

The Future of Fiscal Policy: American Economic Policy Debates in the 21st Century Innovation Policy

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Thanks to Heidi Williams and Glen Weyl for sharing notes/slides, much of which are reproduced here. Stephanie Kestelman provided excellent assistance making these slides.

Outline

1 Motivation

2 Policy

- Rationale for government intervention
- The patent system
- Tax policy: R&E credits
- Immigration: H1-B visas
- Education and antitrust policy (skip)

3 Theory

- Optimal innovation policy
- Optimal patent length
- Policy implications

4 Evidence

- Elasticity of innovation with respect to profits
- Costs of IP protection
- Who profits from patents?
- Mobility and origins of innovators
- Effects of R&E credits on innovation

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Innovation and Economic Growth

Quotes from Jason Furman, former chair of the CEA:

- TFP growth is the main driver of economic growth
 - Increases in TFP accounted for over half of the growth in productivity between 1948 and 2014.
- This is why it is so important to have public policies that are focused not just on increasing business investment and worker skills, but also on more fundamental innovation, as measured by TFP, which is essential if we want to see faster growth in middle class incomes.
- **The need to foster greater innovation and productivity growth is one of the most important economic challenges we face**, and tax policy is one of several important levers that policymakers can use.

Source: Jason Furman speech on innovation policy https://obamawhitehouse.archives.gov/sites/default/files/docs/20160311_innovation_and_tax_policy_itpf.pdf

Evolution of R&D spending

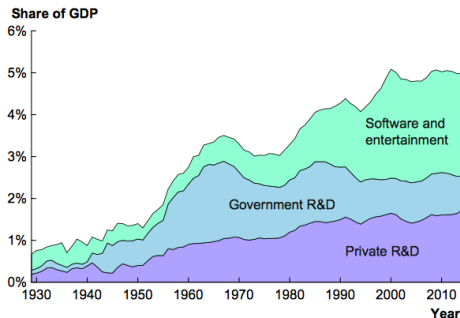


Fig. 9 Research and development spending, United States. Source: *National Income and Product Accounts, U.S. Bureau of Economic Analysis via FRED database*. "Software and entertainment" combines both private and public spending. "Entertainment" includes movies, TV shows, books, and music.

Source: Chad Jones (2016). Note that President Obama's budget proposed a 4% increase in overall R&D funding with focus on investment in basic science, advanced manufacturing, cybersecurity, energy efficiency, and medical science

Overview of innovation policy

Government policies that affect innovation include:

- The patent system
- Tax policy (R&E credits, patent boxes, etc)
- Immigration: H1-B visas
- Education and antitrust policy (skip for time)

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Rationale for government intervention

Rationale for government intervention

- Key question: do competitive markets provide less innovation than is socially desirable?
- Yes if ideas are non-rival and can also be non-excludable, may be under-provided by private market
- **Non-rival:** Non-rivalry implies that the use of an idea by one individual does not limit its simultaneous use by other individuals.
 - Units of labor are rival, in the sense that one unit of labor cannot be used simultaneously by more than one firm, but ideas are non-rival in the sense that the use of an idea by one firm does not preclude its simultaneous use by other firms
- **Non-excludable:** Ideas can also be non-excludable in the sense that it may be difficult to block individuals from using ideas once they exist.
 - This would be the case if, for example, imitators could easily copy or reverse engineer a new technology once it is developed and marketed.

Source: Heidi Williams

Key policy design questions:

- How to structure incentives: patents, public R&D subsidies (NIH, NSF), tax policy, patent boxes, etc?
- Effects on the rate and direction of R&D: which types of innovation are subsidized (from, e.g., 20 year long patent protection)?
- Under -or -over investment relative to social optimum?
 - If producers cannot perfectly price discriminate, some of what could be producer surplus will shift to be consumer surplus
 - Knowledge spillovers: if appropriability is imperfect – in the sense that innovators cannot capture all of the social returns to the knowledge generated by their R&D investments – other firms will benefit from new ideas in a way that the original innovator won't be compensated for

Source: Heidi Williams

The patent system

Patents: a brief primer

Patents are a monopoly right to produce

In the US, inventors wishing to obtain a patent submit an application to the US Patent and Trademark Office (USPTO)

- Two parts of patent applications
 - the “specification” is a written description of the invention which includes references to so-called “prior art,” which are citations to previously filed patent applications, previously granted patents, prior scientific publications, and other sources which are known to the inventor and relevant to the patentability of the invention.
 - the “claims” of the patent are a specific list of what the applicant wishes to claim intellectual property over.

Source: Heidi Williams

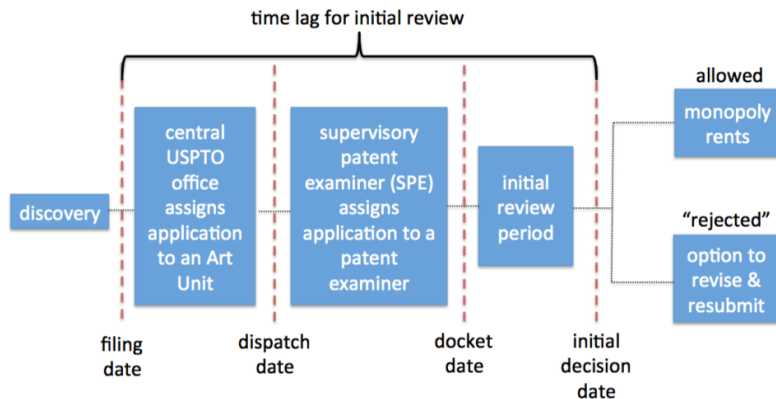
Obtaining a US patent (crash course)

- Discover a novel, non-obvious, useful idea
- Submit application to USPTO central office (“filing date”)
 - ▶ Central office routes application to the supervisory patent examiner (SPE) of the appropriate Art Unit (“dispatch date”)
 - ▶ SPE assigns application to a patent examiner (“docket date”)
- Examiner issues an initial decision (“initial decision date”)
 - ▶ Allowance (roughly 10% of initial decisions) or “rejection”
 - ▶ “Rejection” is a revise & resubmit
 - ▶ Applicant and examiner may engage in many rounds of revision

Source: Kline, Petkova, Williams, Zidar (2017)

Obtaining a US patent (crash course)

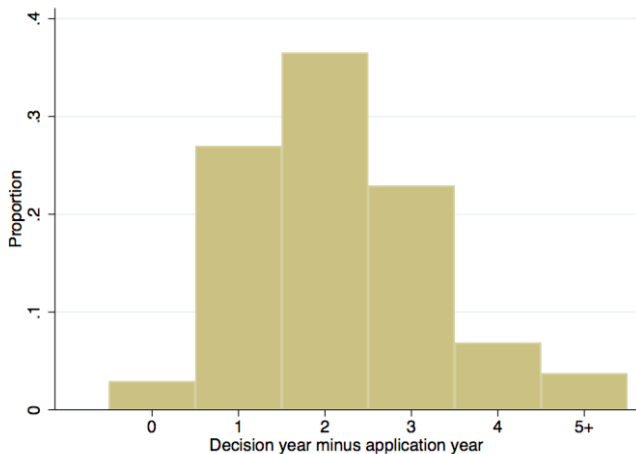
USPTO patent application process



Source: Kline, Petkova, Williams, Zidar (2017)

Obtaining a US patent (crash course)

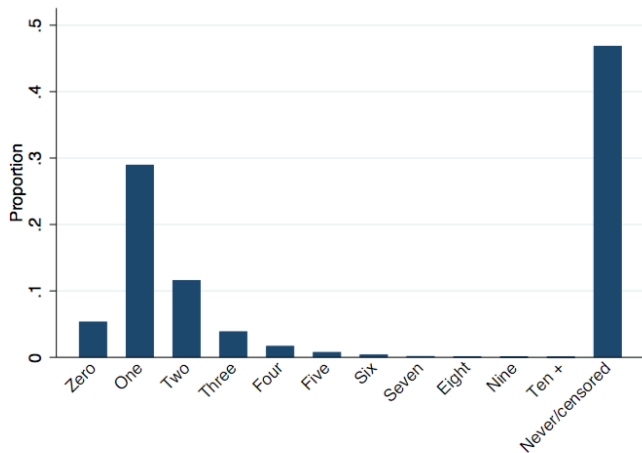
Most initial decisions arrive within three calendar years



Source: Kline, Petkova, Williams, Zidar (2017)

Obtaining a US patent (crash course)

Nearly half of rejected applications are never accepted



Source: Kline, Petkova, Williams, Zidar (2017)

Patent system structure

- Once granted, in order to keep a patent in force the owner must pay maintenance fees.
 - For the USPTO, these fees are currently due at 3.5 years (\$1,600), 7.5 years (\$3,600), and 11.5 years (\$7,400).
 - Pakes (1986) and Schankerman and Pakes (1986) pioneered the idea of using renewal fees to provide lower-bound estimates on the private value of granted patents.
- Two key aspects of how patents can affect innovation incentives:
 - **Patent length** The US patent term length is currently 20 years from the filing date of the patent
 - **Patent breadth** From a theoretical perspective, the economic meaning of patent breadth is clear: how different must rival products be in order to be deemed non-infringing on a given patented product? But from an empirical perspective, measuring the breadth of patent applications or granted patents is quite challenging

Source: Heidi Williams

Tax policy: R&E credits

- Goal: encourage businesses in the US to invest in Research and Experimentation (R&E)
- One of the largest business tax expenditures
 - Estimated tax expenditure is \$148.0B for FY2017-2026
- R&E credit generally not allowed to offset alternative minimum tax (AMT) liability
- Credit amounts not claimed on the current-year tax return receive a one-year carryback or a carryforward of up to 20 years

Calculating Qualified Research Expenditures (QREs)

- R&E credit is only awarded on qualified research expenses (QREs)
- QREs are *expenses incurred in research undertaken to discover knowledge that is technological in nature for a new or improved business purpose*
- QRE include in-house research and contract research expenses
 - In-house expenses include wages and salaries (69% of spending), supplies (15%), and computer leasing expenses
 - Contract research expenses make up $\approx 16\%$ of QREs

Calculating the R&E Credit Amount

- Credit amount x in t equals the applicable credit rate τ times QREs above a base amount (b)

$$x_t = \tau \times (QRE_t - b)$$

- Taxpayer can calculate R&E credit amount in two different ways
 - 1 Traditional calculation
 - 2 Alternative Simplified Credit (ASC)
- τ and b depend on the type of calculation

1. Traditional calculation

- Used by 49% of taxpayers (31% of QRE)
- $\tau = 20\%$
- Base amount is the greater of
 - 50% of current QREs
 - “Fixed base percentage” times the average of the taxpayer’s gross receipts for 4 preceding years
 - Fixed base percentage: ratio of research expenses to gross receipts for the 1984-1988 period
- Note base amount b cannot be less than 50% of QRE for the taxable year (i.e., must have $b \geq .5QRE_t$)

2. Alternative Simplified Credit (ASC)

- Used by 51% of taxpayers (69% of QRE)
- $\tau = 14\%$
- Base amount is 50% of the average QRE for 3 preceding taxable years
- $\tau = 6\%$ if a taxpayer has no QRE in any of the three preceding taxable years

Sample Traditional Calculation for 10% Increase in QRE

				Increase QRE by 10 percent
Line			(1)	(2)
1	Current-year qualified research expenses (QRE)		100	110
2	Average annual gross receipts		1000	1000
3	Fixed-base percentage		6%	6%
4	Tentative base for regular credit	Line 1 X Line 3	60	60
5	Minimum 50-percent base	Line 1 X 0.5	50	55
6	QRE above base	Line 1 - Line 4	40	50
7	Credit Rate		20%	20%
8	Reduced credit rate	Line 7 X 0.65	13%	13%
9	Current-year credit	Line 6 X Line 8	5.2	6.5
10	Increase in current-year credit	Column (2) - Column (1)	n.a.	1.3
11	Increase in QRE	Column (2) - Column (1)	n.a.	10
12	Effective credit rate	Line 10 /Line 11		13%
13	Average credit rate	Line 9/Line 1	5.2%	5.9%

Legislative history from Rao (JPubE, 2016)

Table 1
Legislative history of the Federal Research and Experimentation Tax Credit, 1981–2013.

	Credit rate ^a	Corporate tax rate	Definition of base	Qualified research expenditures	Sec. 174 deduction ^b	Foreign allocation rules	Carryback/ Carryforward
July 1981 to Dec 1981	25%	48%	Maximum of previous 3-year average or 50% of 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. possessions.	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

Note: Based on Hall (1993b), the Senate Budget Committee's 2006 Tax Expenditures compendium and Thomas legislative summaries.

^a 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.

^b 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."

Immigration policy: H1-B visas

H-1B Work Visa

- Largest U.S. high-skilled immigration program
- U.S. firms can sponsor temporary migration of foreign workers for up to 3 years with potential for renewal for additional 3 years
- H-1B is a “non-immigrant” visa because of its temporary nature
- Firms must submit an H-1B visa application for each H-1B worker they wish to hire. The firm must ensure:
 - No qualified and willing Americans are available to fill the position
 - H-1B nonimmigrants will be paid at least the actual wage level paid by the employer to all other individuals with similar experience and qualifications for the specific employment in question
 - Employment of H-1B visa holders does not adversely affect working conditions of other similar workers

Receiving an H-1B Visa

H-1Bs are granted in two ways:

① H-1B Visa Lottery:

- Every April, 20,000 advanced degree petitions and 65,000 regular petitions are selected to meet the regular H-1B cap
- 6,800 spots are reserved for citizens of Singapore and Chile

② Cap exempt petitions are processed separately and are not bound by H-1B petition cap. Petitions are cap exempt if either:

- The nonimmigrant is cap exempt: must have earned a masters degree from an institution that is accredited by a nationally recognized agency and that is public or non-profit in nature)
- The employer is a cap exempt institution (higher education institution, non-profit organization associated with a higher education institution, or non-profit research or government organization)

- FY2017-18:
 - 199,000 non-cap exempt petitions (non-advanced degree petitioners had 36% chance of selection)
 - 336,107 total petitions
 - 197,129 total H-1B holders
- FY2016-17: 236,000 non-cap exempt petitions (30% chance of selection)

Source: United States Citizen and Immigration Services (USCIS)

2016 H-1B Statistics

Trend of H1B Petitions Filed FY 2007 Through 2017: Beneficiary Occupation Category

Occupation Category	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
Computer Related	158,078	144,550	107,525	120,257	134,817	182,695	184,944	210,396	253,003	281,017	231,033	2,008,315
Architecture, Engineering, and Surveying	33,965	30,631	27,349	24,431	29,602	29,036	27,496	29,301	28,902	29,622	26,133	318,670
Occupations in Education	29,827	29,159	26,330	24,364	22,380	21,057	19,571	18,961	19,351	19,253	14,355	244,608
Occupations in Administrative Specializations	27,749	23,689	24,041	21,330	22,015	21,636	19,399	20,047	21,140	22,786	21,472	245,304
Medicine and Health	18,602	18,044	20,304	19,089	17,822	17,386	16,342	15,195	14,957	15,196	12,113	185,050
Managers and Officials	10,988	8,935	9,357	8,413	7,688	7,103	5,731	5,706	5,116	5,124	4,422	78,583
Occupations in Life Sciences	7,683	7,072	6,830	6,063	6,050	5,558	5,054	4,887	5,109	5,172	4,257	63,735
Occupations in Mathematics and Physical Sciences	6,266	5,988	5,993	5,363	5,873	5,451	5,445	5,596	5,983	6,696	7,174	65,828
Occupations in Physical Sciences	6,003	4,942	5,002	4,837	5,024	4,509	4,001	4,284	4,180	3,866	3,337	49,985
Other Occupations Categories	15,480	12,465	13,395	14,125	17,141	13,809	11,707	11,598	11,111	10,417	9,811	141,039

Note: Sum of the percent may not add to 100 due to rounding.

2016 H-1B Statistics

Trend of H1B Petitions Filed FY 2007 Through 2017: Beneficiary Country of Birth (Top Twenty)

Country	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
India	166,575	157,608	122,475	135,931	155,791	197,940	201,114	227,172	269,677	300,902	247,927	2,183,112
China, People's Republic of	26,370	24,434	22,411	21,119	23,227	22,528	23,924	27,733	32,485	35,720	36,362	296,313
Philippines	12,230	10,713	10,407	8,887	9,098	9,400	7,399	6,772	4,147	3,704	3,161	85,918
South Korea	10,730	10,277	10,704	8,721	7,480	7,204	5,576	4,897	4,298	4,269	3,203	77,359
Canada	8,562	7,111	7,871	7,342	6,761	6,688	5,478	5,267	5,050	4,547	3,551	68,228
Taiwan	5,394	4,088	4,308	4,325	4,511	4,172	3,520	3,267	2,555	2,287	2,200	40,627
Mexico	4,259	3,680	3,599	3,260	3,439	3,602	2,985	2,769	2,462	2,315	2,239	34,609
United Kingdom	5,105	4,241	4,270	3,651	3,241	3,130	2,330	1,988	1,697	1,528	1,763	32,964
Pakistan	4,259	3,803	3,683	3,012	3,033	2,765	2,381	2,497	2,512	2,401	1,536	31,882
France	4,112	3,687	3,035	2,660	2,531	2,292	2,192	2,024	2,048	1,998	1,474	28,053
Brazil	3,056	2,498	2,495	2,595	2,644	2,557	2,346	2,353	2,111	1,992	1,517	26,164
Nepal	2,775	2,538	2,724	2,467	2,169	2,066	1,788	1,598	1,512	1,504	1,249	22,390
Japan	2,913	2,374	2,253	2,225	2,172	2,030	1,755	1,664	1,553	1,481	1,077	21,497
Turkey	2,415	2,028	2,041	2,023	2,020	1,966	1,658	1,665	1,711	1,709	1,177	20,413
Germany	3,168	2,482	2,182	1,875	1,737	1,650	1,319	1,256	1,164	1,006	1,127	18,966
Iran	2,531	1,930	1,952	1,897	1,755	1,676	1,362	1,331	1,230	1,152	1,332	18,148
Italy	1,353	1,533	1,437	1,361	1,613	1,922	1,722	1,665	1,894	1,639	918	17,257
Russia	2,446	1,760	1,544	1,434	1,570	1,499	1,318	1,323	1,275	1,154	948	16,271
Venezuela	1,262	1,159	1,302	1,299	1,398	1,540	1,370	1,339	1,247	1,208	873	13,997
Spain	1,079	974	933	1,018	1,233	1,140	1,230	1,201	1,110	1,094	861	11,873
All Other	44,027	36,557	34,500	31,170	30,989	30,475	26,923	25,990	27,114	25,739	21,592	335,076

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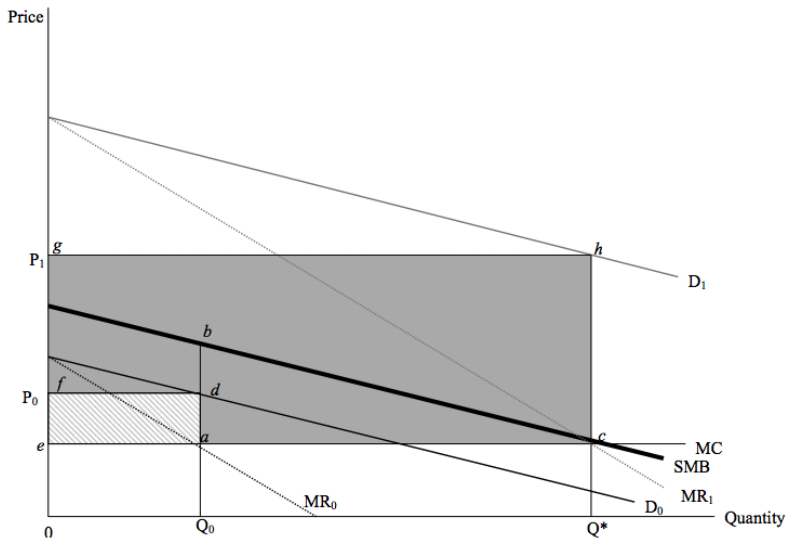
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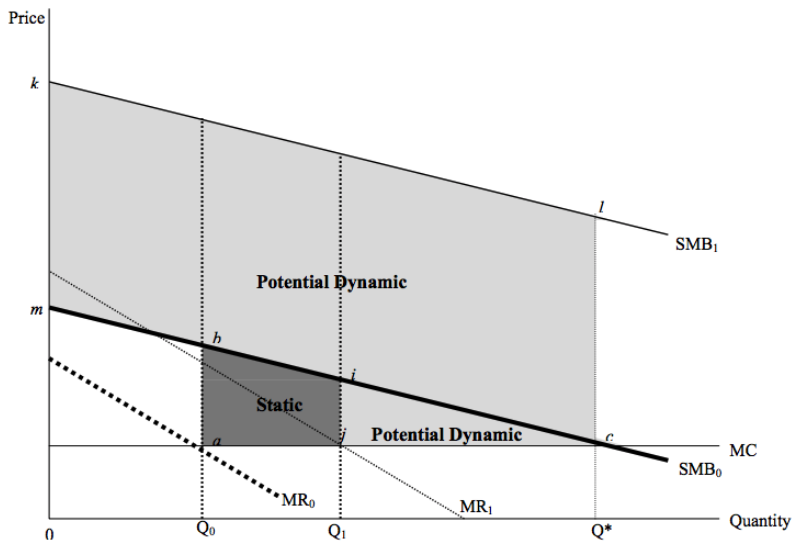
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A few key ideas

- Static versus dynamic efficiency and equity considerations
- What monopoly profits incentivize
- Creative destruction and the dynamics of markets
- Innovation incentives v. ex-post distortion trade-off
- Relationship between IP and criminal justice



Source: Finkelstein (QJE, 2004)



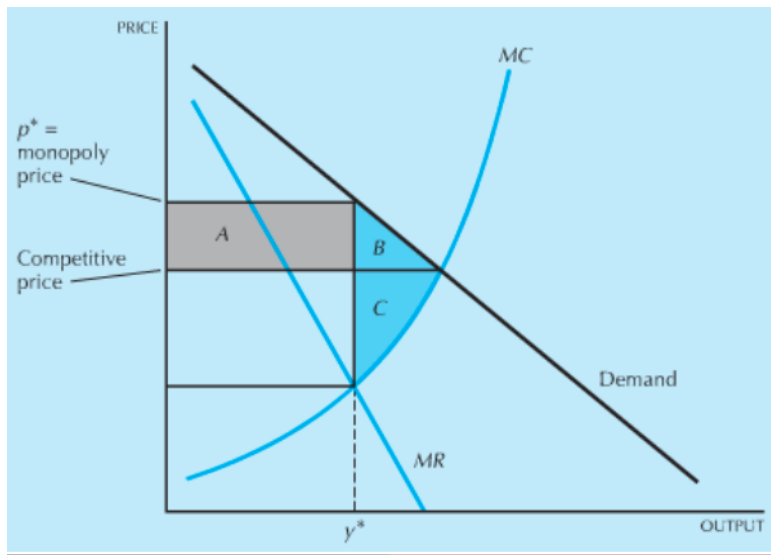
Source: Finkelstein (QJE, 2004)

Monopoly as an incentive

- Monopoly rents/profits encourage pursuit of monopoly
- Some may be left as rent, but substantial elasticity
- If large, we should see monopoly more as price than rent
- What it gives price to depends on how monopoly obtained
 - Activity could be pure waste/rent-seeking (makes monopoly worse b/c profits are DWL too)
 - Could be the creation of new market. Then monopolist only captures profit, not CS. Creating market has positive “entrepreneurial” externality (makes monopoly better than standard static analysis)

Source: Glen Weyl

The profit rectangle often bigger than the DWL triangle



Source: Glen Weyl

Schumpeter's "creative destruction"

Schumpeter emphasized importance of these dynamics

- Most of what matter is innovation, progress
- Static distortions likely fairly small (Harberger, etc.)
- Creative power of capitalism transformed society
 - Be a bit careful: discounting, etc.; but broadly right

⇒ Biggest industrial issues *competitive process?*

- 1 Far too much traditional emphasis on static distortions
- 2 Greatest threat to monopoly is being superseded
 - Comfortable monopolist left behind by new technology
- 3 Most important goal to incentivize this "creative destruction"
- 4 May require concentration to afford R&D
- 5 Innovation in hopes of (temporary) monopoly power

⇒ Industrial policy should focus on new products

- Only eliminate static distortion if does not conflict

Source: Glen Weyl

An analogy may be useful to show importance of dynamics

Much crime is beneficial from a static perspective

- Most (property) criminal activity redistributive
- Much entails little efficiency loss direct, just redistribution
- Most efficiency loss comes from attempts to prevent
- Redistribution good because of declining marginal utility

From static perspective, crime should be legal!

Whenever an absurd conclusion, examine premises. (What are long-term/dynamic effects of crime?)

Source: Glen Weyl

Why dynamics are important in crime and monopoly

Of course crime is illegal because it would encourage:

- 1 Waste on criminal rather than productive activity
- 2 Waste on preventing others from stealing
- 3 Would discourage work more than optimal redistribution

None of these show up in static analysis

⇒ Cannot have a theory of crime without dynamics

- Schumpeter would argue industrial economics similar
 - Without dynamics cannot rationalize most policies
 - Static effects should be kept in mind, but just beginning
 - Do not get overly tied to the DWL triangle
 - Similarities between crime and IO broader
 - In crime, punishments instead of fines
- ⇒ Deterring crime has (static) inefficiency cost
- Similarly encouraging innovation has static DWL

Source: Glen Weyl

A simplified Beckerian theory of crime

Therefore useful for IP to start with more vivid crime model

- Each crime causes harm h , receives punishment p
 - “Demand” for offenses $O(p)$ declines in punishment
 - Surplus to offenders is $\int_p^\infty O(x)dx$
 - Administering punishment costs $c(p)$ per offense
- ⇒ Two sources of inefficiency from punishment
- 1 Harm to criminal directly does not benefit society
 - 2 Harm to criminal also imposes cost on society $c(p)$
- Goal: choose level of punishment p to maximize

$$\underbrace{\int_p^\infty O(x)dx}_{\text{surplus to offenders}} - \underbrace{\left[\underbrace{h}_{\text{direct externality}} + \underbrace{c(p)}_{\text{cost of enforcement}} \right] O(p)}_{\text{social cost of crime}}$$

Source: Glen Weyl

Optimal punishment

Take derivatives and get:

$$\begin{aligned} -O(p) - [h + c(p)] O'(p) - c'(p)O(p) &= 0 \\ [1 + c'(p)] O(p) &= -[h + c(p)] O'(p) \end{aligned}$$

This yields Becker's famous formula:

$$\underbrace{\epsilon_O}_{\text{elasticity of crime}} \cdot \underbrace{\frac{h + c(p)}{p}}_{\text{ratio of harm to punishment}} = \underbrace{1 + c'(p)}_{\text{MC of punishment}}$$

Enforcement should be greater if?

- 1 If the deterrence effect of enforcement (elasticity) is large
- 2 The marginal cost of punishment is low
- 3 The harm created by the crime is high

Source: Glen Weyl

Relationship of punishment theory to IP

- IP is similar, but reversed; explain?
 - ① Creating new products bring social benefits
 - ② No matter how much profits, always positive externality
 - Infra-marginal consumer surplus not captured
 - Get closer with price discrimination
 - ③ But rewarding via market power wasteful
 - Creates deadweight loss
- ⇒ IP theory should closely resemble Becker's, in reverse
 - Greater protection for IP if
 - Supply of innovation more elastic to monetary reward
 - Social benefits of innovation large relative to reward
 - Deadweight loss small relative to profits

Source: Glen Weyl

The fundamental IP trade-off

- ⇒ Fundamental trade-off of incentives v. ex-post distortion
 - ① More IP protection costs DWL
 - ② More IP protection benefits from more innovation
- First protection brings only profits
 - Harberger triangle is triangle, so no loss
- Eventually near peak profits, so only loss
 - Near monopoly optimal price, no gain from more protection
- ⇒ Optimal protection always partial
- Question is where between: costs v. benefits
 - ① Costs?
 - Deadweight loss from lost consumption
 - Deadweight loss from reduced follow-on innovation
 - ② Benefits?
 - Incentives to innovate product
 - Incentives to disclose, rather than holding as trade secret

Source: Glen Weyl

The supply and demand for innovation

Let's focus just on consumption distortion v. incentives

- Each innovation creates market for new product
 - Products have no marginal cost of production
 - Most intellectual goods nearly free to copy
 - All have same (average) demand function $Q(p)$
 - Normalize $Q(0) = 1$ and monopoly price to $p = 1$
 - $CS(p) = \int_{x=p}^{\infty} Q(x) dx$
- Firm earns profits $\pi(p) = pQ(p)$
- Innovations costly to produce; why?
 - Capital, time, most innovations don't actually turn out

⇒ Supply of innovations $S(\pi)$

- Total welfare: consumers plus producers?

$$S(\pi(p)) CS(p) + \int_{\pi=0}^{\pi(p)} S(\pi) d\pi$$

Take first-order condition?

$$\pi'(p)S'(\pi(p))CS(p) + CS'(p)S(\pi(p)) + \pi'(p)S(\pi(p)) = 0$$

- Let $DWL(p) = CS(0) - CS(p) - \pi(p)$
 - Note that $DWL'(p) = -CS'(p) - \pi'(p) > 0$ for $p > 0$
- So we obtain:

$$\pi' S' CS = DWL' S$$

- Leads to central elasticity formula, like Becker?

Source: Glen Weyl

Optimal innovation policy

Thus we obtain the key equation we were looking for:

$$\underbrace{\epsilon_S}_{\text{elasticity of innovation supply}} \cdot \underbrace{\frac{CS}{\pi'}}_{\text{ratio of external to internal benefit of innovation}} = \underbrace{\frac{DWL'}{\pi'}}_{\text{distortion to incentive ratio}} \quad (1)$$

The first factor on the left-hand side represents the responsiveness of innovation to material incentives, the elasticity of innovation supply. The second term represents the ratio of consumer surplus (the external-to-the-innovator benefits of innovation) to the private benefits. The right-hand side represents the ratio of marginal deadweight loss to marginal profits. Note that the right hand side is 0 at $p = 0$ and infinite at $p = 1$ because marginal deadweight loss is 0 at efficient prices (remember Harberger's *triangle*) as prices are efficient there while marginal profits are 0 at the optimal price $p = 1$ as this defines it as optimal. On the other hand, assuming that the elasticity of innovation supply is bounded, the left-hand side is infinite at $p = 0$ as there $\pi = 0$ and becomes finite as p goes to 1. Thus there will be an intersection between the “benefits of incentivizing innovation” represented by the left-hand side and the “costs of incentivizing innovation” on the right-hand side. This will represent the optimal level of IP protection, p .

Source: Glen Weyl

Policy implications: Supreme Court patenting restrictions

- Case for patent reform: length and breadth of patents should reflect patent effectiveness are patents in inducing subsequent innovation
- US Supreme Court decisions based on assumption that patents hinder follow-on innovation have impacted patent system:
 - ① Support of a “high enough bar” on patenting abstract ideas (*Bilski v. Kappos*)
 - ② Concerns that patent law may “improperly [tie] up the future of laws of nature” (*Mayo Collaborative Services v. Prometheus Laboratories, Inc.*, *Association for Molecular Pathology v. Myriad Genetics, Inc.* and *Alice Corp v. CLS Bank International*)
- These US Supreme Court decisions have reduced patent protection in several economically important sectors of the economy, and they were all based on an assumption economists have not fully explored

Outline

1 Motivation

2 Policy

- Rationale for government intervention
- The patent system
- Tax policy: R&E credits
- Immigration: H1-B visas
- Education and antitrust policy (skip)

3 Theory

- Optimal innovation policy
- Optimal patent length
- Policy implications

4 Evidence

- Elasticity of innovation with respect to profits
- Costs of IP protection
- Who profits from patents?
- Mobility and origins of innovators
- Effects of R&E credits on innovation

Elasticity of innovation with respect to profits

Overview of Budish, Rai and Williams (AER, 2015)

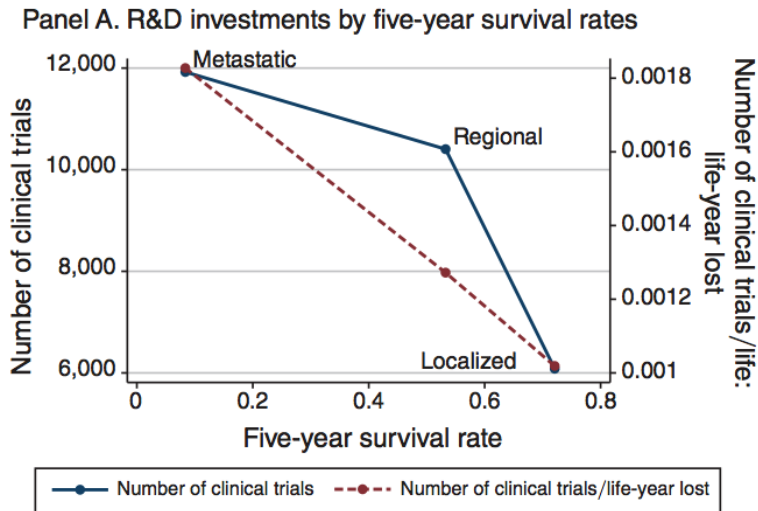
- Observation: although the incentives provided by the patent system are uniform in theory, in practice the patent system can provide remarkably uneven protection across different classes of potential inventions
- This paper identifies a distortion of private research investments away from certain types of research projects
- Fact: most new cancer treatments are approved for use among patients with relatively advanced forms of late-stage cancer, as opposed to patients with early-stage cancer or medicines to prevent cancer
- Hypothesis: private firms may invest more in late-stage cancer treatments - and “too little” in early-stage cancer treatments or cancer prevention drugs - because late-stage cancer drugs can be brought to market comparatively quickly, whereas drugs to treat early-stage cancer or to prevent cancer require a much longer time to bring to market

Variation in commercialization lags/ effective patent length

- Prior to selling their inventions to consumers, firms developing new pharma drugs must complete US Food and Drug Administration (FDA)-required clinical trials documenting evidence that their drugs are safe and effective
- Effective means improving patient survival rates relative to a placebo or relative to another available drug treatment in a randomized control trial
- Standard power calculations suggest that a statistically significant difference in survival outcomes between the treatment and control groups of a randomized trial can be observed more quickly in patient populations with a higher mortality rate: one can observe the relative survival benefits of a new treatment relative to an existing treatment more quickly if patients die more quickly, whereas such a difference will take longer to observe if patients have a relatively longer life expectancy
- This implies that clinical trials must be longer in duration when evaluating treatments for early-stage cancer patients relative to treatments for late-stage cancer patients

Source: Heidi Williams (2017).

R&D investments by five-year survival rates



R&D investments by five-year survival rates

- Panel A plots two measures of clinical trial activity for each stage of cancer against five-year survival rate among patients diagnosed with each stage
- LHS axis: number of clinical trials enrolling patients of each stage
- RHS axis: number of clinical trials enrolling patients of each stage divided by number of life-years lost LYL for stage j :

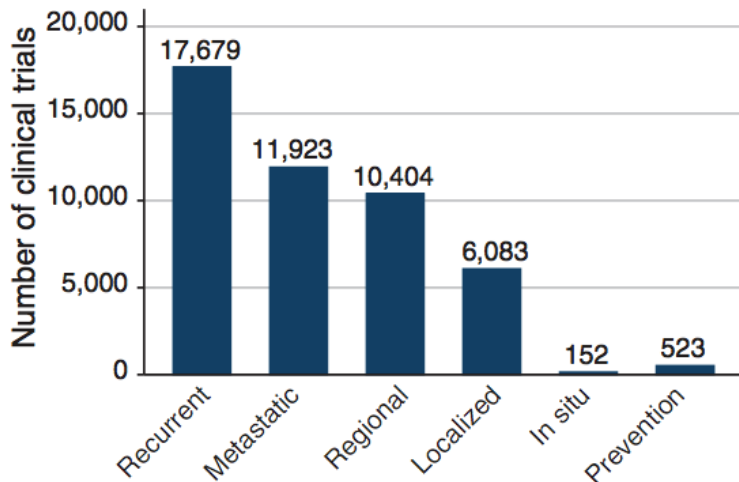
$$LYL_j = \left(\frac{LE_t - S}{n_j} \right) N$$

- t : year of diagnosis
- LE_t : age-gender-year specific life expectancy (absent cancer) in t
- S : observed survival time in years
- n_j : number of patients diagnosed with stage j between 1973-1983
- N : market size

Panel A shows that on average

- Metastatic cancer patients
 - Five-year survival rate $\approx 10\%$
 - Nearly 12,000 clinical trials in the data
- Localized cancer patients
 - Five-year survival rate $\approx 70\%$
 - Nearly 6,000 clinical trials in the data

Panel B. R&D investments by stage



R&D investments by stage

- Panel B plots the number of clinical trials for
 - Localized, regional, and metastatic cancers
 - Preventive technologies
 - In situ and recurrent cancers (advanced, very poor survival prospects)
- Panel B, like Panel A, shows a negative correlation between commercialization lags and R&D investments:
- Contrast recurrent cancers and cancer prevention: fewer than 500 trials in the data aim to prevent cancer, whereas recurrent cancers have more than 17,000 trials

Correlation between survival rates and clinical trials may not be causal

- If patient demand or scientific opportunities are relatively lower for early-stage cancers, then a policy that shortened commercialization lags may have no effect on R&D investments
- Even if this fact did reflect a causal effect of commercialization lags on R&D investments, on its own this fact need not be evidence of a distortion because the social planner is also more likely to pursue research projects that can be completed more quickly

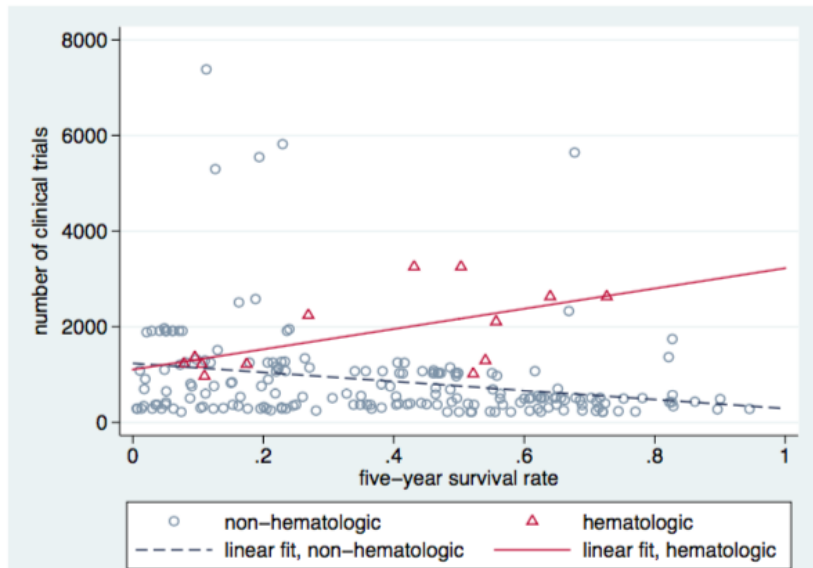
Source: Heidi Williams (2017).

Addressing Inference challenges

- They document that shortening commercialization lags increases R&D investments
 - Some types of cancers are allowed to use surrogate endpoints (non-mortality endpoints), which break the link between patient survival times and clinical trial lengths. Perhaps the most clearly established non-mortality related endpoint is ?complete response? for leukemias, which is measured based on blood cell counts and related bone marrow measures
- They contrast public and private research investments.
 - Commercialization lag-R&D correlation is quantitatively and statistically significantly more negative for privately financed R&D than for publicly financed R&D

Source: Heidi Williams (2017).

Surrogate endpoints, survival time, and R&D investments,



Costs of IP protection

- Nordhaus-style models of optimal patent policy design have traditionally modeled innovations as isolated discoveries, and predict an unambiguously positive relationship between patent strength and the rate of innovation
- However, in practice most innovations are cumulative in the sense that any given discovery is also an input into later follow-on discoveries. In such markets, the overall effectiveness of intellectual property rights in spurring innovation also depends on how patents on existing technologies affect **follow-on innovation**

- Does IP discourage follow on innovation?
- This paper analyzes how one non-patent form of intellectual property on the human genome affected follow on innovation
- Looks at which human genes were covered by Celera's IP and then tries to measure follow on innovation relative to human genes that were always in the public domain (by nature of having first been sequenced by the human genome project)

What is the counterfactual for what follow-on innovation on Celera genes would have been if they had always been in the public domain?

- Start by documenting simplest possible comparison: follow on innovation for Celera genes relative to non-Celera genes that were sequenced in the same year

Innovation outcomes for Celera and non-Celera genes sequenced in 2001

TABLE 1
INNOVATION OUTCOMES FOR CELERA AND NON-CELERA GENES SEQUENCED IN 2001

	Celera Mean (1)	Non-Celera Mean (2)	Difference [(1) - (2)] (3)	<i>p</i> -Value of Difference (4)
Publications in 2001-9	1.239	2.116	-.877	[.000]
1 (known, uncertain phenotype)	.401	.563	-.162	[.000]
1 (known, certain phenotype)	.046	.073	-.027	[.000]
1 (used in any diagnostic test)	.030	.054	-.024	[.000]
Observations	1,682	2,851		

NOTE.—This table compares subsequent innovation outcomes for Celera genes relative to non-Celera genes sequenced in the same year. Gene-level observations. The sample in col. 1 includes all Celera genes; the sample in col. 2 includes all non-Celera genes sequenced in 2001. The *p*-value reported in col. 4 is from a *t*-test for a difference in mean outcomes across cols. 1 and 2. See the text and online App. A for more detailed data and variable descriptions.

Source: Heidi Williams (2013).

This simple cross-tabulation is that it could reflect either a negative effect of Celera's IP on follow-on research, or could reflect that Celera's genes had lower inherent potential for follow-on research. Tries to address this selection concern by:

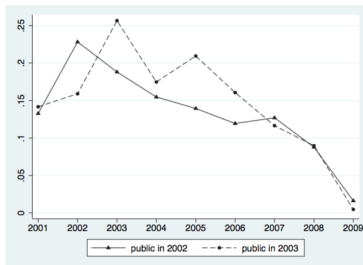
- Restricting attention to within-gene variation in Celera's intellectual property and test whether the removal of Celera's intellectual property increased follow-on innovation on a given gene
- Limiting the sample to Celera genes and test for a link between the amount of time a gene was held with Celera's intellectual property and follow-on innovation

Source: Heidi Williams (2013).

Flow of follow on innovation

Figure plots the average count of scientific publications linked to each gene by year

The flow of scientific publications on genes show a relative uptick in the year that they enter the public domain - 2002 for the 2002 cohort, and 2003 for the 2003 cohort



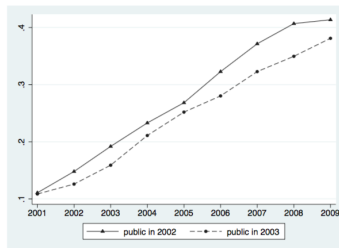
(a) Outcome variable: Scientific publications

Source: Heidi Williams (2013). The solid black lines plot mean follow-on innovation outcomes for Celera genes that were resequenced by the Human Genome Project in 2002 (N=1,047), while the dashed lines plot mean follow-on innovation outcomes for Celera genes that were held with Celera's intellectual property for one additional year, by nature of having been resequenced by the Human Genome Project in 2003 (N=635).

Stock of follow on innovation

Figure plots mean of an indicator variable for whether genes had any conjectured phenotype relationship by that year

Stock of scientific knowledge also shows a relative uptick in 2002 for the 2002 cohort, but the 2003 cohort shows persistently lower levels of this knowledge stock variable



(b) Outcome variable: Conjectured phenotype

Source: Heidi Williams (2013). The solid black lines plot mean follow-on innovation outcomes for Celera genes that were resequenced by the Human Genome Project in 2002 (N=1,047), while the dashed lines plot mean follow-on innovation outcomes for Celera genes that were held with Celera's intellectual property for one additional year, by nature of having been resequenced by the Human Genome Project in 2003 (N=635).

- These two papers attempt to estimate two relevant parameters: the extent to which patents provide incentives for the development of new technologies (Budish, Roin and Williams, 2015), and the extent to which IP on existing technologies hinder subsequent innovation (Williams, 2013)
- The more effective patents are in inducing research investments, the stronger the case for longer or broader patents
- The larger the costs of IP in terms of hindering subsequent innovation, the weaker is this case

Who benefits from IP protection?

Who profits from patents? Rent-sharing at innovative firms

Investigate how winning a patent grant affects firm performance and worker compensation

Kline Petkova Williams Zidar (2017):

- **New linkage of USPTO administrative data to Treasury tax filings**
 - ▶ Census of published USPTO patent applications
 - ▶ Business tax filings record firm outcomes such as revenue, value added
 - ▶ Link to worker-level W2 and 1099 filings
- **Leverage variation in USPTO initial allowance decisions in order to infer the causal effects of patent grants on firm and worker outcomes**
 - ▶ Exploit methodology of Kogan et al (2017) to identify valuable patents
- **New evidence on how winning a valuable patent impacts firms, workers, and inequality** [Hall et al 2005; Balasubramanian-Sivadasan 2011; Farre-Mensa et al 2016; Bell et al 2016; Kogan et al 2017; Aghion et al 2017]

Source: Kline Petkova Williams Zidar (2017).

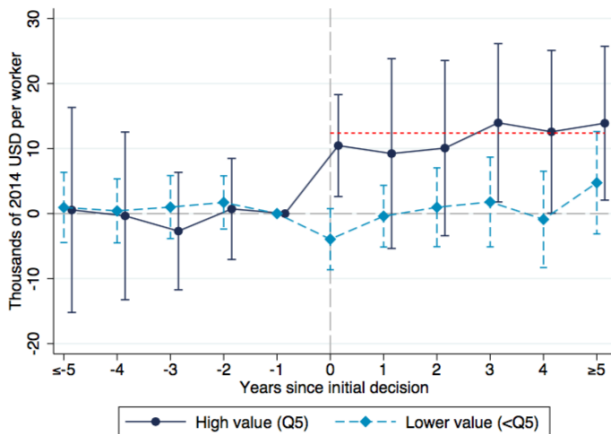
Research design

- Two valuable patent applications submitted by two separate firms to the USPTO in the same year
- They are routed to the same Art Unit
- One is initially allowed and the other is not
- We assume parallel trends for initially allowed/rejected patents (DID)
 - ▶ Validate w/ event studies + balance tests + low-value patents

Source: Kline Petkova Williams Zidar (2017).

Who profits from patents? Rent-sharing at innovative firms

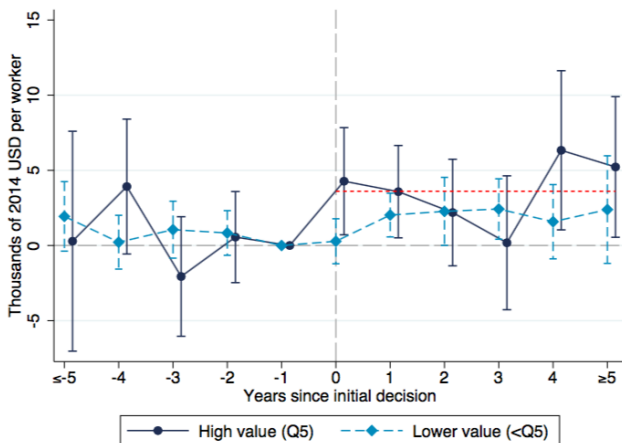
Event study: Surplus (EBITD + W2) per worker



Notes: Two-way standard errors are clustered by (1) art unit, and (2) application year by decision year. Regressions include art unit by application year by calendar year fixed effects and firm fixed effects. Values along the x-axis for the Q5 series are offset from their integer value to improve readability. Surplus is EBITD (earnings before interest, tax, and depreciation) + W2 wage bill. Q5 is quintile 5 of predicted patent value. < Q5 are the remaining four quintiles. 95% confidence intervals shown. Dotted red line is pooled DID impact for a top quintile patent application receiving an initial allowance post-decision.

Who profits from patents? Rent-sharing at innovative firms

Event study: Wage bill per worker



Notes: Two-way standard errors are clustered by (1) art unit, and (2) application year by decision year. Regressions include art unit by application year by calendar year fixed effects and firm fixed effects. Values along the x-axis for the Q5 series are offset from their integer value to improve readability. Q5 is quintile 5 of predicted patent value. < Q5 are the remaining four quintiles. 95% confidence intervals shown. Dotted red line is pooled DID impact for a top quintile patent application receiving an initial allowance post-decision.

US Treasury administrative tax data

We link business tax filings with worker-level filings

- Business filings record firm outcomes such as revenue, value added:
 - ▶ 1120: C corporations
 - ▶ 1120S: S corporations
 - ▶ 1065: Partnerships
- Linked to data constructed from worker-level W2 filings:
 - ▶ Number of employees
 - ▶ Various worker compensation measures
- Linked to data constructed from worker-level 1099 filings

Source: Kline Petkova Williams Zidar (2017).

USPTO administrative patent application data

Link US Treasury data to census of published USPTO patent applications

- Observe both accepted and “rejected” applications filed since 29-Nov-2000 under American Inventors Protection Act
- Link published applications with USPTO PAIR, grants, and other data
- Novel firm-level merge based on assignee organization name
 - ▶ Published applications missing ~ 50% of assignee organization names
 - ▶ Use USPTO patent assignment data to fill in missings where possible
- Re-use inventor-level merge based on inventor name [Bell et al 2016]

Source: Kline Petkova Williams Zidar (2017).

Who profits from patents? Rent-sharing at innovative firms

Example: USPTO patent application 14/776,586



US 20160143910A1

(19) **United States**

(12) **Patent Application Publication**
Arora et al.

(10) **Pub. No.:** US 2016/0143910 A1

(43) **Pub. Date:** May 26, 2016

(54) **METHODS OF TREATING CANCER AND PREVENTING CANCER DRUG RESISTANCE**

(73) **Assignees:** **CONSTELLATION PHARMACEUTICALS, INC.**, Cambridge, MA (US); **GENENTECH, INC.**, South San Francisco, CA (US)

(71) **Applicants:** **Shilpi ARORA**, Cambridge, MA (US); **Michael Robert COSTA**, South San Francisco, CA (US); **Ted LAU**, South San Francisco, CA (US); **Patrick TROJER**, Cambridge, MA (US); **GENENTECH, INC.**, South San Francisco, CA (US); **CONSTELLATION PHARMACEUTICALS, INC.**, Cambridge, MA (US)

(21) **Appl. No.:** 14/776,586

(22) **PCT Filed:** Mar. 14, 2014

(86) **PCT No.:** PCT/US14/29432

§ 371 (e)(1),

(2) **Date:** Sep. 14, 2015

Related U.S. Application Data

(60) Provisional application No. 61/801,414, filed on Mar. 15, 2013, provisional application No. 61/804,083, filed on Mar. 21, 2013.

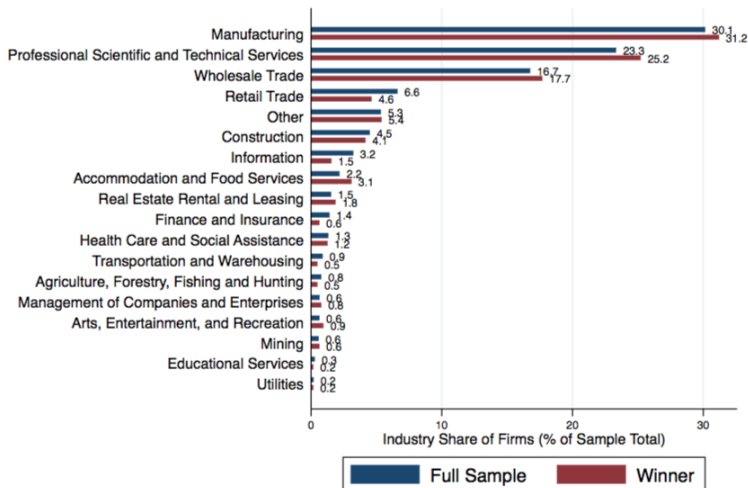
Publication Classification

(72) **Inventors:** **Shilpi Arora**, Cambridge, MA (US); **Michael Robert Costa**, South San Francisco, CA (US); **Ted Lau**, South San Francisco, CA (US); **Patrick Trojer**, Cambridge, MA (US); **Brian K. Albrecht**, Cambridge, MA (US); **Shane Buker**, Cambridge, MA (US); **Marie Classon**, South San Francisco, CA (US); **Victor S. Gehling**, Cambridge, MA (US); **Jean-Christophe Hermange**

(51) **Int. Cl.**
A61K 31/519 (2006.01)
A61K 31/437 (2006.01)
A61K 31/517 (2006.01)
A61K 45/06 (2006.01)

Who profits from patents? Rent-sharing at innovative firms

Industry composition



Power-up: KPSS

- Problem: Many patents worthless [Pakes 1986]
- Kogan, Papanikolaou, Seru, and Stoffman (QJE 2017; KPSS)
 - ▶ Estimate excess stock return responses to patent grant announcements
 - ▶ Empirical bayes posterior valuations ξ_j for each patent j
- Our idea: Use ξ_j to identify valuable patents in a broader sample
 - ▶ To extrapolate: Fit RE Poisson QML explaining ξ_j in terms of firm and application characteristics that are fixed at the time of application
 - ★ Extrapolate to non-public firms and to rejected applications
 - ▶ Very strong explanatory power ($R^2 = .69$)

Who profits from patents? Rent-sharing at innovative firms

Mean $\hat{\xi}$ by technology center

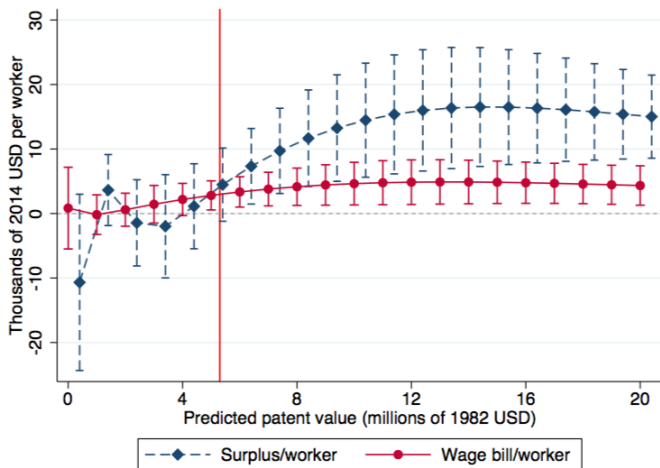
Top 5 tech centers			Bottom 5 tech centers		
Tech center	$\hat{\xi}$	N	Tech center	$\hat{\xi}$	N
Business Methods - Finance	22.356	96	Radio, Robots, & Nucl Sys	1.485	58
Electronic Commerce	14.034	245	Shoes & Apparel	1.424	365
Databases & File Mgmt	11.924	203	Kinestherapy & Exercising	1.236	96
Aero, Agricult, & Weapons	10.927	127	Fluid Handling	0.704	188
Computer Architecture	10.510	48	Chemical Apparatus	0.434	23

Notes: $\hat{\xi}$ is in millions of 1982 US dollars.

Source: Kline Petkova Williams Zidar (2017).

Who profits from patents? Rent-sharing at innovative firms

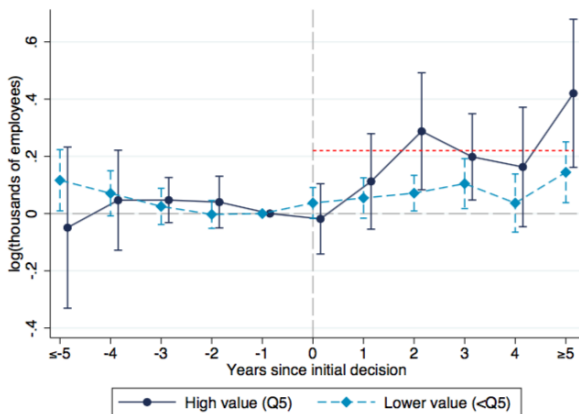
Impacts by predicted patent value: Surplus and wage bill



Notes: The vertical, red line is the cut-off value for the top quintile predicted patent value sample, and is equal to 5.3M 1982 USD. Values along the x-axis for the surplus series are offset from their integer value to improve readability. Surplus is EBITD (earnings before interest, tax, and depreciation) + W2 wage bill. 95% confidence intervals shown.

Who profits from patents? Rent-sharing at innovative firms

Event study: log(Firm size)



Notes: Two-way standard errors are clustered by (1) art unit, and (2) application year by decision year. Regressions include art unit by application year by calendar year fixed effects and firm fixed effects. Values along the x-axis for the the Q5 series are offset from their integer value to improve readability. Q5 is quintile 5 of predicted patent value. < Q5 are the remaining four quintiles. 95% confidence intervals shown. Dotted red line is pooled DID impact for a top quintile patent application receiving an initial allowance post-decision.

Who profits from patents? Rent-sharing at innovative firms

	# Emp > 0	Firm size	Val add / worker	EBITD / worker	Wage bill / worker	Surplus / worker
level						
High value (Q5)	0.00 (0.04)	18.79 (9.36)	15.90 (5.11)	9.11 (3.85)	3.61 (1.51)	12.38 (3.55)
Lower value (< Q5)	-0.01 (0.01)	-2.15 (2.95)	0.87 (3.84)	-1.37 (1.79)	0.78 (0.89)	-0.24 (2.08)
aSinh						
High value (Q5)	. .	0.22 (0.08)	0.10 (0.11)	0.34 (0.22)	0.08 (0.02)	0.44 (0.15)
Lower value (< Q5)	. .	0.03 (0.04)	0.02 (0.06)	-0.07 (0.11)	0.00 (0.02)	-0.09 (0.09)
N	155,682	103,459	103,459	103,459	103,459	103,459

Notes: Two-way standard errors are clustered by (1) art unit, and (2) application year by decision year. Regressions include art unit by application year by calendar year fixed effects and firm fixed effects. EBITD is earnings before interest, tax, and depreciation. Surplus is EBITD + W2 wage bill. Q5 is quintile five of predicted patent value, < Q5 are the remaining four lower quintiles. Sample size: N varies if there are zero workers.

Source: Kline Petkova Williams Zidar (2017).

Key findings

- Patent grants persistently raise firm size / productivity
- Workers: \$0.29-0.50 of every \$1 of "gross surplus" (EBITD+wages)
 - ▶ Elasticity of 0.18-0.20
- Substantial heterogeneity in pass-through:
 - ▶ Inventors receive more than non-inventors
 - ▶ Men receive more than women (even among non-inventors)
 - ▶ Pass-through concentrated among those present at time of application
- Muted response of entry wages
 - ▶ Inconsistent w/ standard frictional models [e.g., Pissarides 2000, 2009]
 - ▶ Consistent w/ incentive contracting & career concerns [Holmstrom 1979, 1982; Gibbons and Murphy, 1992]

Source: Kline Petkova Williams Zidar (2017).

Mobility and origins of innovators

Where do innovators come from?

- Mobility of innovators
- Origins of innovators

Innovation and inventors during the rise of American ingenuity

- Using a new dataset that matches 19th and 20th century patent records with census data, Akcigit, Grigsby, Nicholas (2017) attempts to shed some light on the 'golden age' of US innovation.
- Population density and financial development are found to be important determinants of state innovativeness, while education appears to be the critical input at the individual level

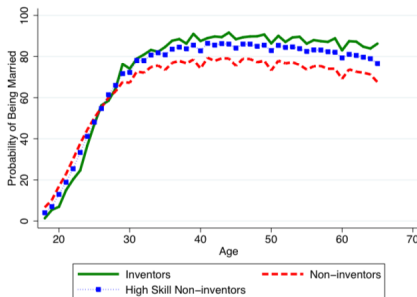
Source: Ufuk Akcigit, John Grigsby, Tom Nicholas (2017).

TABLE 1: THE CHARACTERISTICS OF INVENTORS

	Inventors Full U.S.	
Percent White	97.9%	89.4%
Percent Black	1.8%	9.1%
Percent Male	97.9%	51.0%
Single	16.1%	27.7%
Married	80.2%	65.4%
Percent 19-25	8.4%	22.6%
Percent 26-35	23.8%	27.5%
Percent 36-45	31.0%	22.5%
Percent 46-55	24.1%	16.6%
Percent 56-65	12.7%	10.8%
Av. # Children: ≤ 35 yrs old	1.9	2.3
Av. # Children: > 35 yrs old	3.2	4.7
Percent Interstate Migrant	58.8%	42.8%
Percent International Migrant	21.1%	17.4%
Percent Of Population	0.02%	99.98%

Notes: We use all matched census records to construct this table. Age, race, marital status, and migrant status are reported for all years. Fertility is reported only in 1910 and 1940. Source: 1880 through 1940 Historical Census Data, USPTO patent records.

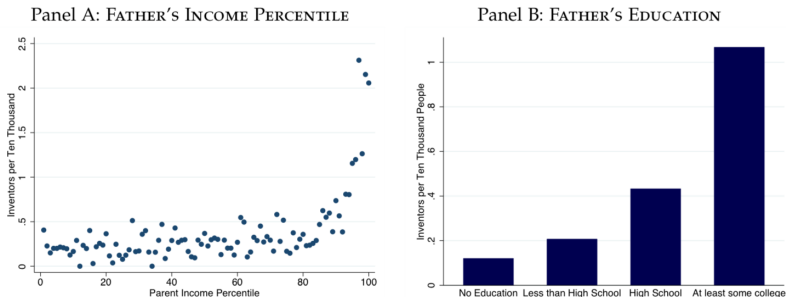
FIGURE 3: FAMILY DECISIONS: PROBABILITY OF BEING MARRIED



Notes: This figure plots the probability that an individual is married over their life cycle using data averaged across our six census years. Source: 1880-1940 Historical Census Data, USPTO patent records.

Source: Ufuk Akcigit, John Grigsby, Tom Nicholas (2017).

FIGURE 8: PARENTAL AFFLUENCE AND THE PROBABILITY OF BECOMING AN INVENTOR

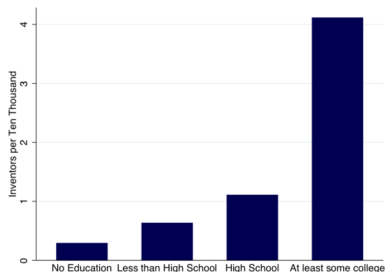


Notes: Figure plots the number of inventors per 10,000 people by their father's percentile of wage income in the 1940 census (Panel A) or their father's education level (Panel B). Only individuals successfully matched to their fathers are included in this plot. Wage income percentiles are calculated using the full sample of matched fathers in the U.S. Source: 1940 Historical Census Data, USPTO patent records.

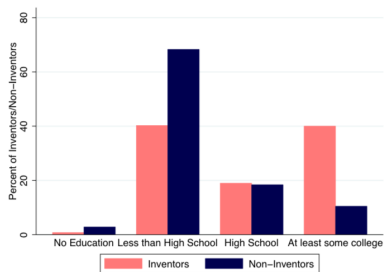
Source: Ufuk Akcigit, John Grigsby, Tom Nicholas (2017).

FIGURE 6: EDUCATION AND PROBABILITY OF BECOMING AN INVENTOR

PANEL A: INVENTORS PER 10,000 BY EDUCATION



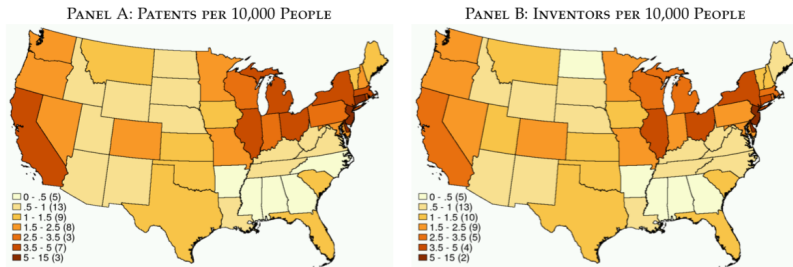
PANEL B: PERCENT OF INVENTORS IN EACH EDUCATION CATEGORY



Notes: Figure plots the education of inventors and non-inventors in the 1940 census, the only census in our sample to provide sufficiently granular education information. Panel A plots the inventors per 10,000 people by education category. Panel B plots the percent of inventors and non-inventors that fall into each educational category. Source: 1940 Historical Census Data, USPTO patent records.

Source: Ufuk Akcigit, John Grigsby, Tom Nicholas (2017).

FIGURE 4: THE GEOGRAPHY OF INVENTIVENESS



Notes: Figure maps the number of patents (panel A) or inventors (panel B) per 10,000 residents in each state of the mainland U.S. in 1940. Darker colors represent more inventive activity per resident. Patent data come from the USPTO's historical patent files, while population counts are calculated using the U.S. Census. Appendix D reports similar maps in different decennial census years.

Source: Ufuk Akcigit, John Grigsby, Tom Nicholas (2017).

FIGURE 5: STATE CHARACTERISTICS AND INNOVATION

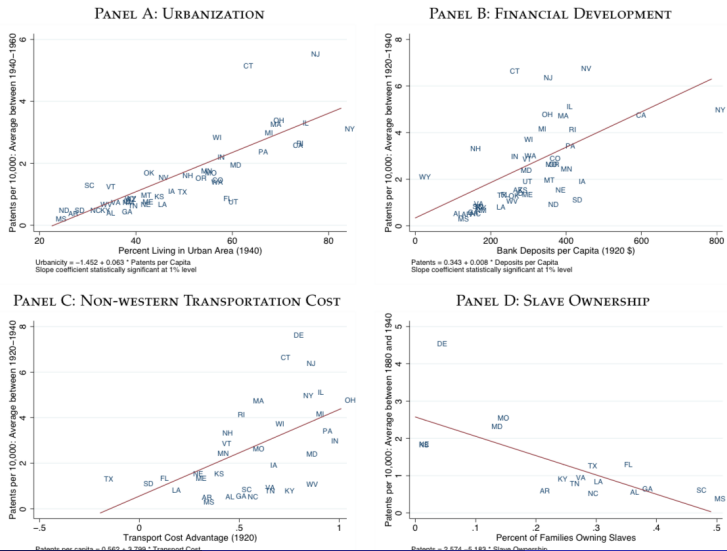
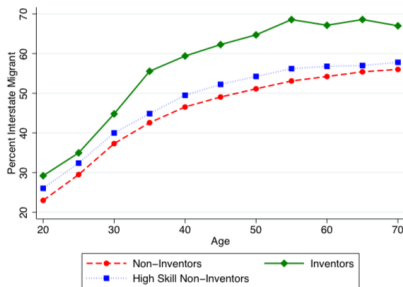


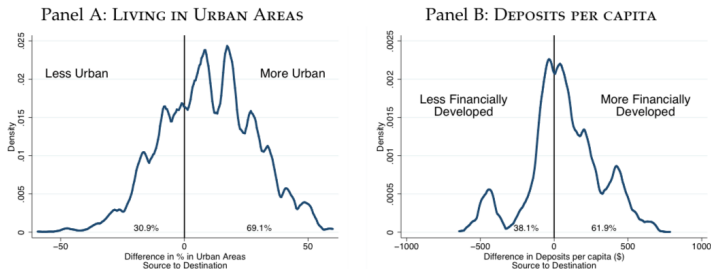
FIGURE 9: INTERSTATE MIGRATION RATES BY AGE



Notes: Figure plots interstate migration rates by age of individual for the population of high skill individuals. An individual is defined to be an interstate migrant if their birth state is different from their current state of residence. Each point represents a 5-year forward-looking bin. For example, the point at age 20 measures the average migration rate for 20 to 25 year-olds. Figure uses data averaged across the four census years for which we have occupation information: 1880, 1920, 1930, and 1940. Source: 1880, 1920-1940 Historical Census Data, USPTO patent records.

Source: Ufuk Akcigit, John Grigsby, Tom Nicholas (2017).

FIGURE 10: TO WHERE DID INVENTORS MOVE?



Notes: Figure shows distribution of difference in characteristic between source and destination states for migrant inventors. The leftmost percentage on each graph corresponds to the share of migrant inventors who move to locations with a lower value of the variable of interest than their source state, while the rightmost percentage corresponds to the share that move to locations with a higher value of this variable. For instance, 30.9% of inventors move from a more urban state to a less urban state, leaving 69.1% of inventors to move to more urban states. Source: 1860, 1940 Historical Census Data, FDIC, USPTO patent records.

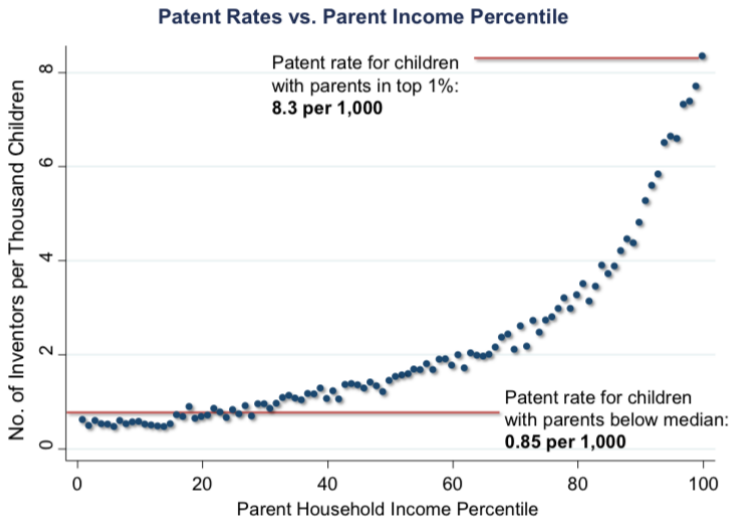
Source: Ufuk Akcigit, John Grigsby, Tom Nicholas (2017).

Who becomes an Inventor?

Bell Chetty Jaravel Petkova Van Reenen (2017)

- First, rates of innovation vary substantially by parent income, race, and gender. Differences in ability account for relatively little of these gaps and inventors from under-represented groups do not have higher quality patents on average, contrary to existing models of selection into innovation.
- Second, exposure to innovation during childhood plays a critical role in determining children's propensities to innovate. Growing up in an area or in a family with a high innovation rate in a particular technology class leads to a higher probability of patenting in exactly that technology class.
- Third, the private returns to innovation are highly skewed and are typically earned many years after career choices are made.
- Using a simple model that matches these facts, we show that providing children from under-represented backgrounds greater exposure to innovation have more potential to increase innovation rates than increasing the private returns to innovation.

Who becomes an Inventor?



Source: Bell Chetty Jaravel Petkova Van Reenen (2017).

Why Do Patent Rates Vary with Parent Income?

- Correlation between parent income and children growing up to be inventors could be driven by three mechanisms:
 1. Endowments: Children from high-income families may have higher innate ability
 2. Preferences: lower income children may prefer other occupations
 3. Constraints: lower income children may face greater barriers to entry (poorer environment, lack of funding)

Source: Bell Chetty Jaravel Petkova Van Reenen (2017).

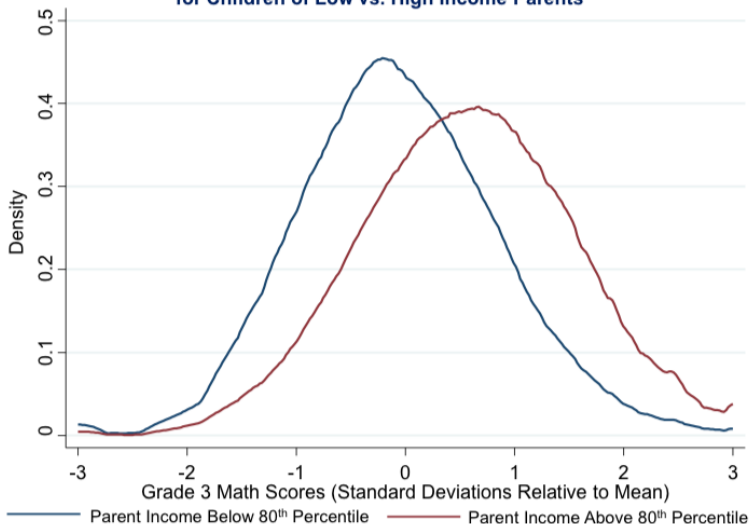
Do Differences in Ability Explain the Innovation Gap?

- Measure ability using test score data for children in NYC public schools [Chetty, Friedman, Rockoff 2014]
 - Math and English scores from grades 3-8 on standardized tests for 430,000 children born between 1979-84

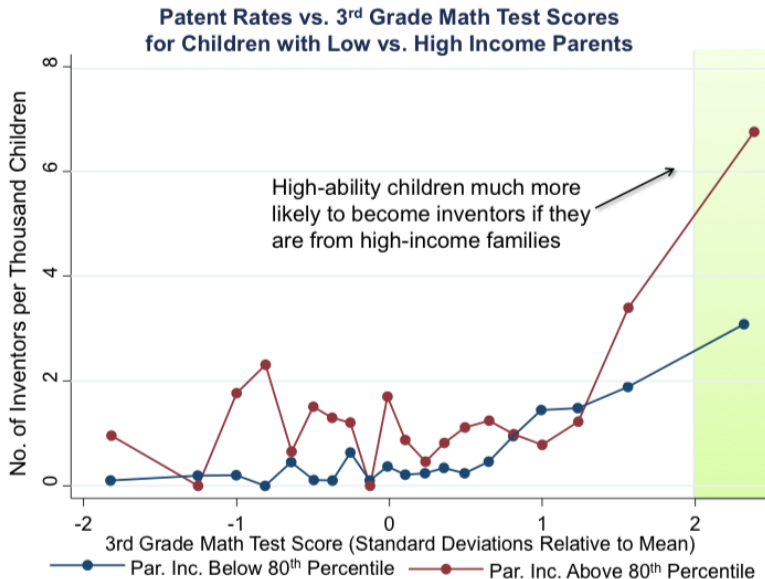
Source: Bell Chetty Jaravel Petkova Van Reenen (2017).

Who becomes an Inventor?

Distribution of 3rd Grade Math Test Scores
for Children of Low vs. High Income Parents



Who becomes an Inventor?



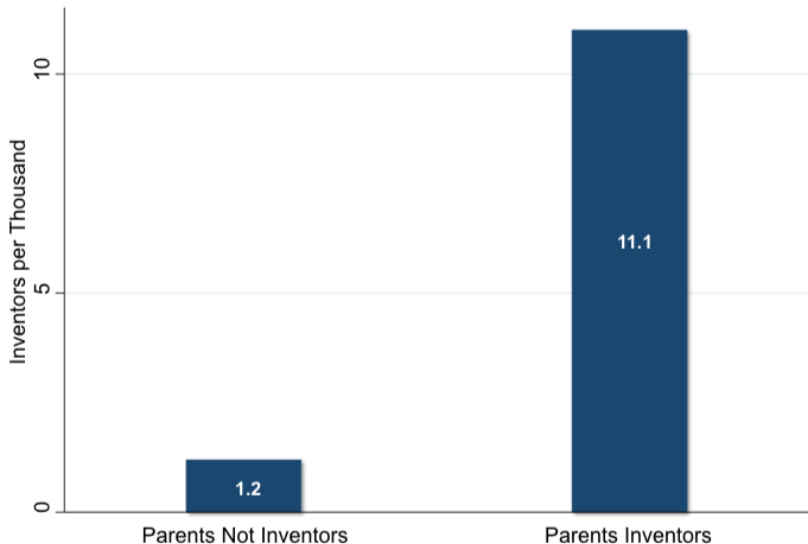
Differences in Environment and the Innovation Gap

- Study role of environment by returning to idea of childhood exposure effects
 - Do differences in exposure to innovation during childhood explain innovation gap?
- Begin by analyzing relationship between children's and parents' innovation rates

Source: Bell Chetty Jaravel Petkova Van Reenen (2017).

Who becomes an Inventor?

Patent Rates for Children of Inventors vs. Non-Inventors

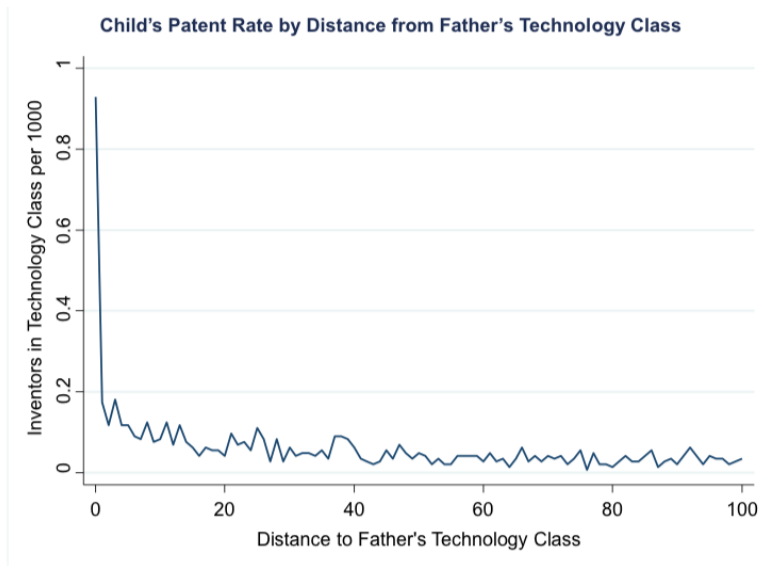


Exposure vs. Genetics

- Correlation between child and parent's propensity to patent could be driven by genetics or by environment
- To distinguish these two explanations, analyze propensity to patent by narrow technology class

Source: Bell Chetty Jaravel Petkova Van Reenen (2017).

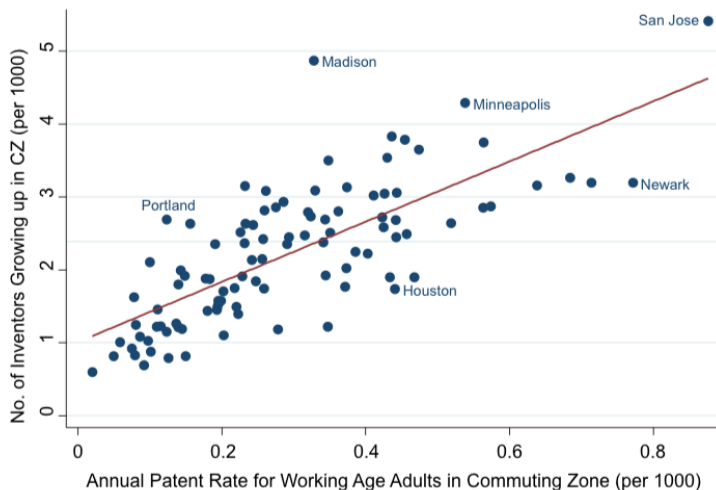
Who becomes an Inventor?



Source: Bell Chetty, Jaravel, Petkova, Van Reenen (2017).

Who becomes an Inventor?

Patent Rates of Children who Grow up in an Area vs. Patent Rates of Adults in that Area



Source: Bell Chetty Jaravel Petkova Van Reenen (2017).

Development of Gender Stereotypes During Childhood

- Bian et al. (Science 2017): conduct experiments to analyze development of gender stereotypes about intellectual ability
- Present children with pictures of men and women ask them to say who is “really nice” and who is “really smart”
 - At age 5: no difference across boys and girls
 - At age 6: girls much more likely to choose man as “really smart”
- Similarly, girls less likely to choose to play games that are for “children who are really smart” at age 6 than age 5

Source: Bell Chetty Jaravel Petkova Van Reenen (2017).

Overview of Moretti and Wilson (2017)

- Paper: Moretti, Enrico and Daniel J. Wilson (2017). “The Effect of State Taxes on the Geographical Location of Top Earners: Evidence from Star Scientists.” *American Economic Review*, 2017(7): 1858-1903.
- Question: How sensitive is internal migration by high- skilled workers to personal and business tax differentials across US states?
- Motivation:
 - Workers and firms are mobile across state borders, so tax differences across states and over time can affect the geographical allocation of highly skilled workers and employers
 - Effect of state taxes on states' ability to attract firms and jobs is prominent in the policy debate
 - Some states openly compete for workers and businesses

- Star scientists
 - are in the private sector, academia or government
 - have patent counts in the top 5 percent of the distribution in year t (defined by year)
- Why star scientists?
 - Studying one group of well educated, highly productive workers with high income levels can help shed some light on the locational decisions of other like workers
 - Locational decisions of star scientists can have large consequences for local job creation since presence of star scientists is typically associated with research, production facilities and fostering of new industries

1 Scientist patent and residence data

- Source: COMETS patent database
- US patents filed between 1976 and 2010, containing
 - Inventors on the patent
 - State of residence of scientist when patent was submitted (patenters must report their home address on their patent application)
 - Roughly 260,000 star-scientist-year observations
- Data summary:
 - Star scientists in the sample average 1.5 patents per year
 - Gross star scientist state-to-state migration rate was 6.5% in 2006
 - Overall, 6 percent of stars move at least once

2 Taxes

- Source: NBER TAXSIM tax simulator
- Personal income:
 - Individual income average tax rate (ATR) faced by a hypothetical taxpayer in the top 1% of the national income distribution
 - ATR takes into account interactions between state and federal tax rates
 - Assumption: scientist income is in the top 1% (realistic given how productive these scientists are)
- Business income:
 - Focus on corporate tax rate
 - Also study effects of investment tax credit (ITC) and R&D tax credit
 - Patenting income is not disproportionately taxed by that state, so labor demand for star scientists in a state is affected by that state's corporate tax rate insofar as they are part of the company's payroll in that state

Construction of patent dataset

- For each scientist observed in two consecutive years, identify their state of residence in year t (*origin* state o) and their state of residence in year $t + 1$ (*destination* state d)
- Calculate **outmigration odds-ratio**:
 - 1 For each origin-destination pair of states (51×51) and year, compute the number of star scientists moving from o to d
 - 2 Outmigration odds-ratio: probability of a star scientist moving from a given origin state to a given d relative to the probability of not moving at all ($d = o$)
- Relate bilateral outmigration to the differential between the destination and origin state in personal and business taxes in each year

Model: Scientist location

- In each t , scientist i chooses the state that maximizes their utility U
- The utility of i who lived in o in $t - 1$ and moves to state d at t is

$$U_{iodt} = \alpha \log(1 - \tau_{dt}) + \alpha \log w_{dt} + Z_d + e_{iodt} - C_{od}$$

- w_{dt} : wage in state d before taxes
- τ_{dt} : personal income taxes in d
- α : marginal utility of income
- Z_d captures amenities and costs specific to d
- e_{iodt} : time-varying idiosyncratic preferences for location
- C_{od} : utility cost of moving from o to d . Cost of moving is assumed to be 0 for stayers ($C_{oo} = 0$)

- Utility gain from moving from o to d is

$$U_{iodt} - U_{ioot} = \alpha [\log(1 - \tau_{dt}) - \log(1 - \tau_{ot})] + \alpha \log \left(\frac{w_{dt}}{w_{ot}} \right) \\ + [Z_d - Z_o] - C_{od} + [e_{iodt} - e_{ioot}]$$

- Individual i only moves to d if $U_{iodt} > \max(U_{iod't}) \forall d' \neq d$
- The condition above realistically implies that there migration in every period, even when taxes, wages, and amenities don't change

Model: Scientist relocation following tax shock

Suppose an unexpected change in taxes:

- The magnitude of the effect of a tax increase on migration depends on how many marginal scientists are in that state \rightarrow depends on the distribution of the term e
- If $e_{iodt} \sim$ i.i.d. Extreme Value Type I, then

$$\log\left(\frac{P_{odt}}{P_{oot}}\right) = \alpha[\log(1 - \tau_{dt}) - \log(1 - \tau_{ot})] \\ + \alpha \log\left(\frac{w_{dt}}{w_{ot}}\right) + [Z_d - Z_o] - C_{od}$$

- P_{odt}/P_{oot} : ratio of scientists who move to the number who stay
- This equation represents the labor supply of scientists to state d

Main specification

- In equilibrium, demand and supply of star scientists in d are equal:

$$\begin{aligned}\log\left(\frac{P_{odt}}{P_{oot}}\right) = & \eta[\log(1 - \tau_{dt}) - \log(1 - \tau_{ot})] \\ & + \eta'[\log(1 - \tau'_{dt}) - \log(1 - \tau'_{ot})] \\ & + \gamma_d + \gamma_o + \gamma_{od} + u_{odt}\end{aligned}$$

- $\eta = \alpha/(1 + \alpha)$: effect of personal taxes
- $\eta' = \beta\alpha/(1 + \alpha)$: effect of corporate taxes
- $\gamma_d = [\alpha/(1 + \alpha)][Z_d + Z'_d]$: state fixed effects, captures amenities in o
- $\gamma_o = [\alpha/(1 + \alpha)][Z_o + Z'_o]$: state fixed effects, captures amenities in d
- $\gamma_{od} = -(C_{od} + C'_{od})$: state-pair fixed effects, captures the cost of moving for individuals and firms
- u_{odt} : idiosyncratic error term

Interpreting and augmenting specification

- η and η' are reduced-form coefficients that quantify the effect of taxes on employment
- Empirical model captures the long run (LR) effect of taxes, which are likely to be larger than the immediate effect due to adjustment costs
- Estimates should be interpreted as measuring the effect of taxes on scientist mobility after allowing for endogenous changes in the supply of public services
- Main specification can also include region-pair by year effects, state-of-origin by year effects or state-of-destination by year effects

Elasticity of probability of moving

Average elasticity of probability of moving w.r.t. the net-of-tax rate:

- Personal taxes:

$$e = \mathbf{E} \left[\frac{d \log P_{odt}}{d \log(1 - \tau_{ot})} \right] = \eta(1 - P)$$

- P : weighted average of P_{odt} over all (d, o, t) observations, weighting each combination by the number of individuals in that observation cell

- Corporate taxes:

$$e' = \mathbf{E} \left[\frac{d \log P'_{odt}}{d \log(1 - \tau_{ot})} \right] = \eta'(1 - P')$$

- P' : weighted average of P'_{odt} over all (d, o, t) observations, weighting each combination by the number of firms in that observation cell

Exploring the timing of migration responses

- Want to understand the timing of migration responses to tax changes
- Use impulse response function, which focuses on the time-difference

$$y_{o,d,t+h} - y_{o,d,t-k} = \beta^h (\tau_{o,d,t} - \tau_{o,d,t-k}) + F_{t,R(o),R(d)} + \epsilon_{o,t,d+h}$$

- k : duration of the treatment period, where the treatment is a net-of-tax rate shock
 - $y_{o,d,t+h} - y_{o,d,t-k}$: change in outmigration (log odds-ratio) from before the treatment ($t - k$) to h periods after the treatment
 - $F_{t,R(o),R(j)}$: year-specific fixed effect for each pair of regions defined by o 's region and d 's region
- Regression estimated separately for each horizon from $h = 0$ to 10
 - Focus on treatment duration of three or five years

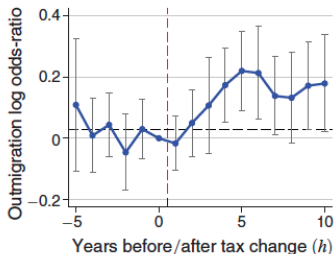
Findings: main model

- Increase in net-of-tax rate due to a cut in the personal income ATR or the corporate tax:
 - Stock of scientists in the state rises by 0.4 or 0.42% per year for as long as the increase in the net-of-tax rate differential lasts
 - Fewer star scientists move out of their current state of residence as after-tax incomes rise
 - Asymmetric responses to changes in net-of-tax rate in o relative to d (might be due to differential level of information on taxes in their state of residence relative to all other states)
 - Effects of changes in corporate income taxes concentrated among private sector inventors, with no effect on academic and government researchers
- Tax incentives have pull effect for individuals and firms
- Policy implication: cost of higher state tax rates should be taken into consideration when deciding whom and how much to tax

Elasticities of mobility relative to taxes

- LR elasticity of mobility relative to taxes is
 - 1.7 for personal income taxes
 - 1.8 for state corporate income
 - 1.6 for the investment tax credit
- Cumulative elasticity of scientist stock to the net-of-tax rate is 6.0.
- In other words, a permanent 1% increase in the net-of-tax rate for personal income taking place between year t and $t + 5$ would lead to a 6.0% increase in the stock of scientists by the end of year $t + 10$

Panel A. Top individual ATR



Panel B. Corporate tax rate

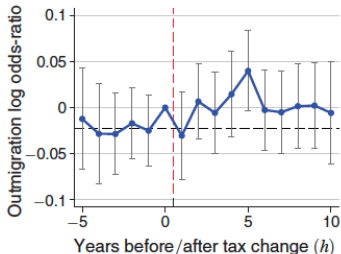


FIGURE 5. OUTMIGRATION BEFORE AND AFTER TAX CHANGE EVENT

Notes: A tax event is a tax change that takes place between 0 and 1. The graph plots the effect of the event in a balanced panel from five years before event to ten years after. For tax increases, the graph shows the effect on the number of star scientists moving from origin state o to destination state d in year t . For tax decreases, it shows the negative of the effect on the number of star scientists moving from origin state o to destination state d in year t . Tax increases and decreases are assumed to have equal and opposite effect. Specifically, the graph plots the coefficient β_h from the regressions: $\log(P_{odt+h}/P_{oot+h}) - \log(P_{odt}/P_{oot}) = \beta_h D_{odt} + \epsilon_{odt}$, where P_{odt} is the number of star scientists moving from o to d in year t ; D_{odt} is an event indicator that takes the value 1 if the destination-origin differential in the net-of-tax rate increases between t and $t + 1$, -1 if the differential decreases between t and $t + 1$, and 0 if the differential does not change. The dashed black line indicates the average coefficient over the pretreatment period. Only permanent tax changes are included (defined as changes that are not reversed in the next five years).

- Large established firms with a presence in multiple states can adjust to tax changes by changing the spatial distribution of employees across establishments in different states
- Taxes affect firms' geographical allocation of scientists:
 - 10% increase in a state's corporate income net-of-tax rate → increase in the average firm's share of star scientists in that state of 0.7pp
 - Investment tax credits and R&D credits have similar effects, while the personal ATR has no effect
- Implication: within-firm geographical reallocation is an important channel explaining the overall effect of business taxes on state employment, although it does not explain the effect of personal taxes

TABLE 9—EFFECT OF TAXES ON SHARE OF SCIENTISTS IN STATE

	All companies (1)	Multistate (2)
ATR, 99th percentile (1 – ATR)	–0.0073 (0.0109)	0.0013 (0.0103)
State CIT rate (1 – CIT)	0.0576 (0.0264)	0.0724 (0.0318)
State ITC (1 + ITC)	0.0470 (0.0196)	0.0443 (0.0199)
R&D credit (1 + cred)	0.0301 (0.0075)	0.0275 (0.0080)
Observations	8,222,730	1,592,781
State fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes

Notes: Level of observation is firm-state-year. Dependent variable is the share of the firm's US-based star scientists who are in state s in year t . Tax variables are relevant tax rate in state s in year t . Sample in column 1 includes all private sector firms. Sample in column 2 includes only private sector firms with presence in multiple states. Standard errors in parentheses clustering by origin-state \times year. All regressions include year fixed effects.

Effects of R&E credits on innovation

Overview of Bloom, Griffith and Van Reenen (2001)

- Paper: Bloom, Nick and Rachel Griffith and John Van Reenen. “Do R&D tax credits work? Evidence from a panel of countries 1979-1997.” *Journal of Public Economics*, Vol. 82 (2001): 1-31.
- Question: What is the impact of R&D tax credits on total level of R&D investment?
- Motivation:
 - Macro and microeconomic models of growth and production emphasize importance of technological progress
 - R&D incentives are often very costly to tax payers
 - Some economists believe R&D is not very post-tax price elastic

- Panel dataset of OECD countries, 1979-1997: Australia, Canada, France, Germany, Italy, Japan, Spain, UK and US
- Tax data: PwC “Doing Business in...” guides
- R&D data: OECD ANBERD database
 - Data reported at the country level on the basis of the location at which the R&D was undertaken
 - Location of R&D can be matched more closely to the tax regime under which it falls
 - Data reports R&D which is conducted by the business sector separately from government- and university-conducted R&D
- Further disaggregate R&D data, which contains info on source of finance. Interested in own-funded (r_{it}^d) and gov-funded (r_{it}^g)
- Focus on the manufacturing sector because easier to measure R&D

- Effect of a 10% fall in the cost of R&D on level of R&D:
 - Short run: just over a 1% rise in the level of R&D
 - Long run: approximately a 10% rise in R&D investment
- Fiscal provisions matter: Differences in tax systems induce variation in the user cost of R&D within and across countries
- Tax changes significantly effect the level of R&D even after controlling for demand, country-specific fixed effects and world macro-economic shocks
- The impact elasticity is not huge, but over the long-run may be more substantial (about unity in absolute magnitude)

Overview of Rao (2016)

- Paper: Rao, Nirupama. “Do Tax Credits Stimulate R&D Spending? The effect of the R&D tax credit in its first decade.” *Journal of Public Economics* 140 (2016): 1-12
- Question: What is the impact of US federal R&D tax credits on research intensity, for both qualified and overall R&D spending?
- Findings:
 - Wages and supplies account for bulk of short run increase in R&D spending
 - Firms respond to user cost changes largely by increasing their qualified spending \Rightarrow the type of R&D deemed qualified is an important margin on which the credit affects firm behavior
 - Firms respond to tax subsidies for R&D by increasing qualified spending much more than R&D spending overall

Do Fiscal Incentives Increase Innovation? An RD Design for R&D

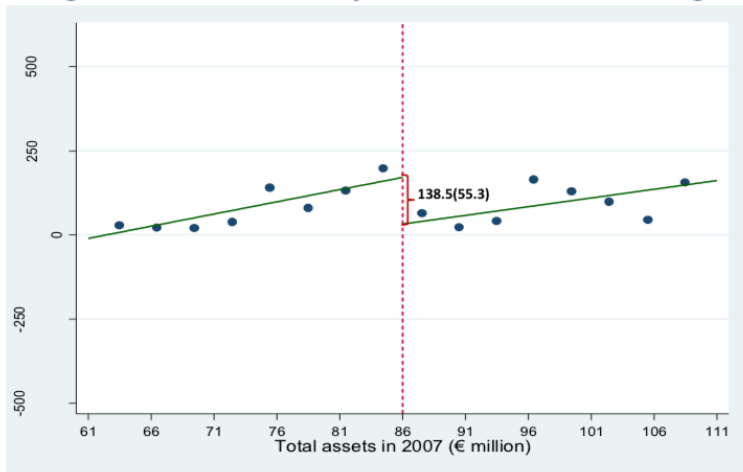
- Lots of evidence on impact of tax incentives on **R&D spend**: (Becker, 2015; OECD, 2012 surveys: +ve effect). But:
 - Difficult to establish causality
 - Little evidence of impacts on **R&D outputs** (innovation). Important because relabelling issue, etc.
- **This paper**:
 - Evaluate impact of current UK R&D Tax Relief Scheme (in 2013 HMRC estimate cost £1.4bn) on firm R&D & patenting.
 - Exploit discontinuity in generosity of R&D relief at new (lower) eligibility thresholds for SMEs in 2008.
 - SME Eligibility determined by pre-2008 financials so can implement a fuzzy Regression Discontinuity Design (RDD)

Do Fiscal Incentives Increase Innovation? An RD Design for R&D

Summary

- Use population tax administrative data & firm accounts.
- 2008 Policy change induced treated firms in 2009-11 to
 - Increase R&D by **~£75k** p.a. (~ double baseline R&D)
 - File **~0.04** additional patents p.a. (~60% up on baseline)
- Implied elasticity of R&D to tax-adjusted user cost = **-2.6**
 - Bigger elasticity than conventional wisdom (elasticity of 1 to 2 typical), but our treatment group is SMEs where credit constraints more are likely (Arrow, 1962)
- R&D tax policy as a whole: (i) £1.7 extra R&D for £1 of taxpayer money; (ii) Aggregate R&D ~16% higher
- We also find evidence for spillovers, suggesting policy passes cost-benefit test

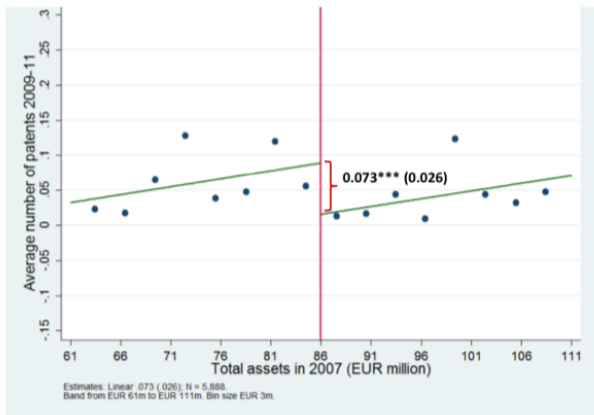
Figure 2: Discontinuity in R&D 2009-11 average



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

Do Fiscal Incentives Increase Innovation? An RD Design for R&D

Figure 3: Discontinuity on patenting 2009-11 average



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 2011.

Do Fiscal Incentives Increase Innovation? An RD Design for R&D

- **UK R&D tax incentives:** *Ex Post:* Bond & Guceri (2012); **Guceri (2014)**. Fowkes, Sousa & Duncan (2015); HMRC (2010); *Ex Ante:* Griffith, Redding & Van Reenen (2001)
- **R&D tax incentives:** *Cross country panel:* Corrado et al. (2015); Bloom, Griffith & Van Reenen (2002); *US states panel:* Wilson (2009); *US firms:* Eisner (1982), Hall (1993), Hines (1994); Rao (2014); *Non-US firms:* Czarnitzki et al. (2011); Lokshin & Mohnen (2012); Agrawal et al. (2014).
- **Impact of R&D subsidies:** Bronzini & Iachini (2014); Einiö (2014); Jacob & Lefgren (2010); Wallsten (2000); Takalo et al., (2013); Howell (2015)
- **Returns to R&D:** Bloom, Schankerman & Van Reenen (2013); Hall et al. (2005, 2013); Griffith et al. (2004); Doraszelski & Jaumandreu (2013)
- **Tax & investment:** Hassett & Hubbard (2002); Hall & Jorgenson (1967)
- **General determinants of innovation:** Hall & Rosenberg survey (2010); *Trade:* Grossman & Helpman (1991); Bloom et al. (2015); *Competition:* Blundell et al. (1999); Aghion et al. (2005)

Appendix

Overview of Kremer and Snyder (2015)

- Question: Why do pharmaceutical firms prefer to invest in drugs to treat diseases rather than vaccines?
- Motivation:
 - Neoclassical perspective undermines view that drugs are more lucrative than vaccines because they can generate a stream of revenue from the consumer rather than just a single payment
 - A consumer should be willing to pay a lump sum for the vaccine equal to the present discounted value of the stream of benefits provided
 - Kremer and Snyder (2015): shape of demand curve for a drug is more conducive to extracting revenue than for a vaccine due to different availability of risk information in drug and vaccine markets

Example: Setup

- Consider a population of 100 risk neutral and fully rational consumers
 - 90 have a low disease risk of 10%
 - Remaining 10 have a high risk (100% for simplicity)
- Disease generates harm equal to the loss of \$100
- Assume pharmaceuticals of either form are costless to produce and administer and are perfectly effective
- Suppose vaccine and drug producer is a profit-maximizing monopolist
- The example could be modified to create a social distortion (e.g., higher R&D cost for the drug or lower drug efficacy)

Example: Vaccine problem

Firm has the choice of a broad or narrow strategy:

- 1 Broad strategy: serve the whole market at price p_B
 - Firm can charge at most the low-risk consumers willingness to pay
 - p_B equals the expected avoided harm of \$10 (the 10% chance times \$100 harm)
 - Revenue equals \$10 \rightarrow total profit of \$1,000
- 2 Narrow strategy: just targeting high-risk consumers at price p_N
 - Charge high risk consumers the expected value of loss, so $p_N = \$100$
 - Producer surplus from this strategy is also \$1,000

Producer surplus is the same \Rightarrow firm is indifferent between the two pricing strategies in the vaccine market

Example: Drug problem

- 19 consumers expected to contract the disease (9 low, 10 high-risk)
- Each of those 19 consumers is willing to pay \$100 to avoid harm
- Total expected producer surplus of \$1,900 → only drugs are produced
- Pharma company will continue to only produce drugs as long as
 - Drug R&D cost is at most \$900 higher than the vaccine R&D cost
 - Drug efficacy is at least 53% as effective as the vaccine
- Monopolist switching to developing the vaccine yields deadweight loss amounting to nearly half of the total disease burden
- If all 100 consumers had the same 19% chance of contracting the disease, vaccine and drug revenue would be the same

Distribution of disease risk and Demand for vaccine

- Disease risk follows a Zipf distribution (special case of power law)
 - Power law: values and probabilities scale in exact inverse proportion
 - \Rightarrow vaccine monopolist earns same revenue regardless of price charged
- Drug is sold after consumers learn their disease status, when consumer values are the same and no longer have a Zipf distribution
- If the Zipf distribution involves a continuum of types:
 - Drug revenue \propto area under the curve (equal to disease prevalence)
 - Vaccine revenue \propto area of rectangle inscribed underneath, which minimizes the ratio of vaccine to drug revenue
- Kremer and Snyder (2015): revenue ration depends on much the distribution resembles a Zipf curve (greater resemblance \rightarrow greater drug bias)

Zipf distributions of disease risks across prevalence rates

