Session 1: Introduction

Part 2: Heidi Williams

The material covered in these slides is partially drawn from: Bryan, Kevin and Heidi Williams (2021) "Innovation: Market Failures and Public Policies," Chapter 13 in the *Handbook of Industrial Organization Volume 4*, edited by Kate Ho, Ali Hortacsu, and Alessandro Lizzeri.

Why a Boot Camp on Innovation? (Take #2)

Innovation: the invention, development, and diffusion of new goods, services or production processes.

- Economic problem that depends on active choices of agents who respond to incentives
- Historically, not treated as a primarily economic concern
  - Prior to 1960, 11 articles in AER, QJE, ECTA (combined) had "invention" or "innovation" in title
  - Development and diffusion of new ideas thought to be psychological, sociological, or simply serendipitous

What about the economics of innovation?

"Economics of innovation" inspired by mid-century developments in industrial practice, government policy, and economic theory:

1. Rise of large-scale industrial research labs [Hounshell and Smith 1988]
2. Successful directed wartime science efforts
   - Led to Vannevar Bush's *Science, The Endless Frontier* [Bush 1945]
3. Schumpeter (1942): creation and diffusion of new goods was a fundamental economic problem
   - Contrast with Neoclassical welfare analysis, which holds technological frontier constant

1951 SSRC Conference: a progress report

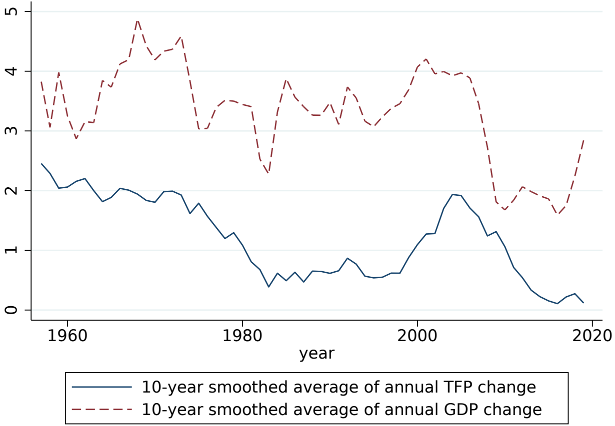
In response to newfound interest in innovation, a 1951 conference "Quantitative Description of Technological Change" was held at Princeton and supported by the Social Science Research Council

- Publication of the conference proceedings was abandoned because "the papers [were] in most cases of a very exploratory character" [Godin 2008]
- At the time, data on government R&D were close to nonexistent, very few papers had analyzed patents to study corporate innovation, and the link between these efforts and economic growth was unclear

Solow (1957): “black box” of innovation

- Share of long-run economic growth unexplained by changes in capital and labor inputs (TFP, total factor productivity) as high as 85%
- By construction, TFP is an unmeasured residual
- However, subsequent work adjusting for labor quality and capital utilization suggested much of “Solow residual” reflects technological progress

Changes in TFP and GDP over time in the US



Notes: This figure displays 10-year smoothed averages of annual changes in TFP and GDP. TFP here is the standard decomposition aside from adjusting for changes in labor and capital utilization (e.g., "labor hoarding" with shorter hours during recessions). Source: Fernald (2012).

1962 NBER Conference: a progress report

Core questions of innovation research agenda:

- How do inventors choose the rate and direction of the research investments they pursue?
- What market structure leads to high levels of innovation?
- Is innovation optimally generated with laissez faire incentives?

Raised in groundbreaking 1962 in NBER conference volume on the Rate and Direction of Inventive Activity and related papers published by the economists who attended the event [NBER 1962, Machlup 1962, Nelson 1959, Schmookler 1962 and 1966]

Despite 60 years of extensive research since the 1962 conference, these questions remain largely open.

- Particularly true for many key policy-relevant questions

Rest of my time today

1. 10,000 foot view of ‘research on research’ data
2. What makes empirically analyzing innovation policy questions challenging, and how have economists made progress in measurement and empirical analysis?
    - Example: Measuring spillovers

Institutional roadmap

- Basic and applied scientific research: Public and private
- Policies aimed at shaping private (and sometimes public) R&D:
    - R&D tax credits
    - Intellectual property rights, including patents
    - Competition policy
    - Labor market policies, including high-skill immigration and non-compete agreements

Optimistic view of the data: Many things are measured!

- Training: Proquest, mathematical genealogy, NSF SED
- Research funding: NSF/NIH grants, UMETRICS
- Scientific papers: Web of Science, OpenAlex, PubMed, preprints
- Patents: USPTO bulk data, PatentsView, EPO DOCDB
- Commercialization: clinical trials, agricultural field trials, start-ups, VC funding, university licensing, SAB participation

Useful for documenting facts, which are often invaluable contributions in shaping our understanding of what questions are worth trying to answer

- Example: Immigrants' contribution to US science / innovation

Pessimistic view of the data: The most important things feel impossible to measure well

- Hard to know the costs of mis-aligned incentives and poorly designed policies: ‘missing’ scientists and inventors / ‘missing’ ideas
- Good science is like good art: Know it when you see it
- By construction, spillovers are slippery to try to measure!

Many or most of the key policy-relevant questions require not only measuring these quantities, but also constructing counterfactuals rather than simply documenting descriptive facts

- Example: “Should” (if their goal is to produce the highest impact science) science funders fund people or projects?

Example of measurement challenges: Spillovers

Knowledge spillovers are frequently cited as the central market failure justifying government intervention in markets for innovation

- Strikingly: evidence of existence and magnitude is quite thin
- Krugman (1991): *"knowledge flows... are invisible; they leave no paper trail by which they may be measured and tracked"*

Measuring innovation: patent data

Zvi Griliches was a pioneer in quantifying innovation during the 1960s, spurring multiple efforts to gather patent data into usable form

> *"In this desert of data, patent statistics loom up as a mirage of wonderful plentitude and objectivity. They are available; they are by definition related to inventiveness, and they are based on what appears to be an objective and only slowly changing standard"*
>
> *[Griliches 1990]*

Key patent-related datasets have built on efforts by Hall, Jaffe, and Trajtenberg (2002) to link Compustat data and granted US patents, and the USPTO's expansion of public access to administrative data

Measuring innovation: limitations of patent data

Despite Griliches' own enthusiasm about the potential of patent data, he (and others) cautioned:

- *"Inventions may be the wrong unit of measurement... and may be a misleading quantum"* [Griliches 1962]

Measuring innovation using patent data has limitations:

- Many inventions are not patented and the propensity to patent a given invention appears to vary tremendously across industries [Cohen et al. 2000, Levin et al. 1987]
- Patents vary in their quality and value [Pakes 1986, Schankerman and Pakes 1986]

Measuring innovation: returning to spillovers

Knowledge flows may sometimes leave paper trails

- Patent citations – acknowledgements of the use of knowledge in subsequent patents – may capture relationships between inventions
    - Imperfect measure: citations can serve a legal purpose (disclosing prior art) and can be added by patent examiners (not applicants)
- Literature has focused on using patent citations to measure technological and geographic distance
    - Jaffe (1986) uses technological distance - based on USPTO-assigned technology classes - to estimate a firm's "potential spillover pool" in patent data
    - Jaffe, Trajtenberg, and Henderson (1993) uses geographic distance between firms to examine whether patent citations are localized

One central issue that arises is the distinction between testing for the existence of spillovers versus quantifying the magnitude of spillovers.

[Bloom et al. 2013]

Inference challenges

Even if we can agree on a measure of innovation, in order to understand how policy shapes inventive activity, we need to construct the appropriate counterfactuals

- Where there is ample variation within a single policy lever (e.g., tax rates) across similar geographic units (e.g., states), generating counterfactuals is relatively straightforward
  - For example: inventor mobility in response to tax rates.
- Contrast with: uniformity of patent terms in the United States

Estimating spillovers

Three broad types of methods:

1. Case studies: Griliches (1958)
   - Feature: possible to do very careful accounting
   - Criticism: "picking winners"
2. Production function approach: B-S-V (2013)
   - Feature: more representative than case studies
   - Criticism: difficult to find plausible identification
3. Patent citations: Jaffe-Henderson-Trajtenberg (1993)
   - Feature: paper trail!
   - Criticism: strategic and examiner-added citations

Two excellent (slightly dated) overviews: Griliches (1979, 1992)

Griliches (1979): Which firms receive spillovers?

- Citations: direct method of inference
- "Trick" in search for spillovers is to define a dimension over which knowledge spillovers are mediated
  - Input-output matrices
    - Is this even relevant to knowledge spillovers?
  - Industry (e.g. Bernstein and Nadiri 1989)
    - No natural ordering of two-digit SIC codes
    - Griliches (1979): *"...is 'leather' closer to 'food' or 'textiles'?"*
- General issue of testing vs. quantification

Griliches (1992):
"...detect the path of the spillovers in the sands of the data."

Where do you look for spillovers?

Focus of recent literature:

1. Technological distance: Jaffe (1986), Bloom-Shankerman-Van Reenen (2013)
2. Geographic distance: Jaffe (1989), Jaffe-Henderson-Trajtenberg (1993)
    - Footnote: closely linked to agglomeration literature

Consistent finding: social returns to R&D higher than private returns

- Lucking et al. (2018): firm-level data and production function-based approach suggest net positive knowledge spillovers

1. Geographic spillovers: Jaffe et al. (1993)
2. Technological spillovers
    - Jaffe (1986)
    - Bloom et al. (2013)

Jaffe-Henderson-Trajtenberg (1993)

Important contribution for two reasons:

1. Tackled question of whether knowledge spillovers had a geographically localized component in a way that took seriously how to construct an appropriate counterfactual
2. Developed a new measurement technique – patent citations – which subsequently became very widely used

Motivation

Policy question: does the research at federal laboratories and US universities affect US international competitiveness?

- Growth literature: often assumes within-country spillovers
- Alfred Marshall on agglomeration:
  1. Pooling of demand for specialized labor
  2. Development of specialized intermediate goods industries
  3. Knowledge spillovers among firms within industries
- Krugman (1991): give up on (3) - no paper trail!
  - Measurement insight: patent citations *do* leave a paper trail

What are patent citations?

- Legal function: delimit scope of property right conveyed by patent
- Applicant has legal duty to disclose to disclose "prior art"
- Some citations may be internalized (contracted)
- Patent examiners can add citations (likely not spillovers)
- Almost certainly an incomplete metric of spillovers

Core idea

Are patent citations geographically localized relative to a "counterfactual" geographic distribution of citations?

- Key question: how to construct a counterfactual
- Example: Stanford and semi-conductors
- J-H-T solution: "control" samples of patents

J-H-T: Construction of control patents

Key idea: compare the geographic location of patent citations with the geographic location of the originating patent they cite

- Concern: would expect some geographic matching without spillovers
- Approach: construct a "control patent" for each citing patent, from the same patent class in the same application year; compare location of control patent with that of originating patent
    - Subsequent criticisms: imperfect match method
    - Idea/data still a key contribution

Defining geography

- Patent data include:
  - Country of residence of each inventor
  - City and state of residence for US inventors
  - But: patents can have multiple inventors
- Procedure used here:
  1. Assigned 98% of US inventors to SMSAs
  2. Assigned locations to *patents* based on pluralities of inventors

Table 3: test of localization

Share of co-located citations, relative to control sample (t-test)

TABLE III
GEOGRAPHIC MATCHING FRACTIONS

	1975 Originating cohort			1980 Originating cohort		
	University	Top corporate	Other corporate	University	Top corporate	Other corporate
Number of citations	1759	1235	1050	2046	1614	1210
		Matching by country				
Overall citation matching percentage	68.3	68.7	71.7	71.4	74.6	73.0
Citations excluding self-cites	66.5	62.9	69.5	69.3	68.9	70.4
Controls	62.8	63.1	66.3	58.5	60.0	59.6
t-statistic	2.28	−0.1	1.61	7.24	5.31	5.59
		Matching by state				
Overall citation matching percentage	10.4	18.9	15.4	16.3	27.3	18.4
Citations excluding self-cites	6.0	6.8	10.7	10.5	13.6	11.3
Controls	2.9	6.8	6.4	4.1	7.0	5.2
t-statistic	4.55	0.09	3.50	7.90	6.28	5.51
		Matching by SMSA				
Overall citation matching percentage	8.6	16.9	13.3	12.6	21.9	14.3
Citations excluding self-cites	4.3	4.5	8.7	6.9	8.8	7.0
Controls	1.0	1.3	1.2	1.1	3.6	2.3
t-statistic	6.43	4.80	8.24	9.57	6.28	5.52

Thoughts on J-H-T test of localization

- Headline estimate: Citations 5-10 times as likely to come from same SMSA as control patents (2-6 times as likely excluding self-citations)
- Two cohorts of originating patents: 1975 and 1980; stronger evidence for localization in 1980 [Unsolicited advice: Probably not a good structure. From the paper: "It is impossible to tell from this comparison whether..." But one possibility is that early citations are more localized.]
- Including vs. not including self-citations [Which is more of interest?]
- Really need to take seriously what patents and citations mean [Since this paper, there have been some efforts to validate these as metrics]

1. Geographic spillovers: Jaffe et al. (1993)

2. Technological spillovers
   - Jaffe (1986)
   - Bloom et al. (2013)

Jaffe (1986)

Very influential paper

- Developed a technological distance measure which enabled him to estimate spillovers from other firms' R&D
- $F = (F_1, ..., F_k)$: technological position of the firm
  - F_k: share of firm's research budget devoted to k, but confidential
  - Instead: leveraged technological classifications assigned by USPTO
    - Related to but different from industries
    - Schmookler example of patent subclass for "dispensing of solids," including both toothpaste tubes and manure spreaders

Data: early version of the NBER patent data

`http://www.nber.org/patents/`

`https://sites.google.com/site/patentdataproject/Home`

Jaffe (1986): Proximity measure

- Leveraged Compustat-USPTO merge (1700 firms; 260,000 patents)
- A firm's "potential spillover pool" is defined as a weighted sum of other firms' R&D in technology space
- Formally, Jaffe defines a measure of proximity between firm i and firm j, P_{ij} as the uncentered correlation of F_i, F_j
  - Equal to 1 when $i = j$ and 0 if no technological overlap
- Potential spillover pool S_i weights other firms' R&D R_j by P_{ij}: $S_i = \sum_{j \neq i} P_{ij} R_j$
  - Note: Assumes constant appropriability across technological areas

Jaffe (1986): Key results (Table 5)

For a firm with mean log(R&D), the elasticity of patents wrt others' R&D is ~ 1.1 (if everyone increased their R&D by 10%, total patents would increase by 20%, with more than one-half increase coming from spillovers)

	Equation for log of:		
	Patents	Profits	Tobin's q
log($R\&D$)	.875	.180	
	(.183)	(.042)	
$R\&D$/Capital			3.31
			(.209)
log($R\&D$) $\times$log(Pool)	.352	.058	
	(.048)	(.020)	
($R\&D$/Capital) $\times$log(Pool)			.803
			(.098)
log(Pool)	.509	−.095	−.058
	(.104)	(.053)	(.031)
log(Capital)		.825	
		(.044)	
log(72 Share) (73 Equation)		.188	.310
		(.055)	(.053)
log(72 Share) (79 Equation)		.057	.123
		(.055)	(.054)

Jaffe (1986): caveat in introduction

"From a purely technological point of view, R&D spillovers constitute an unambiguous positive externality. Unfortunately, we can only observe various economic manifestations of the firm's R&D success. For this reason, the positive technological externality is potentially confounded with a negative effect of others' research due to competition. It is not possible, with available data, to distinguish these two effects."

- Concern: technology neighbors may be product competitors
  $\Rightarrow$ also exists a product rivalry / business stealing effect
- Potential confound in estimating knowledge spillovers
- But also of independent interest!

Bloom, Schankerman, and Van Reenen (2013)

B-S-V pick up this thread from Jaffe

- Key contribution: develop a framework to separately identify effects of technology spillovers and product market spillovers
- Empirical insight: distinguish a firm's position in technology space from a firm's position in product market space using data on distribution of patenting across technology classes together with detailed data on sales activity across four-digit industries
- Tackle reflection problem by leveraging R&D tax credit variation
- Undertake an assessment of over- vs. under-investment in R&D
  - Derive social and private rates of return to R&D, measured in terms of output gains generated by a marginal increase in R&D

Technology vs. product market space

Perhaps surprisingly, significant variation in these two dimensions

Example:

- IBM, Apple, Motorola, and Intel all close in technology space (revealed by patenting, confirmed by research joint ventures)
- IBM and Apple compete in the PC market
- Intel and Motorola compete in the semi-conductor market
- Little product market competition between the two pairs

B-S-V: big picture

Main take-away: social returns to R&D are 2-4x private returns

- Heavy, thoughtful, well-written paper
- Won't cover all of the moving parts
  (can read web Appendices A through G on your own!)
- Will walk through the main parts of the analysis

One-slide summary of analytical framework

Present a simple analytical framework which generates a series of comparative statics that they can then take to the data:

1. R&D of non-technology/product market neighbors should have no influence on firm 0's decisions or market value.
2. Firm 0's R&D positively related to R&D by technology neighbors in other product spaces as long as diminishing returns to knowledge production are not "too strong."
3. Firm 0's R&D a function of R&D done by product market neighbors in other technology spaces: sign depends on whether competition makes output strategic complements or strategic substitutes – that is, whether increase in one firm's R&D raises marginal profits to other firm's R&D.

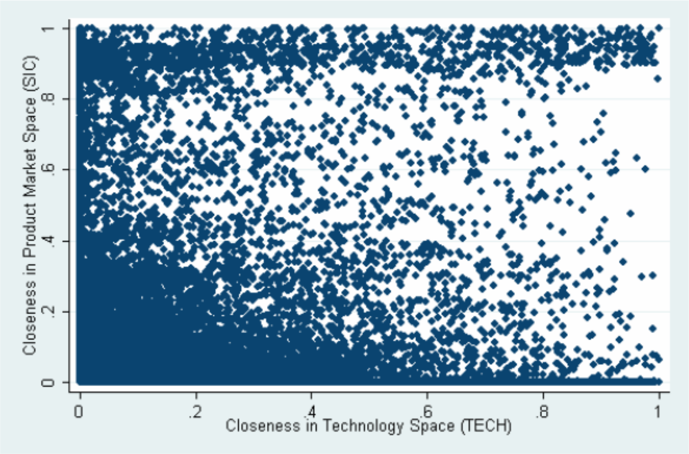
Measurement

- Technological proximity: *SPILLTECH*
  - Knowledge is transmitted when scientists are exposed to each other
  - Mahalanobis extention: incorporate proximity in idea space
- Product market proximity: *SPILLSIC*
- Data:
  - Firm-year level panel data from Compustat for 1980-2001
  - Matched to USPTO data from the NBER (426 classes)
  - Compustat Segment gives sales by four-digit industry

Figure 1: *SPILLTECH* and *SPILLSIC* (0.469)

- Surprisingly, good amount of variation

FIGURE 1 – SIC AND TECH CORRELATIONS



Notes: This figure plots the pairwise values of SIC (closeness in product market space between two firms) and TECH (closeness in technology space) for all pairs of firms in our sample.

Econometrics

Generic equation B-S-V would like to estimate:

$$\ln Q_{it} = \beta_1 \ln G_{it} + \beta_2 SPILLTECH_{it} + \beta_3 \ln SPILLSIC_{it} + \beta_4 X_{it} + u_{it}$$

Three issues:

1. Unobserved heterogeneity. Firm (η_i) and time (τ_t) FEs
2. Endogeneity. Tax-policy instruments for R&D, use predicted values weighted up by *SIC* and *TECH* distance as instruments for spillover variables in second stage equation.
3. Dynamics. Baseline models static, also explore dynamics

Market value equation

Griliches (1981): to mitigate endogeneity lag key RHS variables

$$
\begin{aligned}
\ln\left(\frac{V}{A}\right)_{it} &= \phi\left(\left(\frac{G}{A}\right)_{it-1}\right) + \gamma_2 \ln SPILLTECH_{it-1} \\
&+ \gamma_3 \ln SPILLSIC_{it-1} + \gamma_4 X_{it}^{V} + \eta_i^{V} + \tau_t^{V} + \nu_{it}^{V}
\end{aligned}
$$

- V: market value of firm
- A: stock of non-R&D assets
- G: R&D stock
- $\phi\left(\left(\frac{G}{A}\right)_{it-1}\right)$: sixth-order polynomial

Consistent with theory, *TECH* associated with an increase in market value, *SIC* associated with a decrease in market value

Table 3: market value equation

TABLE 3: COEFFICIENT ESTIMATES FOR TOBIN'S Q EQUATION

	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	OLS	OLS	OLS	OLS	OLS	IV 2nd stage
Distance measure:	Jaffe	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$Ln(SPILLTECH_{t-1})$	-0.064	0.381	0.305		0.903	1.079
	(0.013)	(0.113)	(0.109)		(0.105)	(0.192)
$Ln(SPILLSIC_{t-1})$	0.053	-0.083		-0.050	-0.136	-0.235
	(0.007)	(0.032)		(0.031)	(0.031)	(0.109)
$Ln(R\&D\ Stock/Capital\ Stock)_{t-1}$	0.859	0.806	0.799	0.799	0.835	0.831
	(0.154)	(0.197)	(0.198)	(0.198)	(0.198)	(0.197)
						1st stage F-tests
$Ln(SPILLTECH_{t-1})$						112.5
$Ln(SPILLSIC_{t-1})$						42.8
Firm fixed effects	No	Yes	Yes	Yes	Yes	Yes
No. Observations	9,944	9,944	9,944	9,944	9,944	9,944

Notes: Dependent variable is Tobin's Q = V/A is defined as the market value of equity plus debt, divided by the stock of fixed capital. A sixth order polynomial in $\ln(R\&D\ Stock/Capital\ Stock)_{t-1}$ is included but only the first term is shown for brevity. Standard errors in brackets are robust to arbitrary heteroskedacity and first order serial correlation using the Newey-West correction. A dummy variable is included for observations where lagged R&D stock is zero. All columns include a full set of year dummies and controls for current and lagged industry sales in each firms' output industry. Column (6) uses instrumental variable estimation. "1st stage F-tests" are the joint significance of the excluded tax-based instrumental variables (ln(TECHTAX) and ln(SICTAX)) from each first stage of the endogenous variables, ln(SPILLTECH) and ln(SPILLSIC). See Appendix B3 for details. In column (6) we also control for the firm's own R&D federal and state tax credit values.

Patent equation

Negative binomial model with pre-sample mean scaling

$$
\begin{aligned}
P_{it} &= \exp\left|\lambda_1 \ln G_{it-1} + \lambda_2 \ln SPILLTECH_{it-1}\right. \\
&+ \left.\lambda_3 \ln SPILLSIC_{it-1} + \lambda_4 X_{it}^P + \eta_i^P + \tau_t^P + \nu_{it}^P\right|
\end{aligned}
$$

Consistent with theory, *TECH* variable comes in strongly positive, whereas the *SIC* variable is smaller and statistically insignificant

Table 4: patent equation

TABLE 4: COEFFICIENT ESTIMATES FOR THE CITE-WEIGHTED PATENT EQUATION

Dep Var: Cite weighted Patents	(1)	(2)	(3)	(4)	(5)
Specification:	Neg. Bin.	Neg. Bin.	Neg. Bin.	Neg. Bin.	Neg. Bin. IV 2nd stage
Distance measure:	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$\ln(SPILLTECH)_{t-1}$	0.518	0.468	0.417	0.530	0.407
	(0.096)	(0.080)	(0.056)	(0.070)	(0.059)
$\ln(SPILLSIC)_{t-1}$	0.045	0.056	0.043	0.053	0.037
	(0.042)	(0.037)	(0.026)	(0.037)	(0.028)
$\ln(R\&D\ Stock)_{t-1}$	0.500	0.222	0.104	0.112	0.071
	(0.048)	(0.053)	(0.039)	(0.039)	(0.020)
$\ln(Patents)_{t-1}$			0.420	0.425	0.423
			(0.020)	(0.020)	(0.020)
Pre-sample fixed effect		0.538	0.292	0.276	0.301
		(0.046)	(0.033)	(0.033)	(0.032)
					IV 1st stage F-tests
$\ln(SPILLTECH)_{t-1}$					55.3
$\ln(SPILLSIC)_{t-1}$					15.0
Firm fixed effects	No	Yes	Yes	Yes	Yes
No. Observations	9,023	9,023	9,023	9,023	9,023

Notes: Estimation is conducted using the Negative Binomial model. Standard errors (in brackets) allow for serial correlation through clustering by firm. A full set of time dummies, four digit industry dummies and lagged firm sales are included in all columns. A dummy variable is included for observations where lagged R&D stock equals zero (all columns) or where lagged patent stock equals zero (column (3)). Columns (2) to (5) include the "pre-sample mean scaling approach" to estimate fixed effects of Blundell, Griffith and Van Reenen (1999). The Negative Binomial IV specification in column (5) implements a control function approach which includes the first five terms of the expansion of the residual for the first stage regressions. "1st stage F-tests" are the joint significance of the excluded tax-based instrumental variables (ln(TECHTAX) and ln(SICTAX)) from each first stage of the endogenous variables, ln(SPILLTECH) and ln(SPILLSIC). See Appendix B3 for details.

Productivity equation

Productivity equation uses output Y as outcome:

$$\begin{aligned} \ln Y_{it} &= \psi_1 \ln G_{it-1} + \psi_2 \ln SPILLTECH_{it-1} \\ &+ \psi_3 \ln SPILLSIC_{it-1} + \psi_4 X_{it}^Y + \eta_i^Y + \tau_t^Y + \nu_{it}^Y \end{aligned}$$

As with patent equation, *TECH* variable comes in strongly positive, whereas the *SIC* variable is smaller and statistically insignificant

Table 5: productivity equation

TABLE 5: COEFFICIENT ESTIMATES FOR THE PRODUCTION FUNCTION

Dep. Var: Ln(sales)	(1)	(2)	(3)	(4)	(5)
Specification:	OLS	OLS	OLS	OLS	IV 2nd Stage
Distance measure	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$\text{Ln(SPILLTECH)}_{t-1}$	-0.022	0.191	0.186	0.264	0.206
	(0.009)	(0.046)	(0.045)	(0.064)	(0.081)
$\text{Ln(SPILLSIC)}_{t-1}$	-0.016	-0.005		-0.007	0.030
	(0.004)	(0.011)		(0.021)	(0.054)
Ln(Capital)_{t-1}	0.288	0.154	0.153	0.156	0.152
	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)
Ln(Labor)_{t-1}	0.644	0.636	0.636	0.637	0.639
	(0.012)	(0.015)	(0.015)	(0.015)	(0.016)
$\text{Ln(R\&D Stock)}_{t-1}$	0.061	0.043	0.042	0.043	0.041
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
					First Stage F-Statistic
$\text{Ln(SPILLTECH)}_{t-1}$					112.4
$\text{Ln(SPILLSIC)}_{t-1}$					51.2
Firm fixed effects	No	Yes	Yes	Yes	Yes
No. Observations	9,935	9,935	9,935	9,935	9,935

Notes: Dependent variable is ln(sales). Standard errors (in brackets) are robust to arbitrary heteroskedacity and allow for first order serial correlation using the Newey-West procedure. Industry price deflators are included and a dummy variable for observations where lagged R&D equals to zero. All columns include a full set of year dummies and controls for current and lagged industry sales in each firms' output industry. Column (5) uses instrumental variable estimation. "1st stage F-tests" are the joint significance of the excluded tax-based instrumental variables (ln(TECHTAX) and ln(SICTAX)) from each first stage of the endogenous variables, ln(SPILLTECH) and ln(SPILLSIC). See Appendix B3 for details.

R&D equation

Letting R represent flow of R&D:

$$\begin{aligned} \ln\left(\frac{R}{Y}\right)_{it} &= \alpha_2 \ln SPILLTECH_{it-1} + \\ &+ \alpha_3 \ln SPILLSIC_{it-1} + \alpha_4 X_{it}^R + \eta_i^R + \tau_t^R + \nu_{it}^R \end{aligned}$$

Estimated coefficient on $TECH$ not robust across specifications;
IV $\Rightarrow$ association between R&D, SIC driven by common shocks

Table 6: R&D equation

TABLE 6: COEFFICIENT ESTIMATES FOR THE R&D EQUATION

Dep Var: Ln(R&D/Sales):	(1)	(2)	(3)	(4)	(5)
Specification:	OLS	OLS	OLS	OLS	IV 2[nd] Stage
Distance Measure:	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$Ln(SPILLTECH)_{t-1}$	0.079	0.100	-0.049	-0.176	0.138
	(0.018)	(0.076)	(0.042)	(0.101)	(0.122)
$Ln(SPILLSIC)_{t-1}$	0.374	0.083	0.034	0.224	-0.022
	(0.013)	(0.034)	(0.019)	(0.048)	(0.071)
$Ln(R\&D/Sales)_{t-1}$			0.681		
			(0.015)		
					IV 1[st] stage F-tests
$Ln(SPILLTECH)_{t-1}$					190.7
$Ln(SPILLSIC)_{t-1}$					38.0
Firm fixed effects	No	Yes	No	Yes	Yes
No. Observations	8,579	8,579	8,387	8,579	8,579

Notes: Dependent variable is Ln(R&D/sales). Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation using Newey-West corrected standard errors. All columns include a full set of year dummies and controls for current and lagged industry sales in each firms' output industry. Column (5) uses instrumental variable estimation. "1[st] stage F-tests" are the joint significance of the excluded tax-based instrumental variables (ln(TECHTAX) and ln(SICTAX)) from each first stage of the endogenous variables, ln(SPILLTECH) and ln(SPILLSIC). See Appendix B3 for details. In column (5) we also include the firm's own R&D federal and state tax credit values.

Table 7: model matches data remarkably well

TABLE 7: COMPARISON OF EMPIRICAL RESULTS TO MODEL WITH TECHNOLOGICAL SPILLOVERS AND PRODUCT MARKET RIVALRY

(1)	(2) Partial correlation	(3) Theory	(4) Empirics Jaffe	(5) Empirics Mahalanobis	(6) Empirics Jaffe, IV	(7) Consistency?
$\partial V_0/\partial r_\tau$	Market value with SPILLTECH	Positive	0.381**	0.903**	1.079***	Yes
$\partial V_0/\partial r_m$	Market value with SPILLSIC	Negative	-0.083**	-0.136**	-0.235**	Yes
$\partial k_0/\partial r_\tau$	Patents with SPILLTECH	Positive	0.417**	0.530***	0.407***	Yes
$\partial k_0/\partial r_m$	Patents with SPILLSIC	Zero	0.043	0.053	0.037	Yes
$\partial y_0/\partial r_\tau$	Productivity with SPILLTECH	Positive	0.191**	0.264**	0.206**	Yes
$\partial y_0/\partial r_m$	Productivity with SPILLSIC	Zero	-0.005	-0.007	0.030	Yes
$\partial r_0/\partial r_\tau$	R&D with SPILLTECH	Ambiguous	0.100	-0.176*	0.138	
$\partial r_0/\partial r_m$	R&D with SPILLSIC	Ambiguous	0.083**	0.224**	-0.022	

Notes: The theoretical predictions are for the case of technological spillovers. The empirical results are from the static fixed effects specifications for each of the dependent variables. ** denotes significance at the 5% level and * denotes significance at the 10% level (note that coefficients are as they appear in the relevant tables, not marginal effects).

Many robustness checks

See web appendices A through G :)

Estimates of the private and social returns to R&D

Use estimate to calculate spillovers

- Requires swallowing a lot of assumptions, but this calculation is really going after the “big question” of interest

Marginal social and private returns to R&D

Marginal social return (MSR) to R&D for firm i

- Increase in aggregate output generated by a marginal increase in firm i's R&D stock (including changes in other firms' R&D)
- Footnote: does not fully capture consumer surplus

Marginal private return (MPR) to R&D for firm i

- Increase in firm i's output generated by a marginal increase in firm i's R&D stock

Special case: firms symmetric, no strategic complementarities

- Full-blown model in Appendix G

Wedge between social and private returns to R&D

Depends on importance of technology spillovers in production function (ϕ_2) vs. rivalry effects in market value equation (γ_3)
$\Rightarrow$ social rate of return can be $\gtrless$ private rate of return

- MSR: 58%
- MPR: 21%
- Implies MSR is 2-3 times larger than MPR
  $\Rightarrow$ under-investment in R&D
- Table 9 presents results for full (non-simplified) model

Thoughts on B-S-V

- Headline estimate: Implies MSR is 2-3 times larger than MPR
- On the important/compelling frontier
  [*Great* question to think about working on yourself;
  when not teaching, looking into this question for pharmaceuticals...]
- Instrument is correlated between geographically co-located firms
  [Problematic, or no?]
- Pretty surprising that R&D tax credits work in this context
  [Would be interested in a finer-grained analysis]