1983	100	.59
MRIs	1977	92	.56
Blast Oxygen Steel	1950	72	.73
Electricity	1882	41	.91
Total		69	.80**

Note: All results are for plausible and precise estimates under restricted specification.
* At 5 percent significance level. ** Correlation is weighted average of correlations across technologies.

Source: Comin & Hobijn (2010, AER)

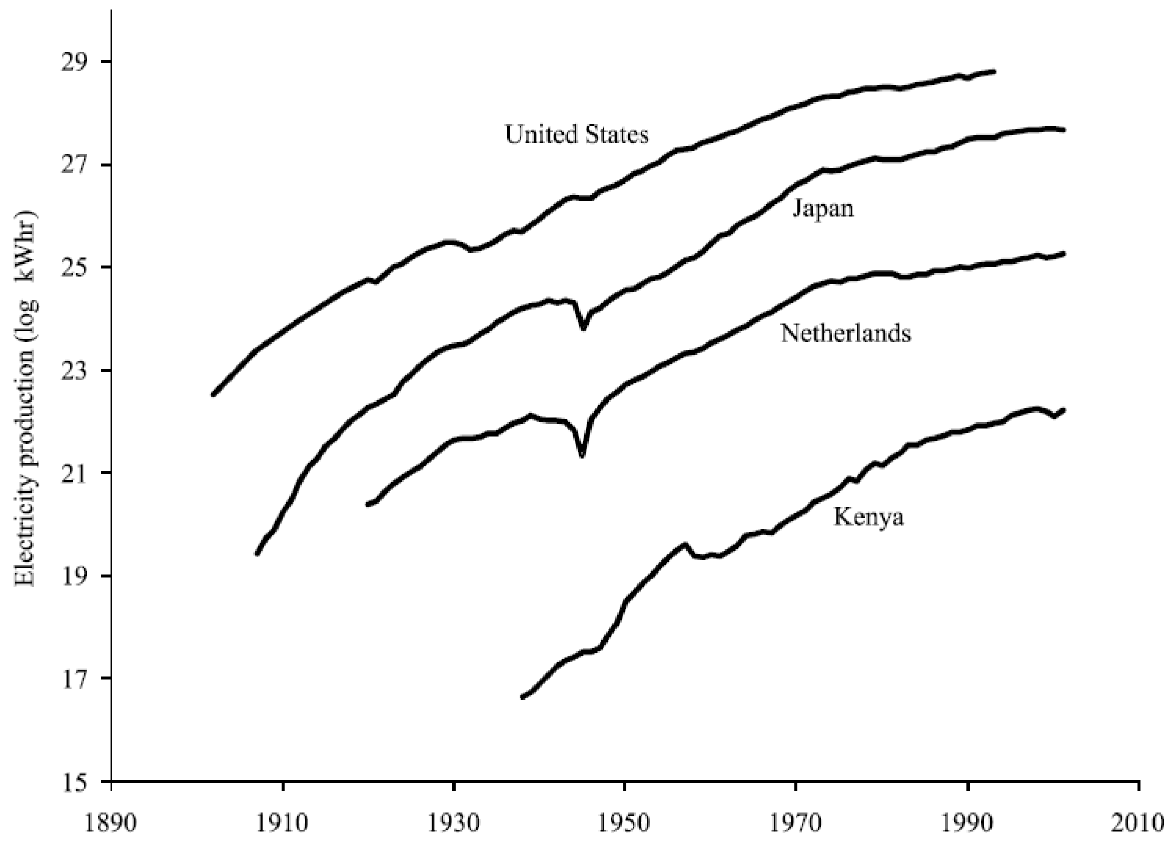


FIGURE 1. ELECTRICITY PRODUCTION IN FOUR COUNTRIES.

Source: Comin & Hobijn (2010, AER)

R&D Tax credits design issues

- Whole of tax system interacts
- "Qualified R&D" (scientific vs. marketing)
- Usually territorial – only if R&D performed in geographical area (e.g. within US)
- Sometimes restricted to certain classes of firms (e.g. SMEs, industries) or activities (labor, collaborative)
- Often capped at a maximum (e.g. France)
- Often targeted incremental R&D dollar
  - Seeks to reduce cost & give political cover
  - But creates many perverse incentives
- Creates complexity, but useful for identification because lots of cross firm heterogeneity!

What are the effects of R&D tax credits? Early studies

- Estimate the user cost over time and how it varies across firms (Eisner et al, 1982)
- Case studies and “industrial surveys” (e.g. Mansfield and Switzer, 1985. on Canada) An IQ test for firms?
- Estimate from R&D user cost without R&D tax credit data – variation from asset prices and depreciation (Bernstein and Nadiri, 1989)
  - Unclear where exogenous variation comes from to separate from general user cost of capital
  - And in absence of tax design unclear how to separate from time dummies
- All these methods up to mid 1990s suggested little effect of R&D tax incentives

What is the "base" of R&D Tax credits?

- **Volume** – simplest, but expensive for any given credit because of deadweight
- **Incremental** over a "base"
  - Previous year's R&D spend (e.g. France)
  - "Rolling base" (US 1981, average of last 3 years R&D)
  - Builds in "ratchet". Firms discouraged from increasing R&D this year as base will be higher next year
    - Reduces the headline generosity of the credit
    - Firms planning rapid growth deterred in order to take advantage of credit (Eisner et al, 1982,1984)
  - Fixed base: US after 1989 using historical average of R&D/sales ratio. But new firms? As time goes on, increasingly inappropriate

Simplified tax-adjusted user cost of R&D capital

$$\rho_{it}^{E} = Tax\ Price = \left(\frac{1 - D_{it}}{1 - \tau_{it}}\right)$$

- $D_{it} = \tau_{it} *$(NPV of allowance claims)*(%deductables) + credit

Effects of tax price on R&D: cross country panel

Table 1
Main results[a]

Dependent variable		(1) r_t OLS	(2) r_t IV	(3) r_t IV	(4) $r_t - y_t$ IV	(5) $r_t - y_t$ IV
Lagged ln (R&D)	r_{t-1}	–	–	0.868	–	–
				0.043		
Lagged ln (R&D/Y_t)	$r_{t-1} - y_{t-1}$	–	–	–	0.859	0.850
					0.047	*0.045*
ln (user cost)	ρ_t	−0.354	−0.499	−0.144	−0.124	−0.143
		0.101	*0.115*	*0.054*	*0.060*	*0.059*
ln (output)	y_t	1.184	1.364	0.143	–	–
		0.224	*0.319*	*0.163*		
Long run elasticity — user cost				−1.088	−0.878	−0.957
(*P*-value)				*0.024*	*0.056*	*0.027*
Wald test (*P*-value)		–	0.000	0.813	0.368	–
Durbin–Watson statistic		0.374	0.428	1.842	1.768	1.753
Country dums		Yes	Yes	Yes	Yes	Yes
Year dums		Yes	Yes	Yes	Yes	Yes
Observations		165	156	155	155	164

Source: Bloom, Griffith & Van Reenen (2002)

Main BGVR Specification

$$\ln R_{it} = \alpha \ln R_{it-1} + \beta_1 \ln \rho_{it} + \gamma \ln GDP_{it} + \eta_i + \tau_t + e_{it}$$

$$\rho_{it} = \left(\frac{1 - D_{it}}{1 - \tau_{it}} \right) \left(i_{it} + \delta - \frac{\Delta p_{it}}{p_{it-1}} \right)$$

i = country, t= year

R&D spillovers

- R&D augmented production function:

$$q_{it} = a_0 + \alpha_L l_{it} + \alpha_K k_{it} + \alpha_G g_{it} + \mu SPILLTECH$$

- SPILLTECH = technology spillovers (weighted sum of R&D stocks of other firms)

- At macro level regression of TFP growth on R&D reflects both private return & spillovers ($\alpha + \mu$). We expect to be larger than micro level (& in principle a comparison reveals private vs social returns to R&D)

- How to measure spillovers?

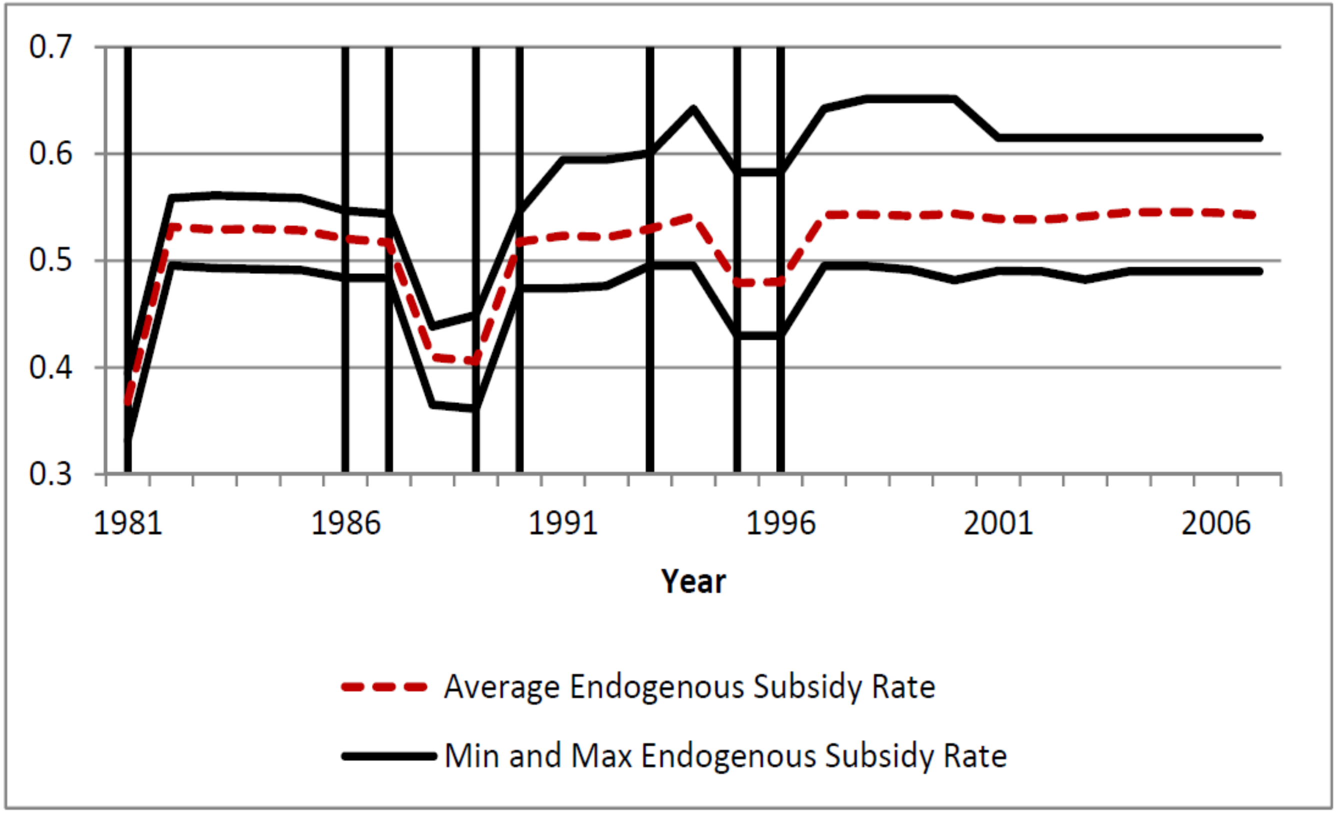
Problem of R&D policy endogeneity

- All papers using policy experiments face issue that policy introduction may be in response to shocks affecting R&D
- Similar issue to assessing impact of fiscal policy as stimulus programmes are introduced when government expects a downturn (Romer & Romer; Ramey, etc.)
- Little work on this
  - BGVR/BSVR: tax credits can’t be Granger predicted by shocks
  - Chang (2013) uses “exogenous” element of state tax credit caused by Federal changes to R&D code.
    - E.g. 1989 change to fixed base was followed (with lag) by other states & this was heterogeneous across states
    - Finds <u>larger</u> effects of R&D tax credits because states cut in “bad times”

Endogeneity of firms R&D user cost

- In panel, lagged values of dependent or independent variable may be "weakly exogenous", i.e. do not immediately respond to shocks
  - Hence can be used to construct instruments
- Synthetic instruments idea (e.g. Gruber & Saez, 2002)
  - Use changes of tax rules interacted with lagged values
  - Applied to firm-level R&D tax credits case by Rao (2013). Rao uses IRS tax data on qualified R&D 1981-1991 constructs IV from lagged R&D values & changes in tax rules
    - Elasticity between -1 and -2

Cross State Heterogeneity of the R&D tax credit

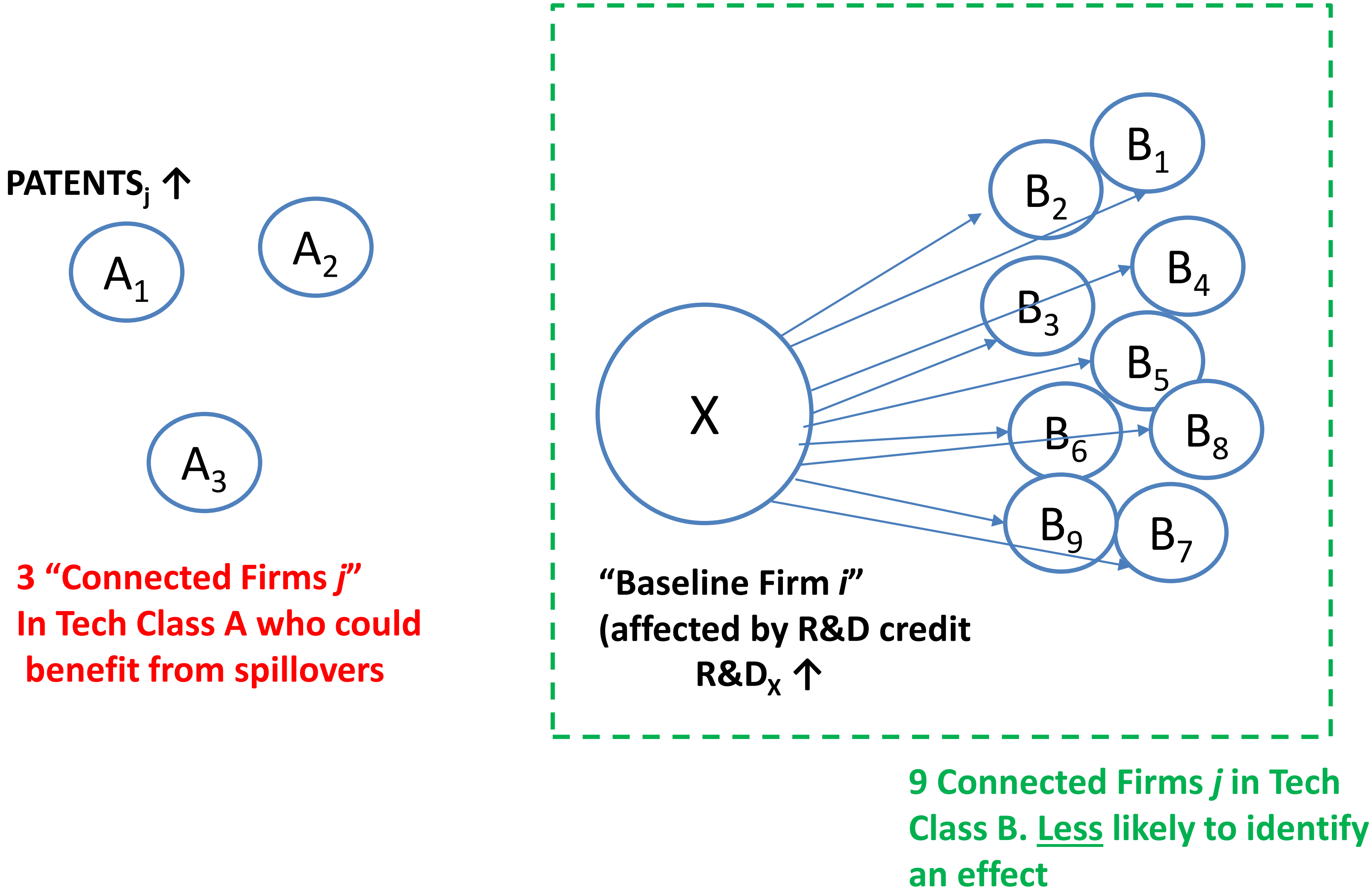


Source: Chang (2013)

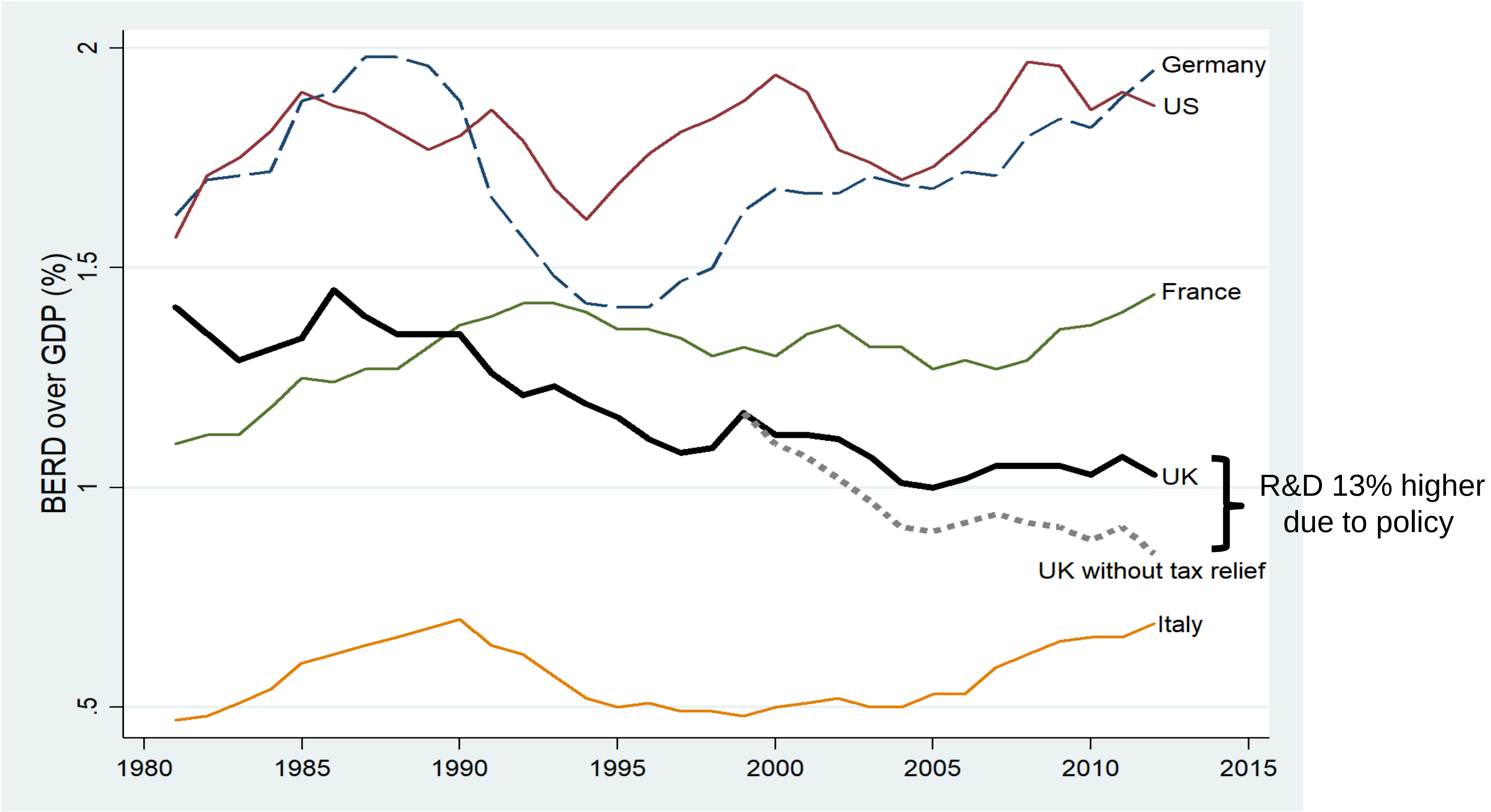
R&D Tax Relief Scheme

- Current R&D always deducted as expense (rather than capitalized as intangible asset)
- Under post-2000 scheme taxable profits can be further reduced by a proportion of a firm's R&D
- Includes SME & Large Company component
  - Eligible firms get enhanced deduction
  - Enhancement of extra 75% of R&D for SMEs vs. 30% for large companies
  - SMEs also get **payable tax credits** (effectively direct government cash via reduced payroll tax) when insufficient corporate income tax liability

Spillovers: Firm X also in tech class B, but large number of peers in this space



Simulation R&D/GDP would be 13% lower in absence of R&D tax policy



Source: Dechezleprêtre, Einiö, Martin, Nguyen and Van Reenen (2022). **Note:** The data is from OECD MSTI. The dotted line ("UK without tax relief") is the counterfactual R&D intensity in the UK that we estimate in the absence of the R&D Tax Relief Scheme.

Introduction

- R&D knowledge spillovers critical to justification for public policy intervention

- **Direct** effect of R&D on performance hard to measure, **indirect** effects even harder!
  - Direct effect is how firm *i* outcomes (e.g. TFP) depend on firm *i* inputs (e.g. R&D)
  - Indirect effect is how firm *i* outcomes on ALL other firm *j*'s inputs
  - Serious curse of dimensionality!

- And many other econometric issues with identifying peer effects, even if we only had one known peer (cf. Manski, 1993)

R&D in the production function

- Example of R&D augmented production function of firm *i* at time *t* (output is *Q*, *q* = *logQ*, etc.):

$$q_{it} = a_0 + \alpha_L l_{it} + \alpha_K k_{it} + \alpha_G g_{it}$$

- Where *g* = *lnG*; *G* = *R&D stock*: e.g. $\boldsymbol{G_{it} = R_{it\,-1} + (1-\delta^G)G_{it-1}}$

R = flow of R&D spending***;*** $\boldsymbol{\delta^G}$ = depreciation rate

- R&D stock one of many “intangible capital stocks” (Corroda, Hulten & Sichel, 2005)

- Note that R&D “double counted.” If all R&D was all scientific labor, then *L* = non-R&D scientists.

Impact of own firm R&D and other technologies on productivity

- Vast empirical literature, with extensive evidence of positive correlations:
  - Griliches (1998); Hall, Mairesse and Mohnen (2010); Doraszelski & Jaumandreu (2013, 2018) survey R&D effects

- Usually use panel data techniques for production functions (see Ackerberg et al, 2007 and de Loecker and Syverson, 2021 for surveys)
  - But not much use of external instruments

Approaches to estimating R&D spillovers

1. **Does neighbours' R&D increase own firm productivity/innovation?** Griliches (1979, 1992)
   - Neighbors' R&D (could also be other measures of innovation such as patents, etc.)
   - Issue of defining neighbors ("distance metric") and the network more generally (cf. peer effects in Angrist, 2014)

Approaches to estimating R&D spillovers

1. **Does neighbours' R&D increase own firm productivity/innovation?** Griliches (1979, 1992)
   - Neighbors' R&D (could also be other measures of innovation such as patents, etc.)
   - Issue of defining neighbors ("distance metric") and the network more generally (cf. peer effects in Angrist, 2014)
2. **Exit of "stars"** Azoulay et al (2010) "Superstar extinction"; Waldinger (2012); Bell, Jaravel & Petkova (2018). Usually from a co-author team. But could be from network.
3. **Patent citations:** Henderson, Jaffe, Trajtenberg (1993) focus on geography (agglomeration literature)
   - But many citations don't indicate true knowledge transfer
   - Many knowledge transfers do not need a patent citation
4. **Macro** approaches: e.g. R&D average social cost-benefit ratio (Jones & Summers, 2022); micro/macro (over)

Micro/Macro comparisons (Griliches, 1992; Jones and Williams, 1998)

Firm Level Micro

$$TFP_{it} = \phi G_{it} + \mu G_t; G_t = \sum_{j,j \neq i} G_{jt}$$

Own R&D

R&D by all other firms

Economy Level Macro

$$TFP_t = (\phi + \mu) G_t$$

Micro-econometric fixed effects model

$$TFP_{it} = \phi G_{it} + \mu G_t + \eta_i + \tau_t + \upsilon_{it}$$

- If time dummies (τ_t) included, cannot identify μ directly
- Comparison of micro vs. macro identifies μ **if** control for all relevant macro variables (NB could also do firm vs. industry level)

Identifying Spillover Effects

- Consider that some units “closer” to others in sense of a distance metric (e.g. geographic)

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- **Example:** Technology spillover pool for firm *i* is *TECH* weighted R&D where $TECH_{i,j}$ is "technology space proximity" between firms *i* and *j* (i,j = 1,…,N)
  - $SPILLTECH_{it} = \Sigma_{\mathrm{j,j\neq i}} TECH_{i,j} G_{jt}$ where G_{jt} is the R&D stock of firm *j* at time *t*
- $TECH_{i,j}$ is proximity between 2 firms ranging from perfect closeness ($TECH_{i,j}$ =1) to perfectly separate ($TECH_{i,j}$ =0)

Identifying Spillover Effects

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- $TECH_{i,j}$ is proximity between 2 firms ranging from perfect closeness ($TECH_{i,j}$ =1) to perfectly separate ($TECH_{i,j}$ =0)
- Many candidates for $TECH_{i,j}$: same technology class, same location, past citation patterns, scientist flows, etc.
- **T** is NxN matrix with elements $TECH_{i,j}$ defining network. Analogous to input-output matrix (and can use similar techniques to examine peturbations)

Productivity equation

Now, spillovers **are** identified independently from time dummy & firm fixed effect

$$TFP_{it} = \phi G_{it} + \mu SPILLTECH_{it} + \eta_i + \tau_t + \nu_{it}$$

Need to specify some kind of distance metric as spillovers not identified non-parametrically (Manski, 1993, “reflection problem”)

Bloom, Schankerman & Van Reenen (BSVR, 2013, *ECMA*)

- Firm neighbors' R&D matters for its performance as well as its own R&D. Two types:
  - Knowledge spillover (Growth literature)
  - Product market rivalry (IO literature)
- Methodology for identifying the distinct effects by using two "distance metrics"
  - In **technology space** for knowledge spillovers using patent classes
  - In **product market space** using SIC-4 industry codes (firms operate in multiple industries)
  - Examples: plasma vs. LED TV screens; IBM & Motorola use some similar technologies, different markets

Measuring Technology Spillovers

- Define Technology closeness by uncentered correlation of firm patent class distribution (Jaffe, 1986)
  - $T_i = (T_{i1}, T_{i2}, \ldots\ldots, T_{i426})$ where T_{ik} is % of firm i's patents in technology class k (k = 1,..,426)
  - $TECH_{i,j} = (T_i T'_j)/[(T_i T_i')^{1/2}(T_j T'_j)^{1/2}]$; ranges between 0 and 1 for any firm pair i and j.

- Define Technology spillover pool as *TECH* weighted *R&D stock*:
  - $SPILLTECH_{it} = \Sigma_{j,j\neq i} TECH_{i,j} G_{jt}$ where G_{jt} is the R&D stock of firm j at time t

- Can generate from a micro model of scientists' random meetings (in conferences, etc.)

Measuring Product Market Rivalry

- Analogous construction of product market "closeness"
  - Define $S_i = (S_{i1}, S_{i2}, \ldots\ldots, S_{i623})$, where S_{ik} is the % of firm i's total sales in 4-digit industry k (k = 1,…,623)
  - $SIC_{i,j} = (S_i S'_j)/[(S_i S_i')^{1/2}(S_j S'_j)^{1/2}]$

- Product market "spillover" pool defined as SIC weighted R&D:
  - $SPILLSIC_{it} = \Sigma_{j,j\neq i} SIC_{i,j}\, G_{jt}$

Generic equations

$$\ln Y_{it} = \phi_1 \ln G_{it} + \phi_2 \ln(SPILLTECH_{it}) + \phi_3 \ln(SPILLSIC_{it})$$
$$+\eta_i + \tau_t + v_{it}$$

- **Dependent variables (*Y*):**
  - Productivity
  - Patents
  - Market Value
  - R&D

- Different predictions on spillovers for different equations (e.g. market value)

Combine Compustat & USPTO Patents Data

- Compustat data (all listed US firms) to measure R&D, Tobin's Q, Sales, Capital, Labor etc
- Compustat line-of business data to define sales by SIC's
  - Sample covers 623 4-digit SIC classes
- NBER patent data with US patents and citations from 1978
- Final sample of 795 firms over 20 years (unbalanced panel). Accounts for most of US industry R&D

Market Value (Tobin's Q)

Dependent variable: Ln (V/A)	(1)	(2)	(3)
	All	Only SPILLTEC	Only SPILLSIC
Ln(SPILLTECH$_{t-1}$)	**0.381** (0.113)**	**0.305** (0.109)**	
Ln(SPILLSIC$_{t-1}$)	**-0.083** (0.032)**		**-0.050 (0.031)**

Identifies magnitude of business stealing

Notes: Includes full set of controls for own R&D/capital, industry sales, time and firm dummies. Estimation period is 1981-2001. Observations=9,944. Newey-West heteroskedasticity and first-order auto-correlation robust standard-errors

Total Factor Productivity (TFP) Equation

Identifies magnitude of knowledge spillover

Dependent Variable: ln(Sales)	(1)	(2)
	Fixed effects	Fixed effects
$Ln(SPILLTECH)_{t-1}$	**0.191*** (0.046)**	**0.186*** (0.045)**
$Ln(SPILLSIC)_{t-1}$	**-0.005 (0.011)**	
$Ln(R\&D\ Stock)_{t-1}$	**0.043*** (0.007)**	**0.042*** (0.007)**

Note: Includes controls for labor, capital, industry sales, time dummies and industry deflators included. Estimation period is 1981-2001; Obs=9,935. Newey-West first order serial correlation and heteroskedasticity robust SEs

Endogeneity of R&D: Using tax changes to construct user costs as an IV for R&D

- Advantage of micro-data is ability to generate more exogenous variation to identify causal effects
- State specific R&D tax credits interacted with firm's initial locations
- Federal R&D tax credit rules changed a lot over time generating heterogeneous effects between firms
- Strong first stage and qualitatively similar results

Special case – symmetric firms with no R&D strategic complementarities

Marginal Private Return $= (Y/G)(\varphi + \lambda)$

$= 21\%$

Marginal Social Return $= (Y/G)(\varphi + \sigma)$

$= 58\%$

(Y/G) = ratio output to R&D stock

φ = prod. function coefficient of own R&D stock

σ = prod. function coefficient of SPILLTECH

λ = market value coefficient of SPILLSIC (divided by 2)

Social returns about three times higher than private.

- Full simulation involves inverting whole spillover network matrix & generates similar results

Problems/extensions

- BSVR Data ends in 2000. Lucking et al (2020) re-do through 2015 & find similar results
- Other spillovers metrics (geographic; input-output linkages; ethnic, etc. e.g. Lychagin et al, 2016)
- Industry-specific effects (find heterogeneity looking at pharma; hardware & medical instruments)
- Statistical properties of spillover terms (Marnessa, 2016)
- Non-Compustat firms in US
- R&D outside the US
- Other inputs into innovation efforts than R&D
- How to get sharper identification of spillovers ?

Conclusions

- *Both* technology spillovers and product market rivalry effects of R&D

- Technology effects dominate, so “too little” R&D overall
  - Consistent with bulk of empirical work

- But what policies can help bridge the gap between social and private returns to R&D….

Backup

Model overview

Two stage game.

Stage 1: Firms choose level of R&D, *r*

Firms' knowledge, *k,* determined by firms' R&D pool

Stage 2: Short run variable (price or quantity), *x*, chosen

Three firms:

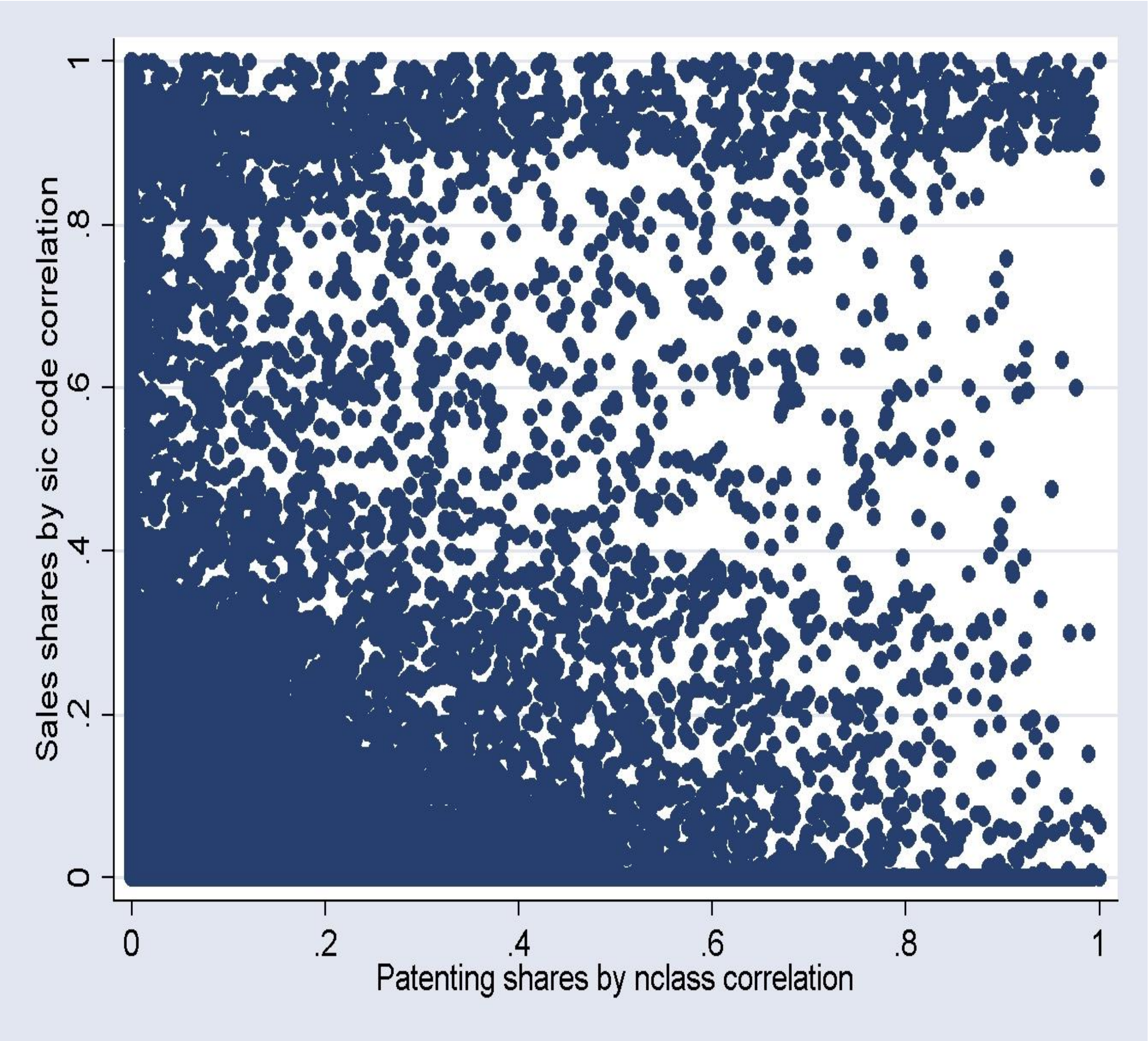
0, *τ* and *m*.

- Firms *0* and *m* compete in the same product market.
- Firms *0* and *τ* operate in same technology area.

Can generalise to many firms with non-binary interactions

Implication: R&D by firms close to me in technology space is good for my value; R&D by product market rivals is bad for my value

Correlation between Technology and Product Market closeness



correlation 0.46

Cite-weighted Patent Count Model

Dependent var: Patent Count	(1)	(2)
	Initial conditions, static	Initial conditions, dynamic
Ln(SPILLTECH) $_{t-1}$	**0.468*** (0.080)**	**0.417*** (0.056)**
Ln(SPILLSIC) $_{t-1}$	**0.056 (0.037)**	**0.043 (0.026)**
Ln(R&D Stock) $_{t-1}$	0.222*** (0.053)	0.104*** (0.039)
Ln(Patents) $_{t-1}$		0.420*** (0.020)

Note: Time dummies and 4 digit industry dummies included. Estimation period is 1985-1998. Negative binomial model; Obs=9,023. Standard errors clustered by firm

R&D Equations

Dep Var: ln(R&D)	(1)	(2)
	Fixed Effects, static	Fixed Effects, Dynamic
Ln(SPILLTECH) $_{t-1}$	**0.100** **(0.076)**	**-0.049** **(0.042)**
Ln(SPILLSIC) $_{t-1}$	**0.083**** **(0.034)**	**0.034*** **(0.019)**

Notes: Includes controls for lagged R&D, sales, industry level sales, time and firm dummies. Estimation period is 1981-2001. Obs=8,579/8,387. Newey-West heteroskedasticity and first-order auto-correlation robust standard-errors

Examples : Computer and chip makers

	Correlation	*IBM*	*Apple*	*Motorola*	*Intel*
IBM	SIC *TECH*		0.32 *0.64*	0.01 *0.47*	0.01 *0.76*
Apple	SIC *TECH*			0.02 *0.17*	0.01 *0.47*
Motorola	SIC *TECH*				0.35 *0.46*
Intel	SIC *TECH*				

IBM, Apple, Motorola and Intel all close in TECH

But a) IBM close to Apple in product market (.32, computers)

b) IBM <u>not</u> close to Motorola or Intel in product market (.01)

Comparing Empirical Results to Predictions of the Model

	Partial correlation	*Theory*	*Empirics*	*Consistency?*
$\partial V_0/\partial r_\tau$	Market value with SPILLTECH	Positive	0.381**	Yes
$\partial V_0/\partial r_m$	Market value with SPILLSIC	Negative	-0.083**	Yes
$\partial k_0/\partial r_\tau$	Patents with SPILLTECH	Positive	0.417**	Yes
$\partial k_0/\partial r_m$	Patents with SPILLSIC	Zero	0.043	Yes
$\partial y_0/\partial r_\tau$	Productivity with SPILLTECH	Positive	0.191**	Yes
$\partial y_0/\partial r_m$	Productivity with SPILLSIC	Zero	-0.005	Yes
$\partial r_0/\partial r_\tau$	R&D with SPILLTECH	Ambiguous	0.100	-
$\partial r_0/\partial r_m$	R&D with SPILLSIC	Positive with strategic complements	0.083**	Yes

Alternative Spillover Measures

- Mahalanobis – using co-location among patent classes to characterize distance between classes and use it in measuring distance between firms. Jaffe measure treats all classes as orthogonal to each other.

- Geography – does physical closeness of R&D labs matter for either type of spillovers?

- Plus range of other variations using different closeness metrics (e.g. Ellison-Glaser, 1997, 2010) & datasets (e.g. BVD Amadeus)

First Stage Regressions for IV results

	(1)	(2)	(3)	(4)
Dependent variable:	**Log(R&D)**	**Log(R&D)**	**Log(R&D)**	**Log(R&D)**
Second stage specification:	**Tobin's Q**	**Patents**	**Productivity**	**R&D**
State Tax Credit component of R&D user cost$_t$	-1.665 (0.407)	-2.452 (0.435)	-0.396 (0.264)	-1.665 (0.407)
Firm Tax Credit component of R&D user cost$_t$	-0.721 (0.108)	-1.080 (0.146)	-0.586 (0.077)	-0.721 (0.108)
F-test of the two excluded instruments	29.59	44.88	29.80	29.59

Note: Includes controls for fixed effects, industry sales and time dummies. Ses clustered by firm

Results using R&D tax credits as an instrument: qualitatively similar

	(1)	(2)	(3)	(4)
	Tobin's Q	Patents	TFP	R&D
Ln(SPILLTECH) $_{t-1}$	1.079*** (0.192)	0.407*** (0.059)	0.206** (0.081)	0.138 (0.122)
Ln(SPILLSIC) $_{t-1}$	-0.235* (0.109)	0.037 (0.028)	0.030 (0.054)	-0.022 (0.071)

Simulation of model to quantify social and private returns to R&D

- Calculate long-run response of productivity to an exogenous increase in R&D – e.g. from a tax credit

- Private returns to R&D include own productivity impact plus the business stealing effects

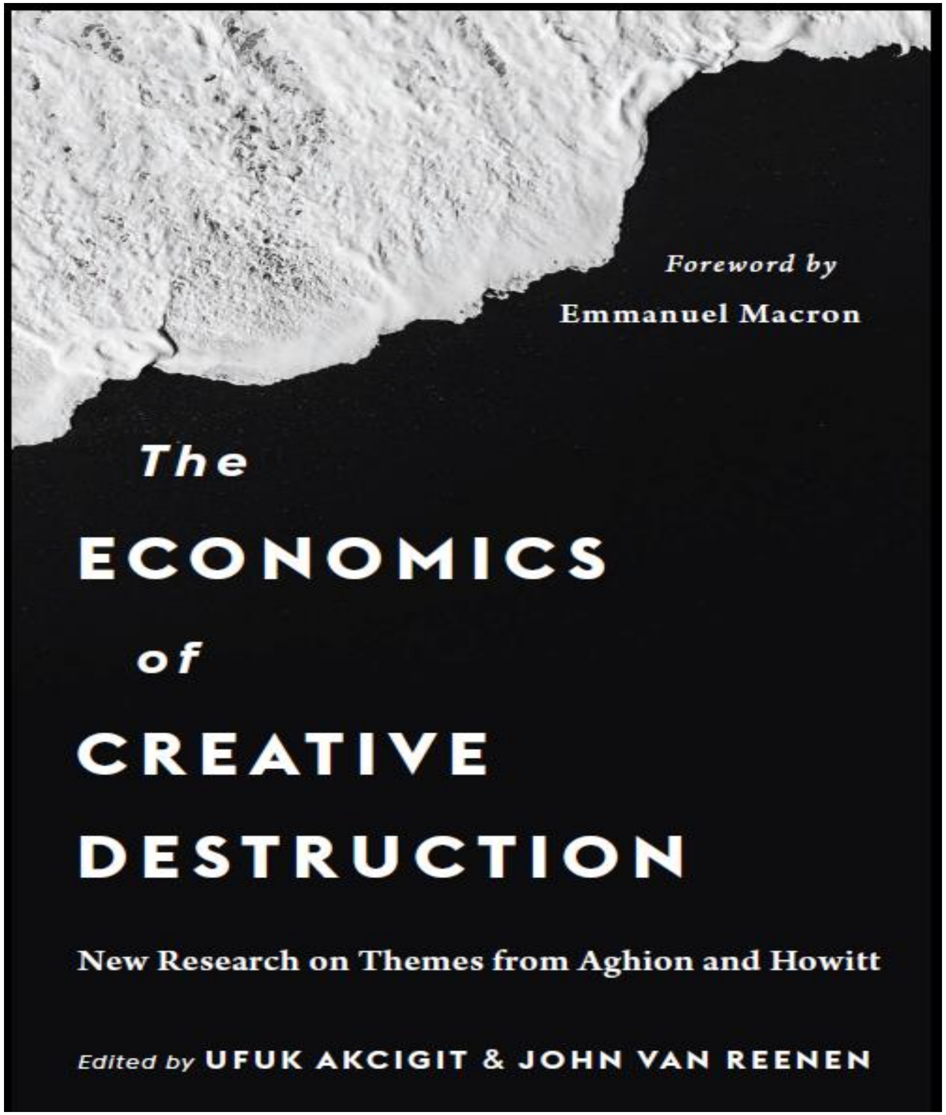
- Social returns include own productivity impact plus technology spillover effects

- Complex because of depends on firm-level distribution of R&D and linkages in TECH and SIC space

Structure of Lectures

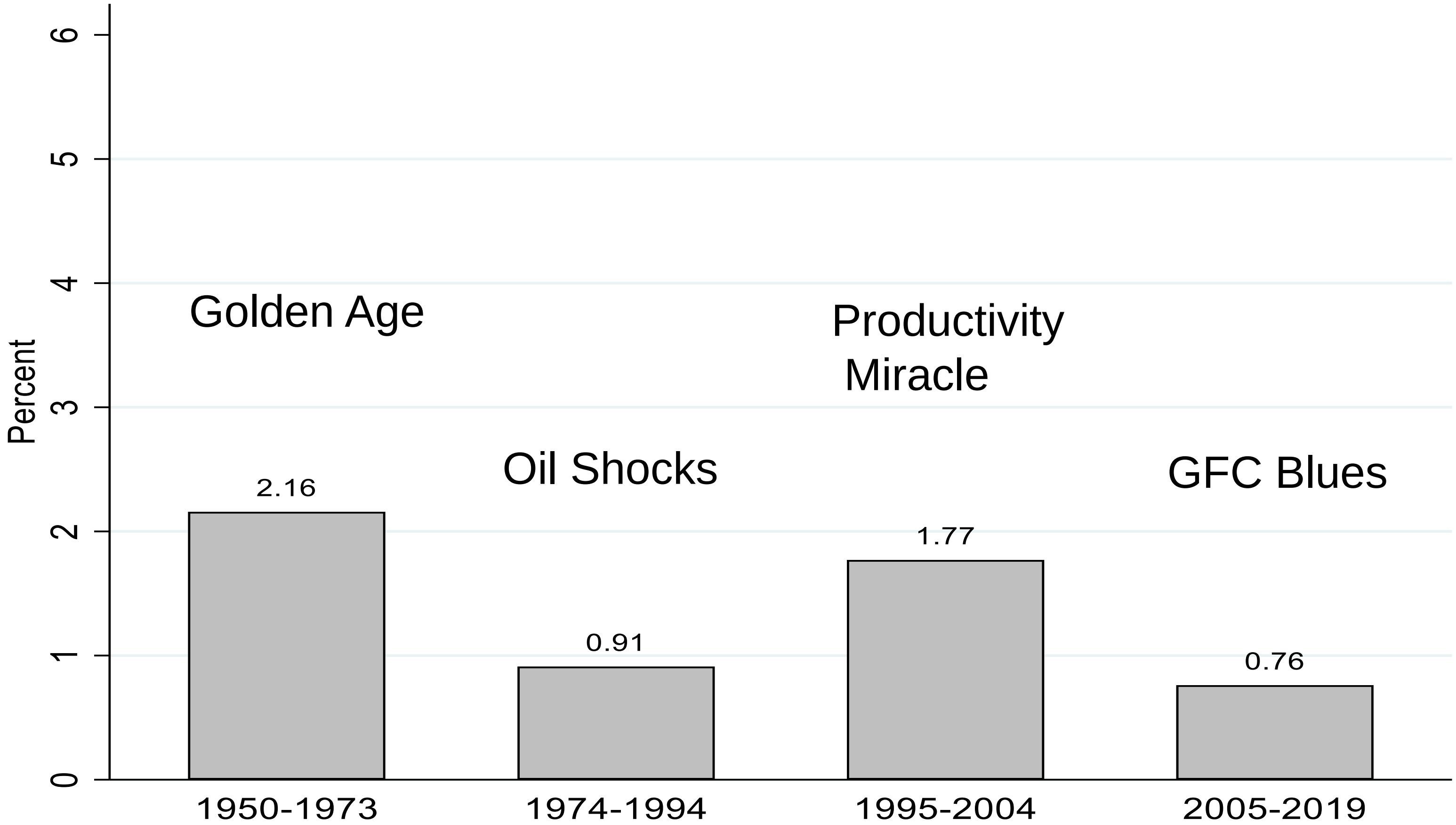
1. Overview
2. Why should governments intervene?
   - Focus on spillovers & their identification
3. How should government intervene?
   - **Innovation policies**
     - *"Demand Side"*
       - Taxation (R&D tax credits & general tax)
       - Direct R&D Grants
     - *"Supply Side"*
       - Human Capital (STEM, University, immigration, Lost Einsteins)
       - (*Other*) Competition & trade
   - **Diffusion policies (focus on management practices)**

Best book not (yet) on the reading list!



Book launch scheduled for Autumn 2023

Productivity problems started long before COVID: US Total Factor Productivity (TFP) growth 1950-2019



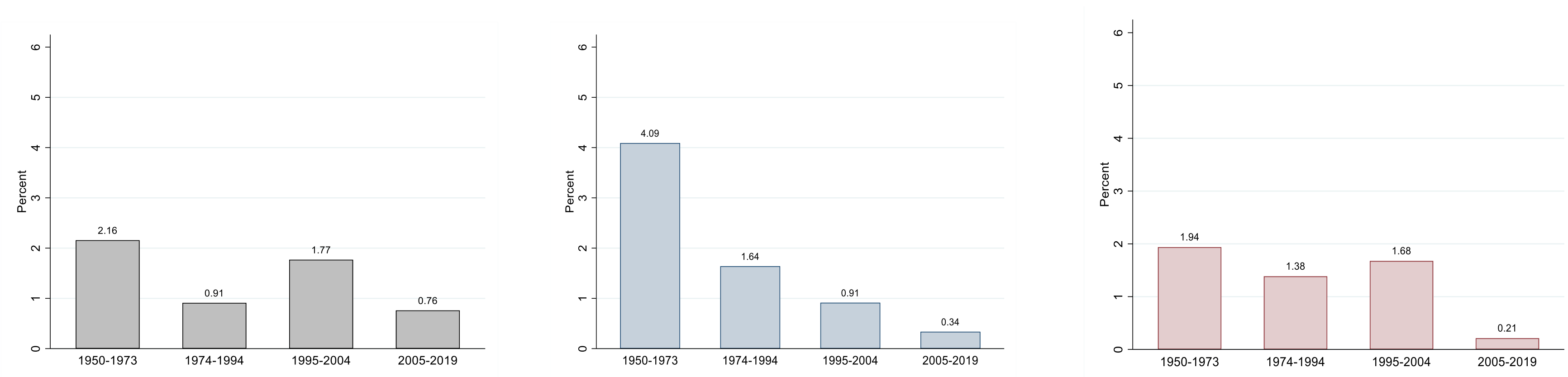
Source: Teichgraber & Van Reenen (2022) Updated data from Bergeaud, Cette, and Lecat (2016). Data publicly available at: http://www.longtermproductivity.com/

Productivity problems started long before COVID: Total Factor Productivity (TFP) growth 1950-2019

A. United States

B. Euro Area

C. United Kingdom



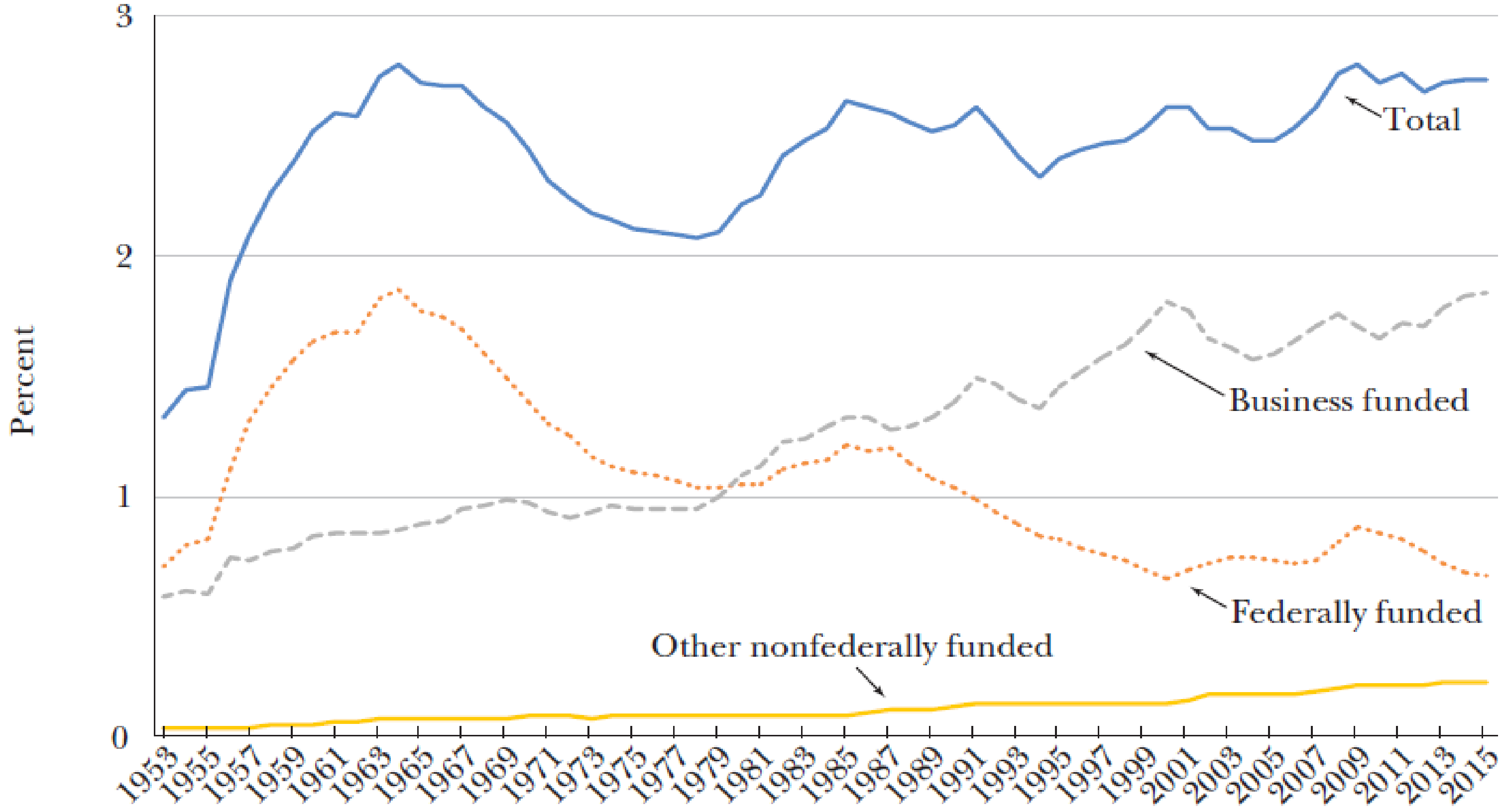
Source: Teichgraber & Van Reenen (2022) Updated data from Bergeaud, Cette, and Lecat (2016). Data publicly available at: http://www.longtermproductivity.com/
Notes: Average annual TFP growth in the US (panel A), Euro-area (panel B), and UK (panel C). Insufficient data for whole Euro-area so Germany, France, Italy, Spain, Netherlands, and Finland are used.

Drivers of Aggregate Productivity

- Pushing out the **global technological frontier (“innovation”)**
  - Important for economically advanced countries, but not the only thing…

- **Catching Up** to frontier
  - **Diffusion** of technology
  - Reducing **Misallocation**

Decline in US federally funded R&D/GDP since mid 1960s



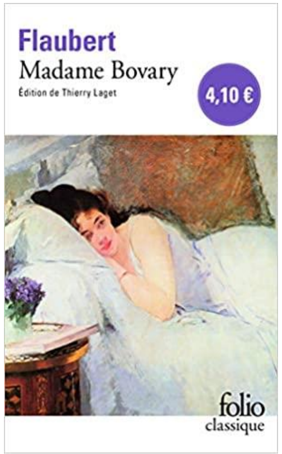
Source: National Science Board (2018)

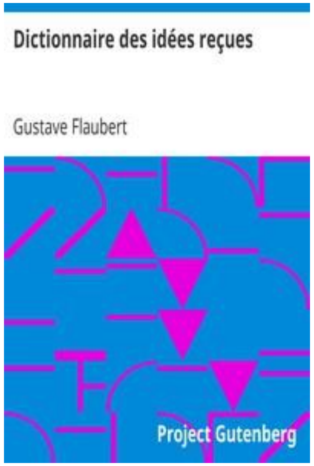
Why should the government subsidize innovation?

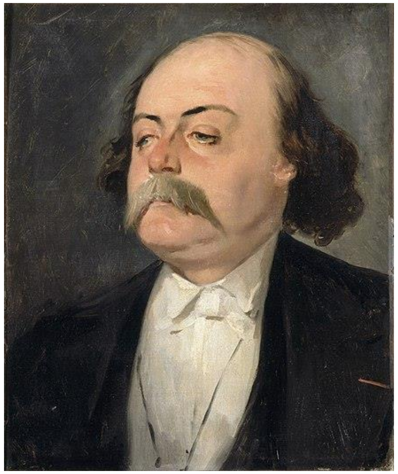
- **Multiple market failures. Main one:**
  - R&D is (partially) non-excludable. "Public good" nature of knowledge means that those who do R&D only get small part of the social benefit.

Le Dictionnaire des idées reçues
("Dictionary of Received Ideas")

Inventors - "All die in the poor house. Someone else profits from their discoveries, it's not fair"







Gustave Flaubert (1911)

Why should the government subsidize innovation?

- **Multiple market failures. Main ones:**
  - Non-excludable and non-rival. "public good" nature of knowledge: those who do R&D only get small part of the social benefit.

  - Frictions in other markets.
    - **Example of Finance.** Upfront research costs: Large, uncertain, asymmetric info means that financial markets will tend to under-provide (especially for SMEs)

Multiple types of R&D spillovers

- **Positive**
  - **Imitative:** Copying by other firms
  - **Intertemporal benefits:** “Building on shoulders” as innovators use ideas from previous generation
  - **Users:** Surplus captured by consumers/downstream firms
- **Negative**

Multiple types of R&D spillovers

- <u>**Positive**</u>
  - **Imitative:** Copying by other firms
  - **Intertemporal benefits:** “Building on shoulders” as innovators use ideas from previous generation
  - **Users:** Surplus captured by consumers/downstream firms

- <u>**Negative**</u>
  - **Business stealing:** market share redistribution (e.g. “me-too” drugs)
  - **Duplicative R&D:** Excess entry/fixed costs
  - **Intertemporal costs:** “Fishing out” of ideas

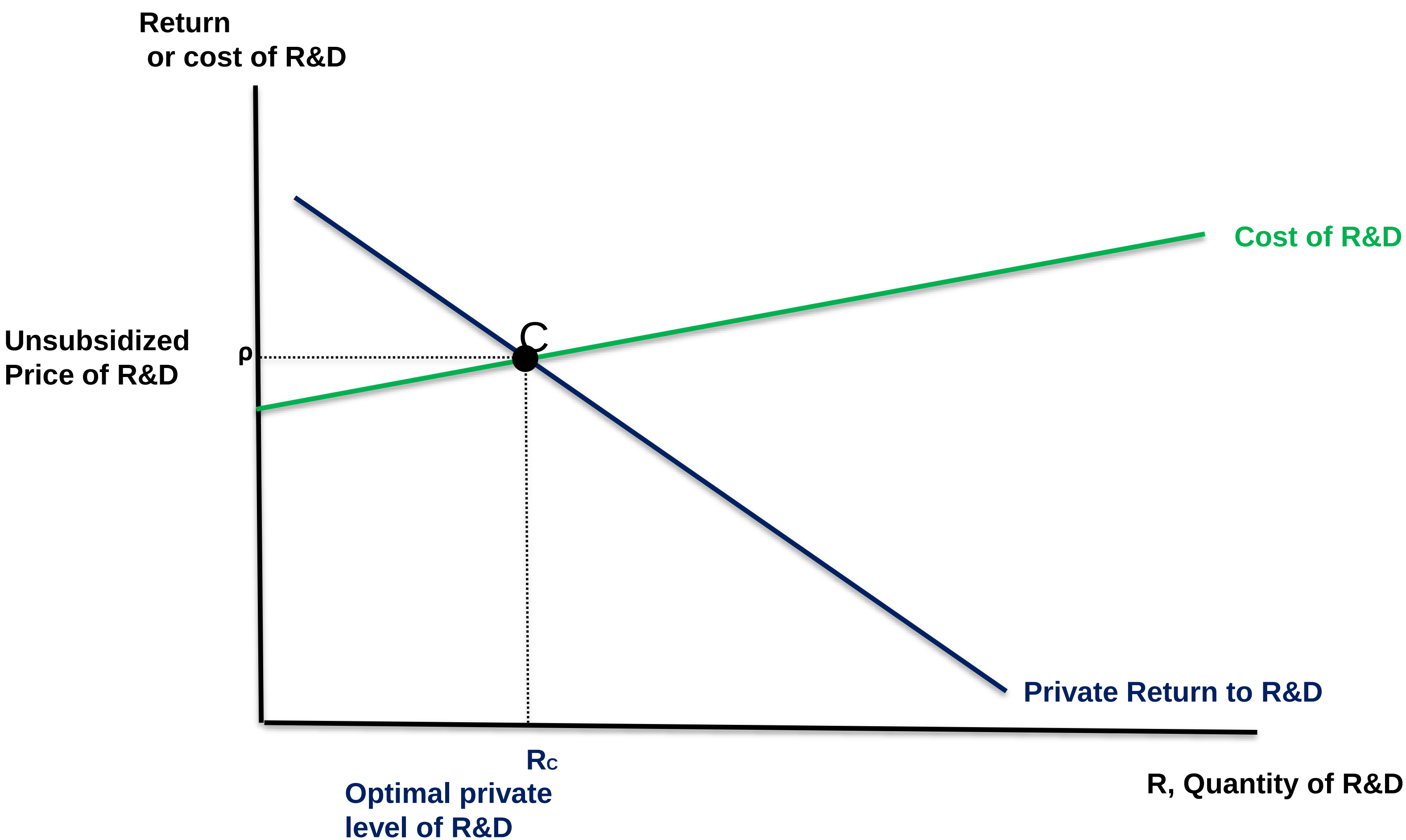
- Which spillover dominates is an empirical issue

Why should the government subsidize innovation?

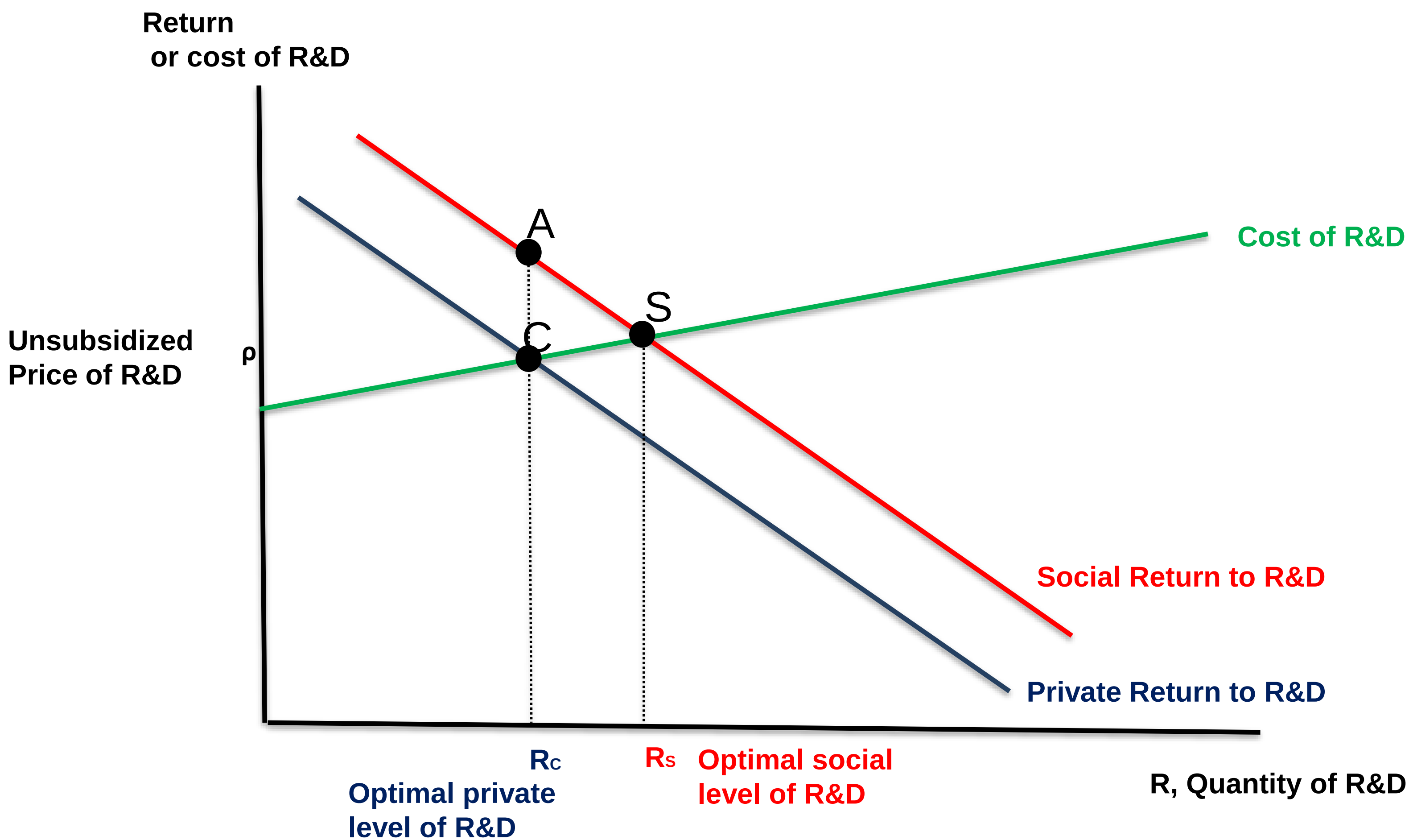
- **Empirical evidence suggests strong role for positive knowledge spillovers.** Examples for US:
  - Bloom, Shankerman & Van Reenen (2013); Lucking, Bloom & Van Reenen (2020); Jones & Summers (2022)
  - Social return to R&D is >3 times as large as the private return. Implies large private under-investment

- **Challenge:** Why not free ride off other countries?
  - Harder for more advanced countries like US
  - "Two faces of R&D?" (Griffith, Redding and Van Reenen, 2004)
    - R&D may help a country's "absorptive capacity" from world knowledge stock

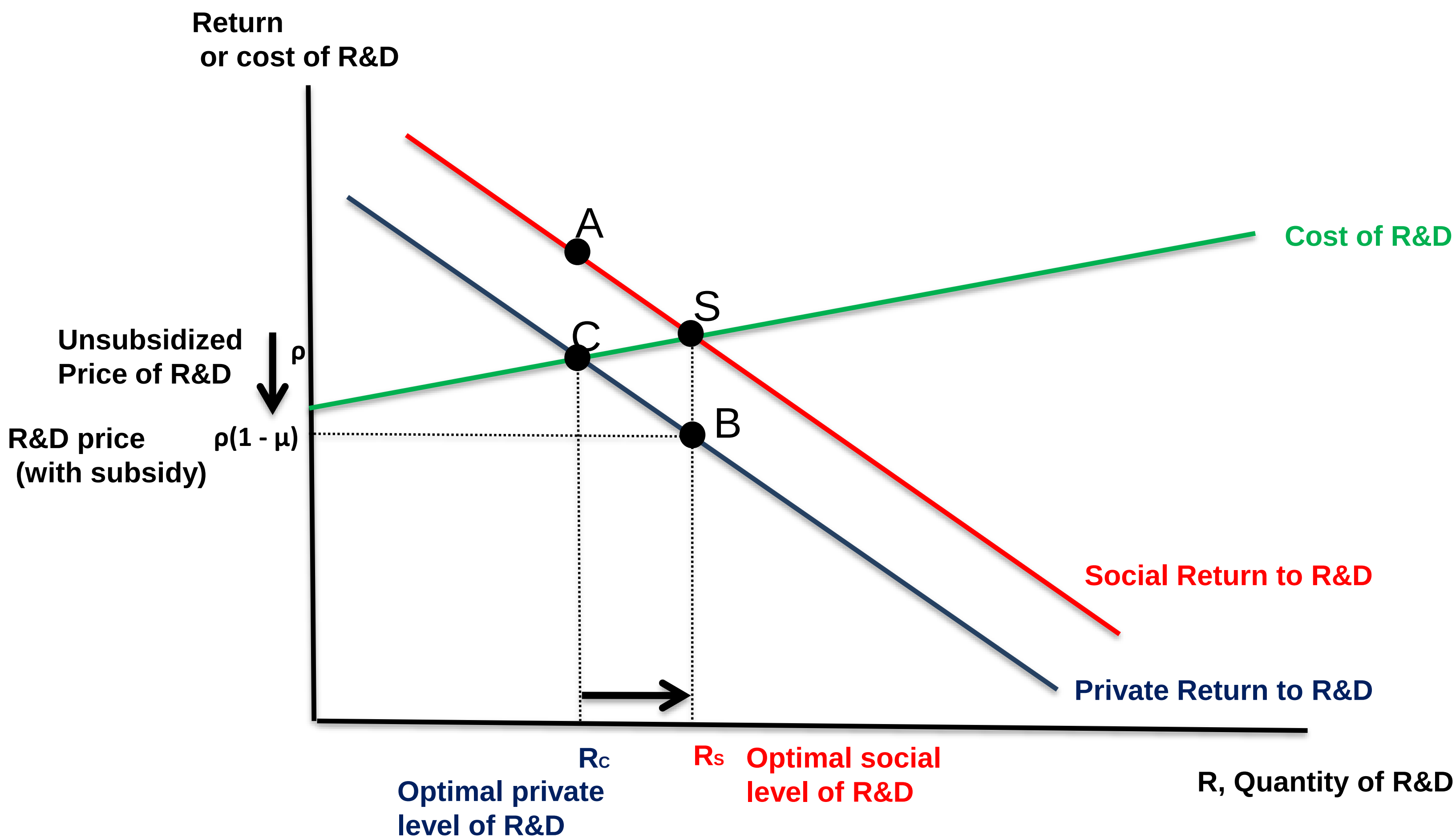
Simplified Model with knowledge spillovers. Decentralized model of R&D spending



Social returns to R&D higher than private returns due to spillovers (A-C)



Optimal R&D policy seeks to equate social returns with cost via subsidy of μ reducing R&D price to $\rho(1-\mu)$



Indicators of Innovation (other than TFP growth)

- **R&D** spending
  - Firm accounts (e.g. Compustat)
  - Administrative surveys (e.g. BERD).
  - Tax records (e.g. from R&D credits)

- **Patents** by firms (NBER/Griliches) and by individuals (Lai et al, 2014 disambiguation)
  - Well-known problems (not all patents are innovations and not all innovations are patented)
  - But a lot of empirical focus on this measure because rich information on patent document (future citations, family size, patent text, stock market responses, etc. to measure quality and type of innovation)

Direct indicators of Innovation (other than TFP)

- **Innovation Surveys** (e.g. EU Community Innovation Survey; SPRU; Von Hippel's user-based innovation,..)

- Shifts of **frontier for specific technologies** (semi-conductors, crop yields, solar panel efficiency, supercomputer performance, etc. – see e.g. Bloom, Jones, Van Reenen & Webb, 2020)

- Academic **Publications**

- **Others:** Venture Capital; new product codes; Prizes at World Fairs; New Molecular Entities; Medical devices, etc.

Some Econometric Issues

- **Standard problems in policy evaluation**
  - Unobserved heterogeneity
  - Endogeneity
  - Spillovers (control group affected by treatment – SUTVA violation): **big issue** for innovation studies

- **Particularly important issues in Innovation Economics**
  - Lots of zeros (real or measurement issue?)
  - Nonlinear outcomes (e.g. patent counts)
  - Long and uncertain dynamic responses
    - I will not less on these, but has been a focus of some of my work (see “Data and Methodological Issues” on reading list)

Innovation Policy: The "Lightbulb" Table

(1)	(2)	(3)	(4)	(5)	(6)
Policy	**Quality of evidence**	**Conclusivenes s of evidence**	**Benefit - Cost**	**Time frame:**	**Effect on inequality**

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

Innovation Policy: The “Lightbulb” Table

(1)	(2)	(3)	(4)	(5)	(6)
Policy	**Quality of evidence**	**Conclusiveness of evidence**	**Benefit - Cost**	**Time frame:**	**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	↑

“Demand”

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

Innovation Policy: The "Lightbulb" Table

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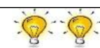
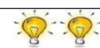
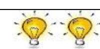
R&D tax credits	High	High		Short-Run	↑
Patent Box	Medium	Medium	Negative	n/a	↑
Skilled Immigration	High	High		Short to Medium-Run	↓
Universities: incentives	Medium	Low		Medium-Run	↑
Universities: STEM Supply	Medium	Medium		Long-Run	↓
Exposure Policies	Medium	Low		Long-run	↓
Trade and competition	High	Medium		Medium-Run	↑

"Demand"

"Supply"

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

Other Innovation Policies (that I won't focus on)

- **Patent** and IP system (Heidi Williams covers)
- **Science funding**/Grants to academics (Azoulay covers)
- Research Joint Ventures/**collaborations** (e.g. Sematech)
- **Prizes** and Forward Commitments (e.g. Vaccines)
- Many **policies/institutions with indirect effects** on innovation (e.g. regulation; unions; minimum wages)
- **Finance**: Venture Capital, angels, etc. (Lerner, 2022)
- **Place-based policies** (MNE literature, agglomeration, etc.)
- General policies towards productivity
- My focus is innovation - things that **shift the global technological frontier outwards** (new to world not just to firm/industry/country). But some diffusion of management

Other Innovation Policy Approaches

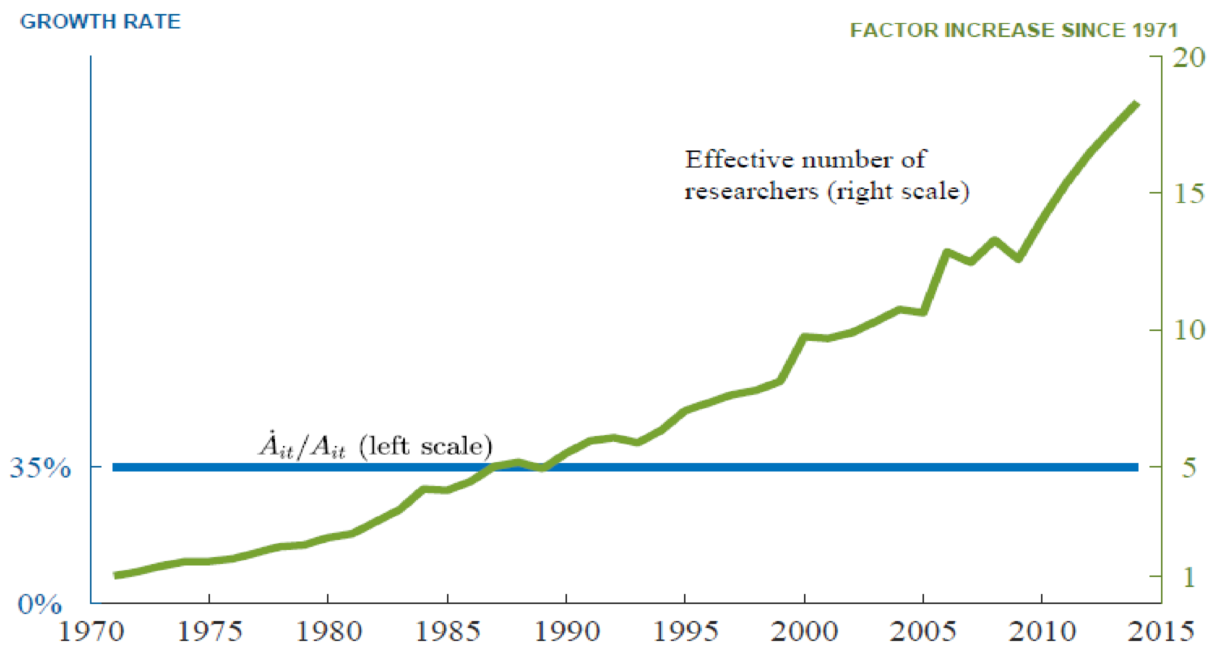
- My focus on **econometric analysis** of policies, mostly on micro data
- Alternative is to build explicit model and consider optimal policies (with some calibration or structural estimation)
- Example of Akcigit, Hanley and Stantcheva (2022) in notes

- See also “Macro Approaches” on reading list for more like:
  - Acemoglu, Akcigit, Alp, Kerr and Bloom (2018)
  - Acemoglu, Akcigit, Hanley and Kerr (2016)
  - Aghion, Bergeaud and Van Reenen (2023)
  - Atkeson and Burstein (2019)
  - Liu and Ma (2022)

Back Up

Ideas Getting Harder to Find? A decline in the productivity of R&D (even in semi-conductors)

Figure 4: Data on Moore's Law



Note: The effective number of researchers is measured by deflating the nominal semiconductor R&D expenditures of key firms by the average wage of high-skilled workers. The R&D data includes research by Intel, Fairchild, National Semiconductor, Texas Instruments, Motorola, and more than two dozen other semiconductor firms and equipment manufacturers; see Table 1 for more details.

Source: Bloom, Jones, Van Reenen and Webb (2020, AER)

Components of "Innovation" Costs

Knowledge Spillovers

High?

- Research
  - Basic
  - Applied
- Development
- Purchase of external IP (patents, copyrights, trademarks and technical know-how)
- Purchase, installation and use of high tech equipment
- Software and database activities
- Training of employees in new processes or in supporting new products
- Marketing associated with the into or new or improved goods & services
- Costs of organizational innovation

Low?

Akcigit, Hanley and Stantcheva (2022)

- Dynamic Mechanism Design model with
  - Knowledge spillovers (needs Pigouvian tax correction)
  - Imperfect Competition (monopoly distortion)
  - Heterogeneous R&D productivity (& changes over time)
  - Asymmetric info (govt. does not observe heterogeneity; wants to screen “good” firms from “bad” firms)
- Optimal policies vary tax nonlinearly with profits & R&D levels

Akcigit, Hanley and Stantcheva (2022)

- Key parameter turns out to be complementarity between:
  1. R&D investment & R&D effort (observable and unobservable innovation inputs)
     - Implies want higher optimal R&D subsidies
  2. R&D investment & R&D productivity
     - Implies lower optimal R&D subsidies as productive firms can just take rents
- They claim (2) is empirically strong, so allocate subsidies away from low productivity firms (otherwise high productivity firms will imitate them)
- Can get close to first best with simple policies that have lower marginal corporate tax rates for more profitable firms and lower marginal subsidies at high R&D investment levels (latter is main thing)

Issues

- Most important primitive elasticities are very hard to observe
  - Could relate to management literature on complementarity

- Profits are very hard to directly observe

- Model is very stylized, how seriously should we take it?

Introduction

- TFP main factor in macro (growth over time & differences across countries) & micro (differences across firms) heterogeneity

- Conventional view was that technical change was exogenous, but endogenous growth theory revolutionized ways of thinking of this

- Policy makers seek to affect innovation in many ways, directly (e.g. R&D grants) and accidentally (e.g. regulation)

Some Indicators of Diffusion

- Diffusion of other specific innovations (robots, Information & Communication Technology - ICT, hybrid corn, seeds, etc.).
- Diego Comin's historical datasets (CHAT): telephone, steam, rail, etc.
- Why are seemingly superior technologies not adopted?
  - Big issue in development economics. Usually agricultural, but Atkin et al (2015) on a manufacturing technology (soccer balls in Pakistan)
  - In developed economies, lots of discussion over ICT diffusion. Discuss later impact of management & complementarities with technology

Policies towards diffusion

1. Adoption of specific technologies (e.g. Broadband)

2. Information provision (e.g. Small Business services)

3. Technology transfer (e.g. FDI support or export credits)

4. University-business linkages (Technology Licensing Offices, 1980 Bayh-Dole Act)

Table 4—Robustness of estimates to unrestricted curvature

Technology	Invention year ($\underline{v}_\tau$)	Percentage H_0 not rejected*	Correlation between Estimated adoption lags
Steam- and motorships	1788	65	.99
Railways - Passengers	1825	67	.89
Railways - Freight	1825	62	.97
Cars	1885	75	.82
Trucks	1885	81	.81
Aviation - Passengers	1903	66	.93
Aviation - Freight	1903	77	.83
Telegraph	1835	59	.95
Telephone	1876	80	.94
Cellphones	1973	67	.70
PCs	1973	59	.41
Internet users	1983	100	.59
MRIs	1977	92	.56
Blast Oxygen Steel	1950	72	.73
Electricity	1882	41	.91
Total		69	.80**

Note: All results are for plausible and precise estimates under restricted specification.
* At 5 percent significance level. ** Correlation is weighted average of correlations across technologies.

Source: Comin & Hobijn (2010, AER)

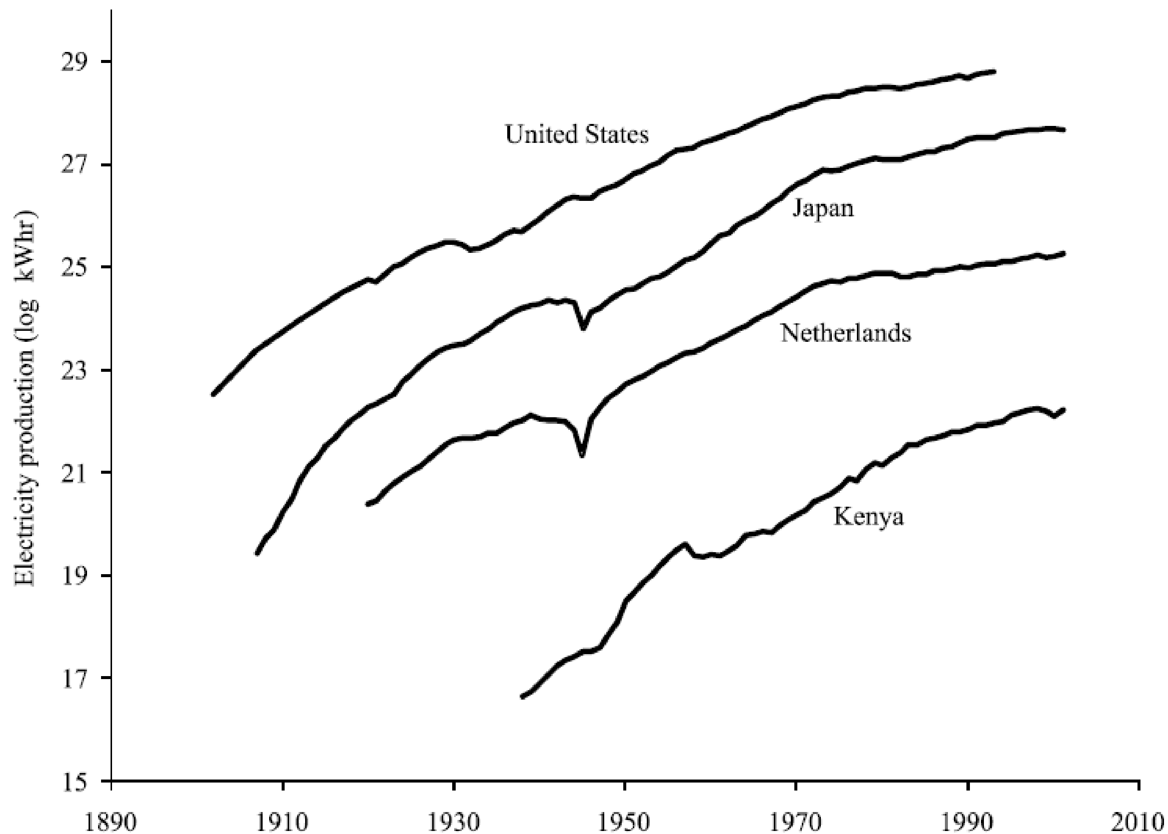


FIGURE 1. ELECTRICITY PRODUCTION IN FOUR COUNTRIES.

Source: Comin & Hobijn (2010, AER)

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F. *DIFFUSION*

Diffusion

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