Innovation policy

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A Toolkit of Policies to Promote Innovation

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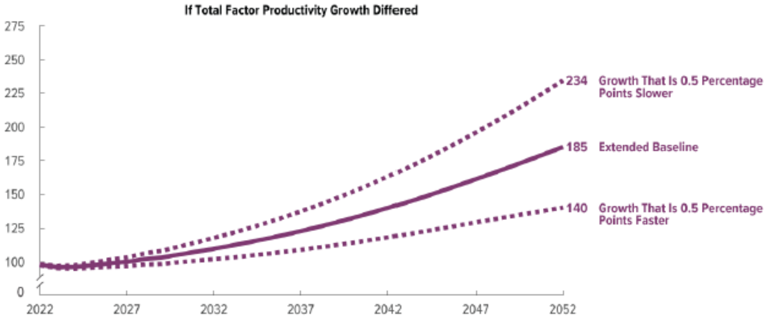
Total factor productivity (TFP) has long been recognized as a key driver of long-term budgetary and economic outcomes

- By construction, TFP is unmeasured - a residual
- But the macroeconomic importance of TFP is nonetheless clear

Figure 4-1.

Federal Debt If Total Factor Productivity Growth or Interest Rates Differed From the Values Underlying CBO's Extended Baseline Projections

Percentage of Gross Domestic Product



Innovation policy: A toolkit

- Natural question from policy makers: what types of changes to innovation policy could spur TFP growth?
- Debates over the costs and benefits of different potential changes to innovation policy levers center on both:
  1. Economic effects: which changes could change TFP, and by how much?
  2. Budgetary effects: how different policies are financed and how the enactment of such policy changes would affect budgetary outlays

- "*In this article, we take a practical approach to addressing this question. If a policymaker came to us with a fixed budget of financial and political capital to invest in innovation policy, what would we advise?*"

Rachel Reeves

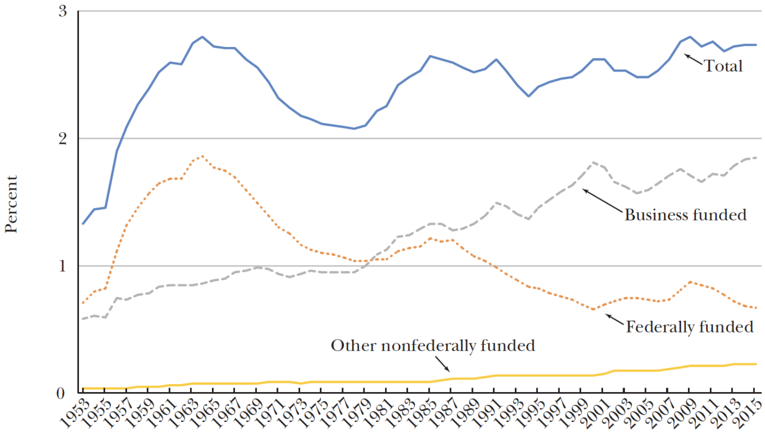
Rachel Reeves to announce economic advisory council to boost UK growth

Exclusive: Chancellor is making appointments for new body that will help guide Labour's 'national mission' of economic renewal

The chancellor, Rachel Reeves, giving a speech on Monday announcing the first steps the government will be taking to deliver economic growth. Photograph: Jonathan Brady/Reuters

Figure 1

US Research and Development as a Share of GDP, by Source of Funds: 1953–2015



Source: This figure displays data from figure 4-3 of National Science Board (2018), chap. 4. The original data are drawn from the National Science Foundation, National Center for Science and Engineering Statistics, National Patterns of R&D Resources (annual series).
Notes: The figure shows how spending on R&D performed in the United States, presented as a share of GDP, has evolved over time from 1953 to 2015, in total and broken down by source of R&D funding.

Table 1

International Comparison of Research and Development Expenditures in 2015

Country	*R&D expenditures (billions of US$)*	*R&D/GDP (%)*
United States	496.6	2.7
China	408.8	2.1
India	50.3	0.6
Japan	170.0	3.3
Germany	114.8	2.9
Russia	38.1	1.1
Brazil	38.4	1.2
France	60.8	2.2
United Kingdom	46.3	1.7
Indonesia	2.1	0.1
OECD (average)	34.7	2.4

Source: These data are drawn from table 4-5 of National Science Board (2018), chap. 4. The original data are drawn from the OECD, Main Science and Technology Indicators (2017/1); United Nations Educational, Scientific, and Cultural Organization Institute for Statistics Data Centre (http://data.uis.unesco.org/; accessed October 13, 2017).

Notes: This table displays data on gross domestic expenditures on R&D (reported in purchasing power parity adjusted billions of US dollars) and R&D as a share of GDP for the United States, the nine other countries with the largest GDP in 2015, and the OECD average (averaged over all 36 member countries as of 2015).

Scientific workforce

- Fraction of workers who are researchers grew through 2000 in the US and has been stable since, between 0.7-0.9 percent
- Temporary work visas covering high-skilled workers:
  - J-1 (growth)
  - H-1B (growth in uncapped sectors)

Table 2
Innovation Policy Toolkit

Policy	*Quality of evidence (1)*	*Conclusiveness of evidence (2)*	*Net benefit (3)*	*Time frame (4)*	*Effect on inequality (5)*
Direct R&D grants	Medium	Medium	💡💡	Medium run	↑
R&D tax credits	High	High	💡💡💡	Short run	↑
Patent box	Medium	Medium	Negative	NA	↑
Skilled immigration	High	High	💡💡💡	Short to medium run	↓
Universities: incentives	Medium	Low	💡	Medium run	↑
Universities: STEM supply	Medium	Medium	💡💡	Long run	↓
Trade and competition	High	Medium	💡💡💡	Medium run	↑
Intellectual property reform	Medium	Low	Unknown	Medium run	Unknown
Mission-oriented policies	Low	Low	💡	Medium run	Unknown

Source: The authors.
Notes: This is our highly subjective reading of the evidence. Column 1 reflects a mixture of the number of studies and the quality of the research design. Column 2 indicates whether the existing evidence delivers any firm policy conclusions. Column 3 is our assessment of the magnitude of the benefits minus the costs (assuming these are positive). Column 4 delineates whether the main benefits (if there are any) are likely to be seen in the short run (roughly, the next three to four years) or in the longer run (roughly ten years or more); NA means not applicable. Column 5 lists the likely effect on inequality.

Today:

1. Why should governments promote innovation?

   [Nelson 1959 *JPE*; Arrow 1962 *NBER* chapter; *Bloom et al. 2019 *JEP*]

2. Testing for and quantifying the extent of market failures

   [Jaffe 1986 *AER*; *Bloom et al. 2013 *Econometrica*; Jaffe et al. 1993 *QJE*]

3. Innovation policy toolkit:
   1. Incentives and institutions affecting innovation
      - Market-provided incentives (traditional focus of economists)
      - Scientific norms and institutions
   2. Theory and evidence on innovation-related public policies
      - $\rightarrow$ **Tax incentives** $\leftarrow$
      - Public funding of research
      - Intellectual property rights
      - Immigration

Why should governments promote innovation?

1. Innovation is endogenous, in the sense of responding to incentives
   - Schumpeter (1942), Schmookler (1966)
   - Incentives vs. "scientific opportunities"
2. Innovation is first-order for growth
   - Both theoretical (Solow 1956, Swan 1956) and empirical (accounting; Solow 1957) approaches suggest technology is key to growth
   - Much subsequent work focused on innovation-based endogenous growth models (Romer 1990, Grossman-Helpman 1991, Aghion-Howitt 1992)
3. Innovation will be under-produced by the free market
   - Credit for this idea often cited to Nelson (1959), Arrow (1962)
   - Like Arrow (1963), Arrow (1962) verbally (no math) lays out an incredibly prescient research agenda for the field

Arrow (1962)

- Largely cited (especially in IO) for the relatively small discussion of how competition vs. monopoly affects incentives for innovation
- My read (also drawn out in Arrow *AR* 2009) is that Arrow's emphasis was much more on laying out the economic nature of information
  - Parallels with health insurance), e.g. "moral factor" as a limit (here, managerial incentives)
  - Violations of assumptions required for welfare theorems
  - Basic research especially unlikely to be privately rewarded
  - Key questions:
    1. How should amount of public subsidies to R&D be determined?
    2. How shall efficiency of their use be encouraged?

Footnote: Arrow (2012)

Highlights patents as his first priority for future research:

- Measurement caveat from 1962 conference by Zvi Griliches: "*[I]nventions may be the wrong unit of measurement. What we are really interested in is the stock of useful knowledge or information and the factors that determine its rate of growth. Inventions may represent only one aspect of that process and be a misleading quantum at that. . . [T]heir fluctuations may not be well correlated with changes in the over-all rate of growth.*"
- "*. . . many authors have ascribed an important role to...intellectual property...in stimulating technological progress. . . On the other hand, in informal conversations with presumably knowledgeable lawyers and businessmen, I derive the impression that patent protection is important only for a limited range of products, such as pharmaceuticals. . . Is there no way of measuring the significance of the patent system as an incentive for invention?*"

Nelson (1959) on basic (vs. applied) research

- Basic research more likely to generate spillovers
  - Difficult to predict applications (Azoulay et al. 2019)
  - Often cannot be quickly patented (§101)
- For-profits have incentives to keep findings secret (disclosure)
- Concerned about corporate short-termism (corporate finance Q)
- Bottom line: "*It is socially desirable that as much of our basic research effort as possible be undertaken in institutions interested in the quick publication of research results if marginal costs are comparable...This is not to say that universities cannot effectively undertake applied research. Rather it is to say that their comparative advantage lies in basic research.*"

Central market failure: Knowledge spillovers

- If one firm creates something truly innovative, this knowledge may spill over to other firms that either copy or learn something from the original research – without having to pay the full R&D costs
- Ideas are promiscuous: even with a well-designed intellectual property system, the benefits of new ideas are difficult to fully monetize

- That said, R&D in a market economy can also be too high, depending on net size of knowledge spillovers vs. product market spillovers
- Classic example: Pharmaceutical "me too" drugs

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: leaving out Myers-Lanahan (2022) b/c Kyle taught that

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. Estimating spillovers
   - Geographic spillovers: Jaffe et al. (1993)
   - Jaffe (1986)
   - Bloom et al. (2013)
2. Taxation
   - R&D tax credits
   - Taxes, migration & innovation
3. Wrap-up

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. Estimating spillovers
   - Geographic spillovers: Jaffe et al. (1993)
   - Jaffe (1986)
   - Bloom et al. (2013)

2. Taxation
   - R&D tax credits
   - Taxes, migration & innovation

3. Wrap-up

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($R\&D$) ×log(Pool)	.352	.058	
	(.048)	(.020)	
($R\&D$/Capital) ×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.

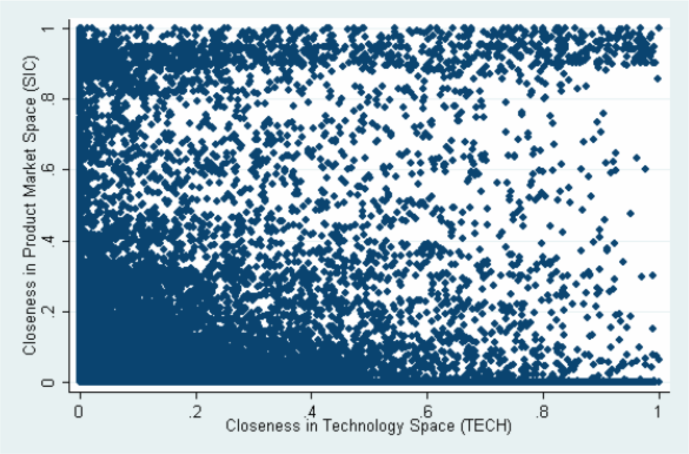
Measurement

- 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 2^{nd} 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 1^{st} 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. "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.

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
$Ln(SPILLTECH)_{t-1}$	-0.022	0.191	0.186	0.264	0.206
	(0.009)	(0.046)	(0.045)	(0.064)	(0.081)
$Ln(SPILLSIC)_{t-1}$	-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)
$Ln(R\&D\ Stock)_{t-1}$	0.061	0.043	0.042	0.043	0.041
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
					First Stage F-Statistic
$Ln(SPILLTECH)_{t-1}$					112.4
$Ln(SPILLSIC)_{t-1}$					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:

$$\begin{aligned}\ln\left(\frac{R}{Y}\right)_{it} &= \alpha_2 \ln SPILLTECH_{it-1} + \\ &+ \alpha_3 \ln SPILLSIC_{it-1} + \alpha_4 X^R_{it} + \eta^R_i + \tau^R_t + \nu^R_{it}\end{aligned}$$

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 2nd 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 1st 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. "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 (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]
- Instrument is correlated between geographically co-located firms

  [Problematic, or no?]
- Pretty surprising that R&D tax credits work in this context

  [Mylers-Lanahan (2022) a nice example of a finer-grained analysis]

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

2. Taxation
   - R&D tax credits
   - Taxes, migration & innovation

3. Wrap-up

Hall (2019): Tax policy for innovation

If we accept the rationale for governments to encourage innovation, what policies should be used?

- Tax based subsidy is market-oriented response
- Leaves choice and pursuit of R&D programs with private sector (relative to public spending, where government has a larger role in choosing projects)

Bloom-Van Reenen-Williams (2019) on R&D tax incentives

- Tax code automatically treats R&D expenditures by firms more generously than tangible capital investment
  - Because most R&D expenses are current costs – like scientists' wages and lab materials – can be written off in the year in which they occur
  - By contrast, investments in long-lasting assets such as plant, equipment, and buildings must be written off over a multiyear period; reduces tax liabilities only at some point in the future

- But over and above this tax structure advantage, many countries provide additional fiscal incentives for R&D, such as allowing an additional deduction to be made against tax liabilities

Bloom-Van Reenen-Williams (2019) on R&D tax incentives

- Reagan introduced the first R&D tax credit in the US in 1981
  - Costs US federal government ∼$11 billion/year in foregone tax revenue
  - Additional $2 billion a year of lost tax revenue from state-level R&D tax credits (started in Minnesota in 1982)
- 33 of 42 countries examined in a recent OECD report provided some material level of tax generosity toward R&D
  - US federal credit is in the bottom 1/3 of OECD nations in terms of generosity, reducing the cost of US R&D spending by about 5%
  - This is mainly because the US tax credit is based on the incremental <u>increase</u> in a firm's R&D over a historically defined base level, rather than being a subsidy based on the total amount of R&D spending
  - In countries with the most generous provisions (France, Portugal, Chile), corresponding cost reduction is more than 30%
- Frequent policy changes

Hall & Van Reenen (2000)

Many levers within R&D tax policy

- Credit against taxes vs. super-deduction of R&D
- Size of credit or deduction
- Incremental vs. level credit
- Whether or not SMEs are treated more favorably
- Details of expense allowed
- Can unused credits be carried forward to when firm is profitable

Hall & Van Reenen (2000): Table 1

Table 1
The tax treatment of R&D around the world

(1) Country (date enacted)	(2) Definition of R&D for tax credit	(3) R&D depreciation rate	(4) R&D capital depreciation rate	(5) Tax credit rate	(6) Base for incremental tax credit	(7) Carryback (CB) and carryforward (CF)	(8) Credit taxable?	(9) Special treatment for SMEs	(10) Foreign R&D by domestic firms	(11) R&D by foreign films
Canada (1960s)	Frascati, excl. soc sci. marketing, routine testing, etc.	100%	100% or 20% DB, 20% ITC, not buildings	20%	0	3 yr CB, 10 yr CF	yes	40% to R = C$200 K grant if no tax liab., 35% cap eq ITC to $2 M	expense no ITC, etc.	20% only?
France (1983)	Frascati, incl. patent dep. contract R, excl. office expenses & support personnel incl. upgrades, SW, overhead	100% or 5 yr cap.	3-yr SL (not buildings) accelerated	50%	[R(−1) +R(−2)]/2 (real)	5-yr CF, 5-yr for OL, TC refunded	no (recaptured)	yes TC < 50MFF	no accel dep unless cons. no credit	?
Germany	Frascati, incl. Development, improvements, software	100% cap. If acq.	30% DB, 4% SL — bldgs, cash grants?	none	NA	1/5 yr	NA	assistance via cash grant/ITC		25% on royalties
Italy	Frascati, incl. Software	100% or 5 yr cap.	accelerated	none	NA	NA	?	yes, ceiling		
Japan (1966)	Frascati, incl. depreciation of P&E, deferred charges benefit > 1 yr, incl. Software	100% or 5 yr cap.	accelerated 5% TC — bldgs	20% (max at 10% tax liab.)	max R since 1966	5-yr usual but credit limited to 10%	no	6% R instead (cap < Y100 m), 6% for envir./ disease	6% credit for coop with foreign labs	20% on royalties
UK	no special definition; treated as an expense, however	100%	100% if "scientific research"	none	NA	5-yr CF	NA			25% on royalties
US (July 1981)	excl. contract R (for doer), rev. engineering, prod. improv., 35% contract R	100%	3-yr., 15-yr. for bldgs	20%	avg of 84–88 R	3/15 yr	yes	R&D to Sales 3% for startups	not eligible	same as domestic
Australia (July 1985)	Frascati, excl. soc sci, some testing, marketing overhead, software	150%	3-yr SL (not buildings)	none	NA	3/10 yr	NA	ceiling; reduced credit for small R&D programs	up to 10% of project cost incl in 1995?	no special provisions
Austria	Dev. and improv. of valuable inventions	105%	accelerated	none	NA	5-yr CF	NA			
Belgium	incl. Software	100% or 3 yr cap.	3-yr SL 20-yr — bldgs	none	NA	5-yr CF	NA	10–15% addl capital deduction		

Hall & Van Reenen (2000): Table 1

Table 1
The tax treatment of R&D around the world

(1)	(2)	(3)	(4)	(5)	(6)
Country (date enacted)	Definition of R&D for tax credit	R&D deprecia-tion rate	R&D capital depreciation rate	Tax credit rate	Base for incremental tax credit
Canada (1960s)	Frascati, excl. soc sci. marketing, routine testing, etc.	100%	100% or 20% DB, 20% ITC, not buildings	20%	0
France (1983)	Frascati, incl. patent dep. contract R, excl. office expenses & support personnel incl. upgrades, SW, overhead	100% or 5 yr cap.	3-yr SL (not buildings) accelerated	50%	$[R(-1) + R(-2)]/2$ (real)
Germany	Frascati, incl. Develop-ment, improvements, software	100% cap. If acq.	30% DB, 4% SL — bldgs, cash grants?	none	NA
Italy	Frascati, incl. Software	100% or 5 yr cap.	accelerated	none	NA

Hall & Van Reenen (2000): Table 1

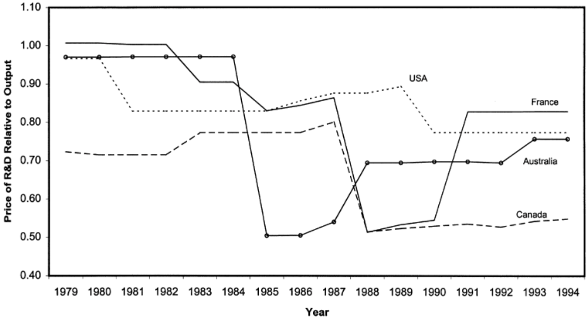


Fig. 1. Tax component of R&D user cost — four most generous countries. Source: Bloom et al. (2000).

Figure: Y-axis plots the price of R&D relative to output to examine the change in tax treatment of R&D over time. Specifically, the authors plot the cost of R&D relative to other expenditures after accounting for tax system generosity. A value of 1 suggests that the tax system is neutral w.r.t R&D.

Bloom-Van Reenen-Williams (2019) on R&D tax incentives

Do R&D tax credits actually work to raise R&D spending?

- Looks like yes
- Narrow approach: does quantity of R&D increase when tax price falls
- Early studies used cross-country panel data or US cross-state data and related changes in R&D to changes in tax rules
- More recent studies: firm-level data exploiting differential effects of tax rules across e.g. firm size thresholds (Dechezleprêtre et al. 2016)
- Taking macro and micro studies together, a reasonable overall conclusion would be that a 10 percent fall in the tax price of R&D results in at least a 10 percent increase in R&D in the long run

Bloom-Van Reenen-Williams (2019) on R&D tax incentives

Potential concerns:

1. Re-labeling of existing expenditures as R&D
   - Chen et al. (2019) on Chinese corporate tax rules
   - Can look at "real" outcomes such as patenting or productivity
2. May not raise aggregate R&D but rather simply cause a relocation toward geographical areas with more generous fiscal incentives and away from geographic areas with less generous incentives
   - Explicit goal of some policies (e.g. Amazon's second HQ)
   - Some evidence of relocation in response to tax incentives (Moretti-Wilson 2017, Akcigit-Baslandze-Stancheva 2016)
   - Overall, evidence suggests some relocation but that aggregate affects of R&D tax credits on R&D and productivity are substantial

Bloom-Van Reenen-Williams (2019) on patent boxes

- First introduced by Ireland in 1970s
- Special tax regimes that apply a lower tax rate to revenues linked to patents relative to other commercial revenues
- By end of 2015, used in 16 OECD countries
- Purport to incentivize R&D, but in practice induce tax competition
  - Firms – particularly multinationals – have considerable leeway in deciding where to book taxable income from intellectual property
  - Little evidence of effect on real location or quantity of R&D
  - Some evidence on patent transfers (Gaessler et al. 2018; Choi 2019)

Hall (2019): R&D tax credits vs. patent boxes

- R&D tax credits do not cover non-R&D innovation, and patent boxes do not cover non-patentable innovation
- R&D tax credits target inputs, while patent boxes target an output
- Patent boxes target the most appropriable part of innovation
- Patent boxes effectively subsidize patent assertion (income of firms that specialize in patent litigation/enforcement is patent income)
- Provide incentive to renew patents that would be abandoned

Dechezleprêtre et al. (2016)

Regression discontinuity design exploiting a 2008 increase in size threshold for Small- and Medium-sized Enterprises (SMEs) in the UK, which allowed more firms to have access to more generous tax regimes

Dechezleprêtre et al. (2016): Institutional Context

- UK: R&D Tax Relief Scheme has existed in UK since 2000, based on total amount of R&D
  - Deduction of R&D from taxable income: 50% for SMEs and 25% for larger firms.
  - SMEs not making any profits can surrender enhanced losses in return for a tax credit, equal to 16% of enhanced R&D
- Pre-2008: UK used European Commission definition of SME
- August 2008: UK SME assets threshold increased from 43m to 86m euros, employment threshold from 249 to 499, and sales threshold from 50m to 100m euros
- Post-2008: More companies qualify as SMEs and, thus, for more generous tax deductions and credits

Dechezleprêtre et al. (2016): Empirical Strategy

- Do we see a change in R&D expenditures as more firms qualify for more generous tax deductions and credits?
- Do we see a change in patenting?
    - Where patents function as a proxy for true innovation

Dechezleprêtre et al. (2016): Empirical strategy

Company assets are used as a predictor of R&D expenditures (fewer missing values than sales, employment variables)

$$(R\&Dexpenditures)_{i,t} = \alpha_{1,t} + \beta_{FS,t}E_{i,2007} + f_{1,t}(z_{i,2007}) + \epsilon_{1i,t} \tag{1}$$

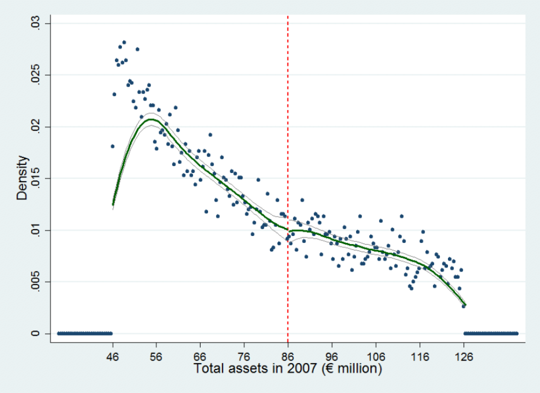
- $t = 2009, 2010, 2011$, following the 2008 policy change
- $\epsilon_{1i,t}$ is an error term
- $rd_{i,t}$ is R&D expenditure of firm i in year t
- $E_{i,2007}= I\{z_{i,2007} \leq \widetilde{z}\}$ is a binary indicator equal to 1 if assets in 2007 ($z_{i,2007}$) are less than or equal to the new SME threshold, $\widetilde{z}$ established in mid-2008
- β_{FS} (FS = First Stage), the main coefficient of interest, estimates the effect of the difference in tax relief schemes between SMEs and large firms on R&D spending

Dechezleprêtre et al. (2016): Empirical strategy

Assumptions:

1. Distribution of all predetermined variables is smooth around threshold
2. Firms cannot manipulate $z_{i,2007}$

No discontinuity around threshold in 2007 suggests (2) holds (McCrary test for discontinuity in distribution of total assets at SME threshold):



Dechezleprêtre et al. (2016): Data & sample

1. British corporate tax returns (from IRS-equivalent HMRC) & R&D Tax Credit dataset
    - Universe of UK firms
    - Firm R&D expenditures as claimed under R&D tax relief scheme
    - Financial years: 2000-01 through 2011-12
    - Observe R&D only if R&D tax relief is claimed (selection resolved by merging with (2))
2. Bureau Van Dijk's FAME dataset
    - Data on accounts for all UK firms
    - Total assets reported for all firms, so SMEs can be identified
3. PATSTAT data
    - Patents from UK firms filed in 60 patent offices globally
    - Linked to firms

Baseline sample of 5,888 firms in 2007 which survive at least until 2008; 3,651 below 2008 SME threshold.

Dechezleprêtre et al. (2016)

Table 3: Checks first RD assumption – predetermined variables are smooth around the threshold

Table 3. Pre-treatment covariate balance tests and placebo tests

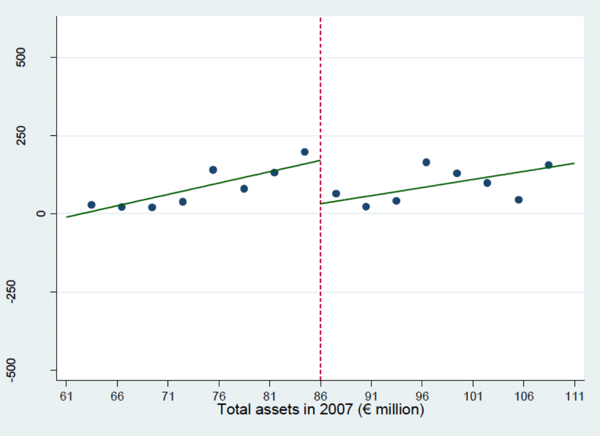
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	**Ln(Sales)**		**Ln(Employment)**		**Ln(Capital)**		**R&D exp. *(£ '000)***	
Year	2006	2007	2006	2007	2006	2007	2009-11 average	
Below asset threshold dummy (in 2007)	-0.124	0.086	0.118	0.151	0.020	-0.007	-16.5	48.6
	(0.162)	(0.161)	(0.135)	(0.131)	(0.112)	(0.103)	(41.7)	(77.1)
SME threshold (€)	86m	86m	86m	86m	86m	86m	71m	101m
Sample bandwidth	61-111m	61-111m	61-111m	61-111m	61-111m	61-111m	46-86m	86-126m
Firms	4,155	4,348	2,973	3,091	4,763	5,079	7,095	3,354

Note: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e. between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold are included. Robust standard errors are in brackets. Columns 1-6 report pre-treatment covariate tests for sales, employment, and capital. Columns (7) and (8) report placebo tests using placebo asset threshold of €71m and €101m.

Dechezleprêtre et al. (2016): Figure 2

From 2009 on, firms just below the SME threshold have significantly higher R&D expenditures than firms just above

Figure: **Discontinuity in average R&D expenditure over 2009-11**



Dechezleprêtre et al. (2016): Figure 3

Firms just below the SME threshold filed significantly more patents

Figure: **Discontinuity in average number of patents over 2009-11**

Dechezleprêtre et al. (2016): Measuring spillovers

Spillover estimate using IV strategy: 0.704 (i.e. with a £1m increase in R&D, spillovers amount to 1.7x direct effect on innovation)

Table 9: Estimating R&D technology spillovers

	(1)	(2)	(3)	(4)	(5)	(6)
Specification	First stage, OLS		Reduced form, OLS	IV		
Dependent variable: (2009-2011 average)	***spilltechRD***	**R&D exp. (*£ million*)**	**All patent count**	**R&D exp. (*£ million*)**	**All patent count**	**All patent count**
spilltechSME (sum tech. distance x dummy)	11.18***	0.011	0.183**			
	(2.16)	(0.093)	(0.079)			
Below asset threshold dummy (in 2007)	0.40	0.159**	0.073**	0.159**	0.066*	
	(1.36)	(0.064)	(0.030)	(0.064)	(0.040)	
spilltechRD (sum tech. distance x £ million)				0.001	0.016**	0.016
				(0.009)	(0.008)	(0.011)
R&D expenditure (*£ million*), 2009-11 average						0.416
						(1.666)
Mean of dependent variable (2006-08)	*25.02*	*0.068*	*0.057*	*0.068*	*0.057*	*0.057*
Firms	8,818	8,818	8,818	8,818	8,818	8,818

Note: Sample of firms with total assets in 2007 between €51m and €121m. *** Significant at 1% level, ** 5% level, * 10% level. Standard errors in brackets are corrected using 1,000 bootstrap replications over firms. Controls include second order polynomials of total assets in 2007, separately for each side of the asset threshold of €86m; $G(z_{j,2007}) = \sum_{j \neq i} \omega_{ij} g(z_{j,2007})$ where $g(z_{j,2007})$'s are second order polynomials of technology-connected firms' total assets in 2007, also separately for each side of the asset threshold (as described in sub-section 5.8); and $techconnect_i = \sum_{j \neq i} \omega_{ij}$ – a measure for firm i's level of connectivity in technology space. In column (5), adjusted first-stage F-statistic is 26.9 and p-value of Anderson-Rubin weak-instrument-robust inference test is 0.02, indicating that the IV estimate is statistically different from zero even in the possible case of weak IV. In column (6), the instrument variable for *spilltechRD* is *spilltechSME* and instrument variable for R&D expenditure is below-asset-threshold dummy.

Dechezleprêtre et al. (2016): Takeaway thoughts

- Substantial improvement over existing literature
- Fantastic data (see also Jacqueline Pless's work)

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

2. Taxation
   - R&D tax credits
   - Taxes, migration & innovation

3. Wrap-up

Moretti & Wilson (2017)

- Workers and firms are mobile across state borders
- Quantify sensitivity of internal migration to taxation
  - Personal income taxes (average tax rate for individual at 99th percentile; 8.1% in CA vs. 0% in 9 states)
  - State corporate income taxes
  - State investment tax credits
- Focus on location of “star” scientists
  - Patent counts in top 5% of distribution

Moretti & Wilson (2017): Data

COMETS Patent Database (1977-2010)

- Name/address for each inventor of a patent
  - No economic incentive to misreport address
  - No legal link between inventor home address and taxation of assignee
- "Star" scientists above 95th percentile in patents in last 10 years
  - 260,000 "star" scientists-year observations
  - Observe location only at time of patenting

Moretti & Wilson (2017): Identification

Checks on specification:

1. Look for pre-trends to tax changes
2. Three additional tests:
    - Changes in corporate taxes should not have an effect on scientists at universities, government agencies and non-profit institutions
    - Non-corporate inventors should respond to changes in personal taxes
    - In states where corporate tax rates are determined by payrolls (instead of sales), response to tax changes should be sharpest

Moretti & Wilson (2017): Scatter-plots

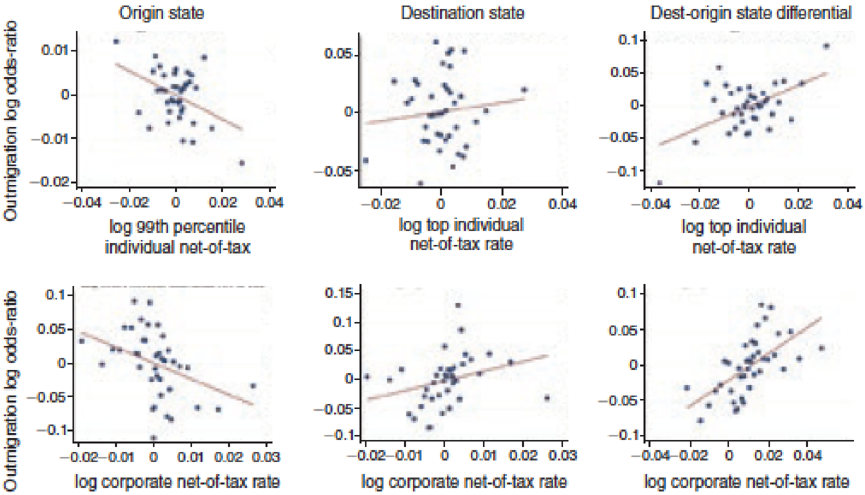


FIGURE 4. OUTMIGRATION VERSUS NET-OF-TAX RATES

Notes: The two left-most figures show outmigration between a given origin-destination pair versus the indicated net-of-tax rate in the origin state. If taxes affect the migration decisions of scientists, one would expect the relationship between origin net-of-tax rate and outmigration to be negative, as higher net-of-tax rates in the origin state (i.e.,

Moretti & Wilson (2017): Event studies

- No evidence of concerning pre-trends
- Significant effect of increasing (decreasing) outmigration in response to increase (decrease) in taxes

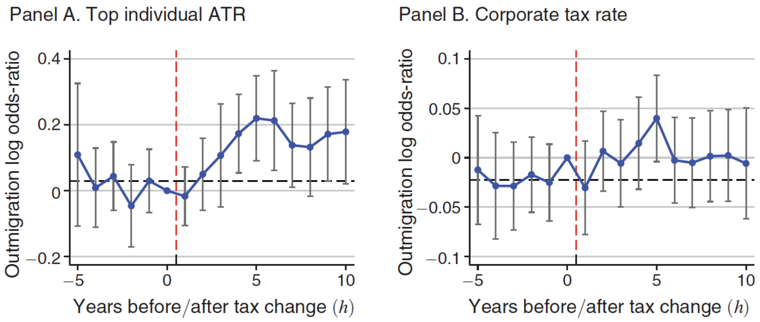


FIGURE 5. OUTMIGRATION BEFORE AND AFTER TAX CHANGE EVENT

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 coef-

Moretti & Wilson (2017): Regressions

Significant effect of net of tax rates on star scientist outmigration (preferred specification column (6)), Table 2a

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATR, 99th perc. (1 − ATR)	2.7805	2.0938	1.8950	1.8046	2.0697	1.8895	0.8027	2.8686
	(0.8332)	(0.6324)	(0.6564)	(0.5696)	(0.6527)	(0.6160)	(0.6499)	(1.0557)
State CIT rate (1 − CIT)	−4.0473	1.9865	1.8802	1.4655	1.1897	1.9286	2.1107	1.9095
	(0.9367)	(0.7036)	(0.7037)	(0.6081)	(0.7320)	(0.6615)	(0.6801)	(1.1785)
State ITC (1 + ITC)	5.6643	1.8245	1.7198	1.6948	1.8006	1.7253	2.2891	1.5642
	(1.4646)	(0.4683)	(0.5498)	(0.5674)	(0.5079)	(0.5825)	(0.7705)	(0.7760)
R&D credit (1 + cred)	3.3101	0.3428	0.3621	−0.0349	0.0734	0.3978	1.0309	−0.4218
	(0.7070)	(0.2021)	(0.2196)	(0.2179)	(0.2117)	(0.2301)	(0.2869)	(0.3335)
Origin, destination state FE	No	Yes	No	No	No	No	No	No
Origin × destination pair FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Origin region × year FE	No	No	No	Yes	No	No	No	No
Destination region × year FE	No	No	No	No	Yes	No	No	No
Origin and destination pair region × year FE	No	No	No	No	No	Yes	No	No
Origin state × year FE	No	No	No	No	No	No	Yes	No
Destination state × year FE	No	No	No	No	No	No	No	Yes

Notes: Each column is from a separate regression. Coefficients are estimates of η or η' from equation (3). Standard errors in parentheses, with three-way clustering by origin-state × year, destination-state × year, and state-pair. All regressions include year fixed effects, and have 15,247 observations.

Moretti & Wilson (2017): Scatter-plots

Table 6—The Effects of Net-of-Tax Rates on Outmigration of Star Scientists: Selected Subsamples

	Baseline (1)	Corporate scientists (2)	Academic and gov. scientists (3)	Individual inventors (4)
Average tax rate	1.8895	2.4348	0.4544	−0.9877
	(0.6160)	(0.6825)	(1.6091)	(0.6359)
State CIT rate	1.9286	1.9803	0.1109	−0.4956
	(0.6615)	(0.7520)	(1.5054)	(0.9013)
State ITC	1.7253	1.8127	−0.7212	1.4812
	(0.5825)	(0.6554)	(0.7883)	(0.6499)
R&D credit	0.3978	0.3843	0.8454	0.8625
	(0.2301)	(0.2518)	(0.3679)	(0.2575)
Observations	15,247	12,564	2,011	4,081
Origin × destination pair FE	Yes	Yes	Yes	Yes
Origin and destination pair region × year FE	Yes	Yes	Yes	Yes

Notes: Each column is from a separate regression. Coefficients are estimates of η or η' from equation (3). Column 1 includes all scientists, and reproduces our baseline estimate from Table 2 column 6. Column 2 includes only scientists working at a for-profit firm. Column 3 includes only scientists working for universities, governments, and nonprofit entities. Column 4 only includes unaffiliated scientists. Standard errors in parentheses, with three-way clustering by origin-state × year, destination-state × year, and state-pair. All regressions include year fixed effects.

Moretti & Wilson (2017): Takeaway Thoughts

- Contributions to tax literature and innovation literature
- Data is...messy
- Thoughtful set of falsification tests

Wrap-up

Open-access course materials teaching the economics of innovation. Together with Kevin Bryan, I co-wrote a chapter for the 2021 *Handbook of Industrial Organization* on innovation policy. As a companion effort to that chapter, Kevin and I created an open-access set of lecture slides aimed at reducing the cost of others teaching this material. We designed these lecture slides to be modular, so that individual lectures could be used in a stand-alone fashion as part of a field course (e.g. a lecture on immigration and innovation that could be used as part of a labor economics course), but the lecture slides also fit together into a coherent framework for any faculty like myself who want to use them for a full course on the economics of innovation. Kevin and I taught an early version of this material in a 2021 Continuing Education course at the American Economic Association (AEA) meetings, and I taught this material in a Stanford PhD course (Economics 244: Market Failures and Public Policy).

- 2021 *Handbook of Industrial Organization* chapter
- Zipped folder with editable TeX and figure files
- Lecture 1: Introduction
- Lecture 2: Science as a non-market incentive
- Lecture 3: Taxes and innovation
- Lecture 4: Intellectual property rights
- Lecture 5: Competition policy
- Lecture 6: Labor market policies
- Lecture 7: Innovation, diffusion, and growth
- Lecture 8: Innovation and inequality
- Lecture 9: Wrap-up
- Syllabus and webcasts from 2021 American Economic Association (AEA) Continuing Education course

Let me also recommend Matt Clancy's New Things Under the Sun.