Innovation Policies: R&D Spillovers

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Introduction

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

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

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

R&D in the production function

- R&D augmented production function:

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

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

- R&D stock one of many “intangible capital stocks”

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

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

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

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

Approaches to estimating R&D spillovers

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

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2. **Exit of "stars"** Azoulay et al (2010) "Superstar extinction"; Waldinger (2012); Bell, Jaravel & Petkova (2018). Usually from a co-author team. But could be from network.
3. **Patent citations:** Henderson, Jaffe, Trajtenberg (1993) focus on geography (agglomeration literature)
   - But many citations don't indicate true knowledge transfer
   - Many knowledge transfers do not need a patent citation
4. **Macro** approaches: e.g. R&D average social cost-benefit ratio (Jones & Summers, 2022); micro/macro (over)

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

Firm Level Micro

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

Own R&D

R&D by all other firms

Economy Level Macro

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

Micro-econometric fixed effects model

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

- If include fixed effects & time dummies, can't identify μ directly
- Comparison of micro vs. macro identifies μ **if** control for all relevant macro variables (NB could also do firm vs. industry level)

Identifying Spillover Effects

- Consider that some units "closer" to others in sense of a distance metric (e.g. geographic)
- **Example:** Technology spillover pool for firm *i* is *TECH* weighted R&D where $TECH_{i,j}$ is "technology space proximity" between firms *i* and *j* (i,j = 1,…,N)
  - $SPILLTECH_{it} = \Sigma_{j,j\neq i} TECH_{i,j} G_{jt}$ where G_{jt} is the R&D stock of firm *j* at time *t*
- $TECH_{i,j}$ is proximity between 2 firms ranging from perfect closeness ($TECH_{i,j}$ =1) to perfectly separate ($TECH_{i,j}$ =0)
- Many candidates for $TECH_{i,j}$: same technology class, same location, past citation patterns, scientist flows, etc.
- **T** is NxN matrix with elements $TECH_{i,j}$ defining network. Analogous to input-output matrix (and can use similar techniques to examine peturbations)

Productivity equation

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

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

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

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

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

Measuring Technology Spillovers

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

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

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

Measuring Product Market Rivalry

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

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

Generic equations

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

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

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

Combine Compustat & USPTO Patents Data

- Compustat data (all listed US firms) to measure R&D, Tobin's Q, Sales, Capital, Labor etc

- Compustat line-of business data to define sales by SIC's
  - Sample covers 623 4-digit SIC classes

- NBER patent data with US patents and citations from 1978

- Final sample of 795 firms over 20 years (unbalanced panel). Accounts for most of US industry R&D

Market Value (Tobin's Q)

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

Identifies magnitude of business stealing

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

Total Factor Productivity (TFP) Equation

Identifies magnitude of knowledge spillover

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

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

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

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

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

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

$= 21\%$

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

$= 58\%$

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

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

σ = prod. function coefficient of SPILLTECH

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

Social returns about three times higher than private.

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

Problems/extensions

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

Conclusions

- *Both* technology spillovers and product market rivalry effects of R&D
- Technology effects dominate, so “too little” R&D overall
  - Consistent with bulk of empirical work
- But what policies can help bridge the gap between social and private returns to R&D….

Backup

Model overview

Two stage game.

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

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

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

Three firms:

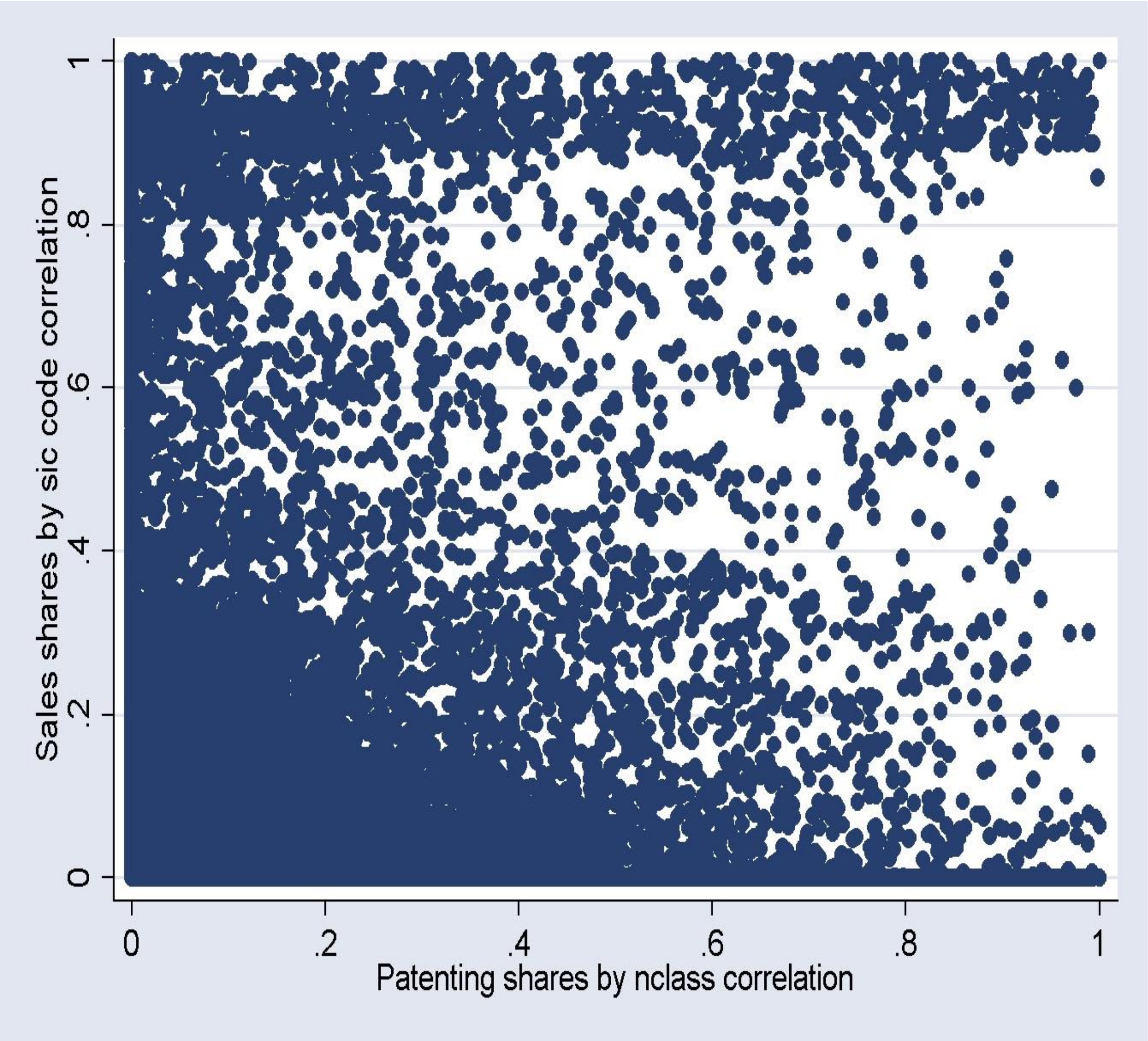
0, τ and *m*.

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

Can generalise to many firms with non-binary interactions

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

Correlation between Technology and Product Market closeness



correlation 0.46

Cite-weighted Patent Count Model

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

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

R&D Equations

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

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

Examples : Computer and chip makers

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

IBM, Apple, Motorola and Intel all close in TECH

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

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

Comparing Empirical Results to Predictions of the Model

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

Alternative Spillover Measures

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

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

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

First Stage Regressions for IV results

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

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

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

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

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

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

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

- Social returns include own productivity impact plus technology spillover effects

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