# Peer Effects and Spillovers

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# Lecture Content

1. Localized (within-firm) peer effects among low skilled workers:
   *Mas and Moretti (2009), Bandiera, Barankay and Rasul (2010)*
2. Peer effects among high-skilled workers:
   Localized "within-firm": *Waldinger (2012)*
   Within research areas: *Borjas and Doran (2012)*, see also Moser, Voena, and Waldinger (2014)
3. Localized spillovers across firms. Why do we see agglomeration?
   *Ellison, Glaeser, and Kerr (2010), Greenstone, Hornbeck, and Moretti (2010).*
4. Looking at knowledge spillovers among firms in more detail; product market rivalry vs. knowledge spillovers:
   *Bloom, Schankerman, and Van Reenen (2012)*

# Peer Effects

- Why could firm-level peers affect productivity?
    1. Peer pressure (other workers have to observe your productivity)
    2. Pro-social behaviour (focal worker needs to know what the others are doing but not vice versa)
    3. Knowledge-spillovers
- Understanding peer effects is important. If there is an externality the market will not optimally allocate workers

# Peer Effects among Low-Skilled Workers

- Mas and Moretti (2009) investigate peer effects among 394 super-market cashiers from 6 stores
- If a cashier works slowly customers can choose another line
- Scanner data allow them to observe individual level productivity: number of items scanned per second
- They relate ten-minute changes in each cashier's productivity to changes in the average permanent productivity of co-workers
- Average permanent productivity of co-workers varies because worker shifts do not perfectly overlap

# Supermarket Cashiers

# Empirical Specification

- They estimate the following regression model:

$$y_{itcs} = \theta_i + \beta\overline{\theta}_{-itcs} + \pi \;\#\; \textit{workers}_{tcs}$$
$$+\tau \;\textit{register location FE}_{ics} + \gamma \;\textit{time * day * store FE}_{tds} + e_{itcs}$$

- where i indexes a worker, t time (10-minute interval), c calender date, s store
- $\theta_i$ measures permanent productivity of worker i
- $\overline{\theta}_{-itcs}$ measures average productivity of co-workers (leave-out mean)
- They take first differences to estimate:

$$\Delta y_{itcs} = \alpha + \beta\Delta\overline{\theta}_{-itcs} + \pi \;\Delta\; \#\; \textit{workers}_{tcs} + e_{itcs}$$

# Estimation Details

- To calculate $\overline{\theta}_{-itcs}$ they need unbiased estimates of all $\theta_i$
- Estimation Steps:
  1. To get these they estimate the following regression model:

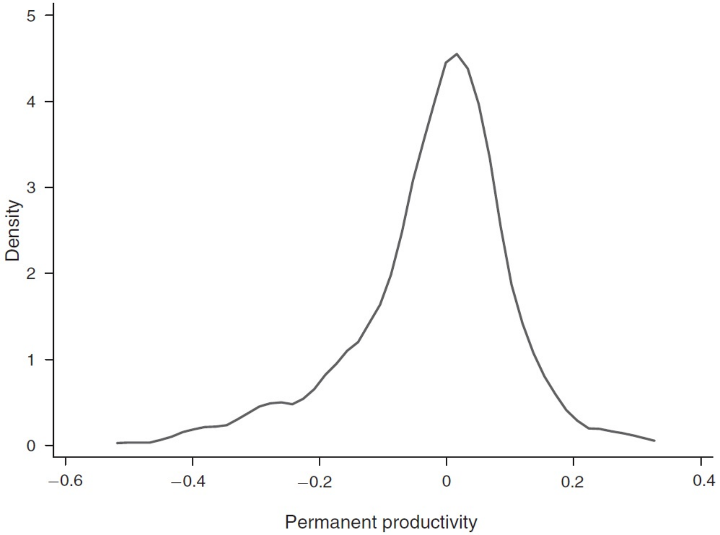
     $y_{itcs} = \theta_i + M'\varphi_{\mathrm{Ci}} + \pi \ \# \ workers_{tcs}$
     $+\tau \ register\ location\ FE_{ics} + \gamma \ time * day * store\ FE_{tds} + e_{itcs}$

     - where $\varphi_{\mathrm{Ci}}$ is a very large set of dummy variables: one for every possible combination of coworker composition
     - For example, one dummy for every instance worker 1 works with workers 2,3,4 and another dummy for every instance 1 works with 2,9, and 12
  2. take the estimated $\theta_i$'s and calculate $\overline{\theta}_{-itcs}$ for every worker and shift
  3. Estimate regression equation (2) (previous slide)

# Descriptive Statistics

| | Store # 1 (1) | Store # 2 (2) | Store # 3 (3) | Store # 4 (4) | Store # 5 (5) | Store # 6 (6) | All stores (7) |
|---|---|---|---|---|---|---|---|
| Share of ten-minute interval that checkers are transacting | 0.67 [0.32] | 0.61 [0.25] | 0.64 [0.28] | 0.69 [0.26] | 0.68 [0.24] | 0.60 [0.26] | 0.65 [0.27] |
| Minutes per customer | 1.4 [1.0] | 1.2 [1.1] | 1.6 [1.1] | 1.3 [1.1] | 1.4 [0.86] | 1.4 [0.91] | 1.4 [1.0] |
| Productivity in ten-minute intervals | 0.18 [0.09] | 0.16 [0.07] | 0.17 [0.08] | 0.16 [0.07] | 0.18 [0.07] | 0.20 [0.08] | 0.17 [0.08] |
| Checkers on duty in ten-minute intervals | 5.8 [1.9] | 5.9 [1.6] | 4.7 [1.7] | 7.7 [2.1] | 8.3 [2.4] | 7.0 [2.3] | 6.9 [2.4] |
| Estimated individual fixed effects | [0.07] | [0.12] | [0.08] | [0.08] | [0.09] | [0.09] | [0.09] |
| Average coworker permanent productivity | [0.04] | [0.06] | [0.04] | [0.03] | [0.04] | [0.04] | [0.04] |
| Change in coworker permanent productivity | [0.02] | [0.03] | [0.03] | [0.02] | [0.02] | [0.02] | [0.02] |

# Permanent Productivity Differs Across Workers

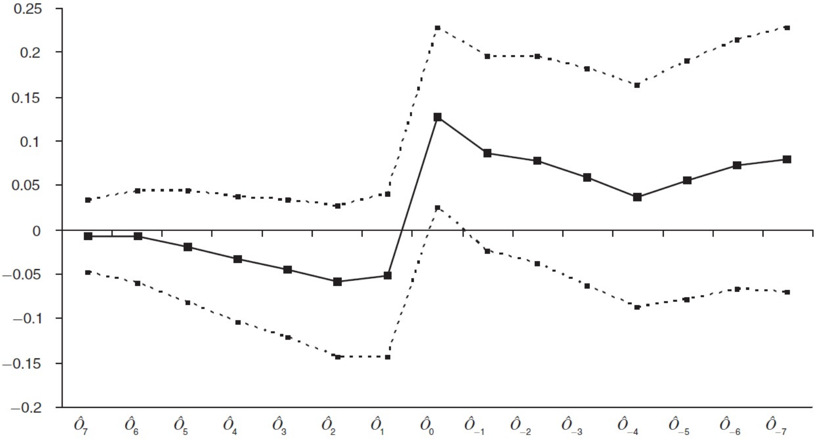


# 10% Increase in Co-Worker Quality Increases Prod. by 1.5%

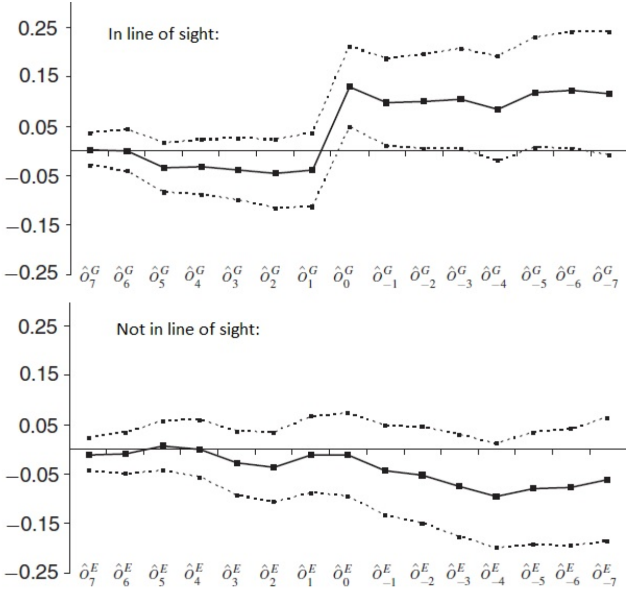
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\Delta$ Average coworker permanent productivity | 0.15<br>(0.02) | 0.15<br>(0.02) | 0.13<br>(0.03) | −0.03<br>(0.03) |
| $\Delta$ Average coworker permanent productivity × positive $\Delta$ indicator | | | | 0.24<br>(0.05) |
| Positive $\Delta$ indicator | | | | 0.004<br>(0.001) |
| Entry of above average productivity worker | | | | |
| Exit of an above average productivity worker | | | | |
| Observations | 1,718,052 | 1,718,052 | 823,274 | 1,718,052 |
| Additional controls? | | Yes | | |
| No net change in number of workers from $t-1$ to $t$? | | | Yes | |

Column (4) indicates that increases in worker quality (as opposed to decreases) have particularly significant effects

# Effect of a High-Productivity Worker Starting at t=0



# Co-Workers Only Affect Workers Who are in Line of Sight



# Localized Spillovers Among Academics

- In Waldinger (2012) I analyze localized peer effects among university scientists.
- Estimating spillovers among academics is challenging:
  1. Selection of scientists
  2. Omitted variables
  3. Measurement error
- I therefore use the dismissal of scientists in Nazi Germany as an exogenous source of variation that affected:
  - the number of peers
  - the quality of peers

# Dismissal of Scientists

TABLE 1
*Number of dismissed scientists across different subjects*

| | Physics | | Chemistry | | Mathematics | |
|---|---|---|---|---|---|---|
| Year of dismissal | Number of dismissals | % of all physicists in 1933 | Number of dismissals | % of all chemists in 1933 | Number of dismissals | % of all mathematicians in 1933 |
| 1933 | 33 | 11·5 | 50 | 10·7 | 35 | 15·6 |
| 1934 | 6 | 2·1 | 11 | 2·4 | 6 | 2·7 |
| 1935 | 4 | 1·4 | 5 | 1·1 | 5 | 2·2 |
| 1936 | 1 | 0·3 | 7 | 1·5 | 1 | 0·4 |
| 1937 | 1 | 0·3 | 3 | 0·6 | 2 | 0·9 |
| 1938 | 1 | 0·3 | 4 | 0·9 | 1 | 0·4 |
| 1939 | 1 | 0·3 | 2 | 0·4 | 1 | 0·4 |
| 1940 | 1 | 0·3 | 0 | 0·0 | 1 | 0·4 |
| 1933–1934 | 39 | 13·6 | 61 | 13·1 | 41 | 18·3 |

# Dismissal Across Different Universities

| University | Physics: Scien-tists 1933 | Dismissed 1933–1934: No. | Dismissed 1933–1934: % | Dismissal induced Δ to department quality |
|---|---|---|---|---|
| Aachen TU | 3 | 0 | 0 | 0 |
| Berlin | 38 | 8 | 21·1 | – |
| Berlin TU | 21 | 6 | 28·6 | – |
| Bonn | 12 | 1 | 8·3 | + |
| Braunschweig TU | 4 | 0 | 0 | 0 |
| Breslau | 12 | 2 | 16·7 | + |
| Breslau TU | 1 | 0 | 0 | 0 |
| Darmstadt TU | 9 | 1 | 11·1 | + |
| Dresden TU | 6 | 1 | 16·7 | – |
| Erlangen | 4 | 0 | 0 | 0 |
| Frankfurt | 12 | 1 | 8·3 | – |
| Freiburg | 8 | 0 | 0 | 0 |
| Giessen | 5 | 1 | 20·0 | – |
| Göttingen | 21 | 9 | 42·9 | – |
| Greifswald | 6 | 0 | 0 | 0 |
| Halle | 4 | 0 | 0 | 0 |
| Hamburg | 11 | 2 | 18·2 | + |
| Heidelberg | 8 | 0 | 0 | 0 |
| Jena | 13 | 1 | 7·7 | + |
| Karlsruhe TU | 8 | 0 | 0 | 0 |

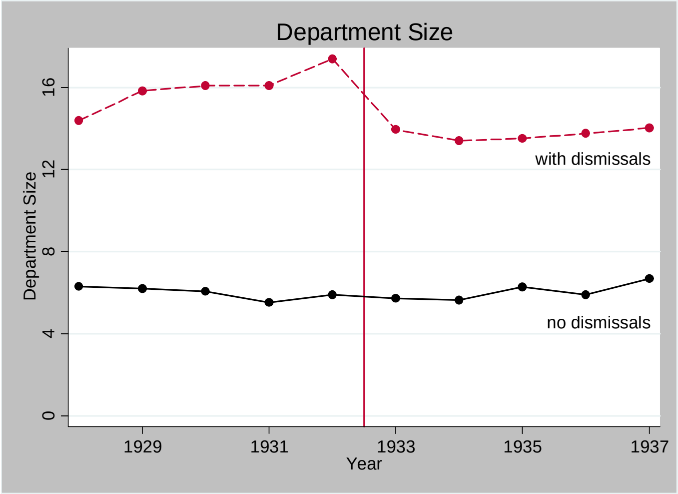
# Dismissal Across Different Universities

| | | | | |
|---|---|---|---|---|
| Kiel | 8 | 1 | 12·5 | – |
| Köln | 8 | 1 | 12·5 | + |
| Königsberg | 8 | 0 | 0 | 0 |
| Leipzig | 11 | 2 | 18·2 | + |
| Marburg | 6 | 0 | 0 | 0 |
| München | 12 | 3 | 25·0 | + |
| München TU | 10 | 1 | 10 | + |
| Münster | 5 | 0 | 0 | 0 |
| Rostock | 3 | 0 | 0 | 0 |
| Stuttgart TU | 5 | 0 | 0 | 0 |
| Tübingen | 2 | 0 | 0 | 0 |
| Würzburg | 3 | 0 | 0 | 0 |

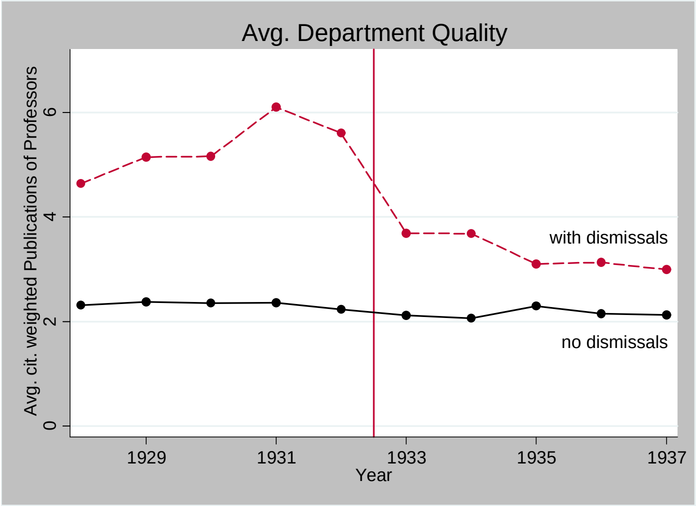
# Summary Statistics Dismissed vs. Stayers

| | Physics | | | |
|---|---|---|---|---|
| | | | Dismissed 1933–1934 | |
| | All | Stayers | No. | % Loss |
| Researchers (beginning of 1933) | 287 | 248 | 39 | 13.6 |
| Researchers (beginning of 1933) | 287 | 248 | 39 | 13.6 |
| No. of chaired professors | 109 | 97 | 12 | 11.0 |
| Average age (1933) | 49·5 | 50·2 | 45·1 | — |
| No. of Nobel Laureates | 15 | 9 | 6 | 40.0 |
| Publications 1925–1932 | | | | |
| Average publications | 0·47 | 0·43 | 0·71 | 20.5 |
| Average publications (citation weighted) | 5·10 | 3·53 | 14·79 | 39.4 |
| % co-authored | 32·0 | 32·1 | 31·4 | — |
| % co-authored with faculty | 11·1 | 10·3 | 14·5 | — |
| (with dismissed) | (3·1) | (2.0) | (8·1) | |
| % co-authored with faculty (same uni) | 3·7 | 2·9 | 7·4 | — |
| (with dismissed) | (1·5) | (0·5) | (5·9) | |

# Effect on Department Size



# Effect on Peer Quality



# Estimating Localized Peer Effects

- OLS model to estimate peer effects among university researchers:

$$\#Pub_{idt} = \beta_1 + \beta_2(Avg.\ Peer\ Quality)_{dt-1} + \beta_3(\#\ of\ Peers)_{dt-1}$$
$$+\beta_4 Age\ Dummies_{idt} + \beta_5 YearFE_t + \beta_6 Dep.FE_d + \beta_7 Indiv.FE_i + \varepsilon_{idt}$$

- Using the dismissals to instrument for the two endogenous variables. The 2 first stages are:
  1. $Avg.Peer\ Quality_{dt} = \gamma_1 + \gamma_2(Dismissal\ induced \Downarrow Peer\ Quality)_{dt}$
     $+\gamma_3(\#\ Dismissed)$
     $+\gamma_4 Age\ Dummies_{idt} + \gamma_5 YearFE_t + \gamma_6 Dep.FE_d + \gamma_7 Indiv.FE_i + \varepsilon_{idt}$
  2. $\#\ of\ Peers_{dt} = \delta_1 + \delta_2(Dismissal\ induced \Downarrow Peer\ Quality)_{dt}$
     $+\delta_3(\#\ Dismissed)$
     $+\delta_4 Age\ Dummies_{idt} + \delta_5 YearFE_t + \delta_6 Dep.FE_d + \delta_7 Indiv.FE_i + \varepsilon_{idt}$

# First Stages

| | (1) | (2) |
|---|---|---|
| | Physics | |
| Dependent variable | Peer quality | Department size |
| Dismissal induced fall in peer quality | −0·644** | −0·147 |
| | (0·099) | (0·130) |
| Number dismissed | 0·017 | −0·570** |
| | (0·098) | (0·117) |
| Age dummies | Yes | Yes |
| Year dummies | Yes | Yes |
| Individual FE | Yes | Yes |
| Observations | 2261 | 2261 |
| No. of researchers | 258 | 258 |
| $R^2$ | 0·59 | 0·90 |
| $F$—Test on instruments | 81·9 | 103·10 |
| Cragg–Donald EV statistic | 12·8 | |

# OLS and IV Results

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| | Physics | | | |
| Dependent variable: | Publi-cations | Publi-cations | Cit. weigt. Pubs. | Cit. weigt. Pubs. |
| Peer quality | 0·004 | −0·054 | −0·048 | −0·488 |
| | (0·005) | (0·035) | (0·075) | (0·496) |
| Department size | −0·007 | 0·035 | −0·177** | 0·016 |
| | (0·004) | (0·034) | (0·062) | (0·553) |
| Age dummies | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Observations | 2261 | 2261 | 2261 | 2261 |
| No. of researchers | 258 | 258 | 258 | 258 |
| $R^2$ | 0·39 | | 0·25 | |
| Cragg–Donald EV Stat. | | 12.79 | | 12.79 |

# Are We Considering the Correct Peer Group? Specialization Level Results

| | (1) | (2) |
|---|---|---|
| | IV | IV |
| | Physics | |
| Dependent variable | Publications | Cit. weighted Publications |
| Specialization peer quality | −0·021 | −0·410 |
| | (0·029) | (0·581) |
| No. of specialization peers | −0·021 | −0·727 |
| | (0·029) | (0·482) |
| Age dummies | Yes | Yes |
| Year dummies | Yes | Yes |
| Individual FE | Yes | Yes |
| Observations | 2257 | 2257 |
| No. of researchers | 256 | 256 |
| Cragg–Donald EV Stat. | 81·80 | 81·80 |

# Do High Quality Peers Matter?

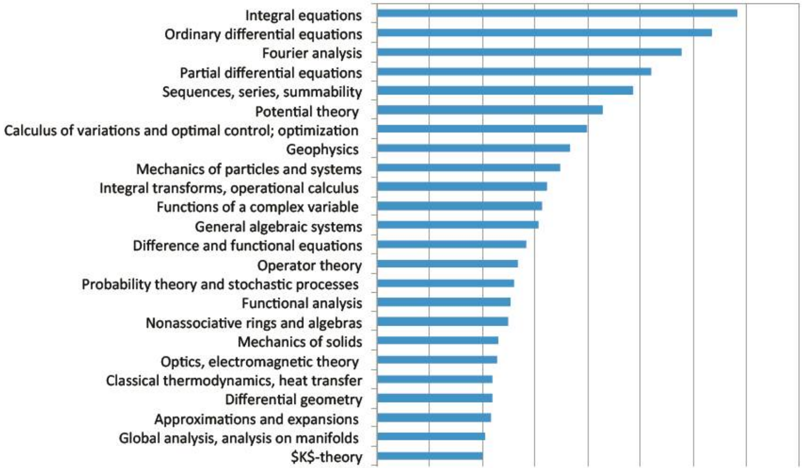
| | IV | IV |
|---|---|---|
| | Physics | |
| Dependent variable | Publi-cations | Cit. weighted publications |
| Number of peers | −0·003 | −0·329 |
| | (0·013) | (0·198) |
| First-stage $F$-statistic | *195·5* | *195·5* |
| Number of top 50th percentile peers | −0·003 | −0·221 |
| | (0·009) | (0·142) |
| First-stage $F$-statistic | *241·1* | *241·1* |
| Number of top 25th percentile peers | −0·015 | −0·637* |
| | (0·016) | (0·239) |
| First-stage $F$-statistic | *423·7* | *423·7* |
| Number of top 10th percentile peers | −0·011 | −0·695 |
| | (0·032) | (0·395) |
| First-stage $F$-Statistic | *29·6* | *29·6* |
| Number of top 5th percentile peers | −0·031 | −1·336* |
| | (0·043) | (0·626) |
| First-stage $F$-statistic | *201·6* | *201·6* |
| Age dummies | Yes | Yes |
| Year dummies | Yes | Yes |
| Individual FE | Yes | Yes |

# Spillovers in Ideas Space Among Academics

- Borjas and Doran (2012) study the arrival of Soviet mathematicians in the United States after the collapse of the Soviet union.
- Their main regressions do not use geographic variation (which would be endogenous) but variation at the level of 63 research fields.
- On average Soviet and US mathematicians specialized in different fields of mathematics.
- US mathematicians who worked in more "Soviet" fields therefore were more affected by the potential influx of Soviet mathematicians after the collapse than US mathematicians who worked in different fields.
- Note: they basically look at the reduced form: How are US mathematicians affects by a *potential* influx of Soviet mathematicians

# US Versus Soviet Mathematics

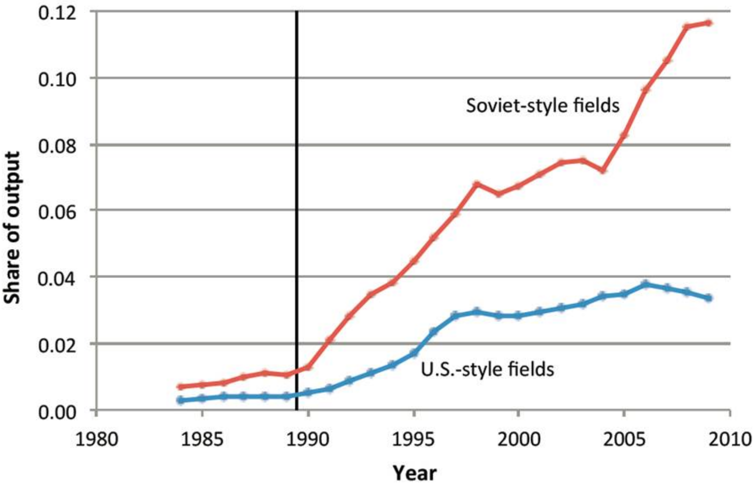
**Ratio of Soviet papers to American papers, by field, 1984-89**



# Soviet Emigres to the US Are High Quality Mathematicians

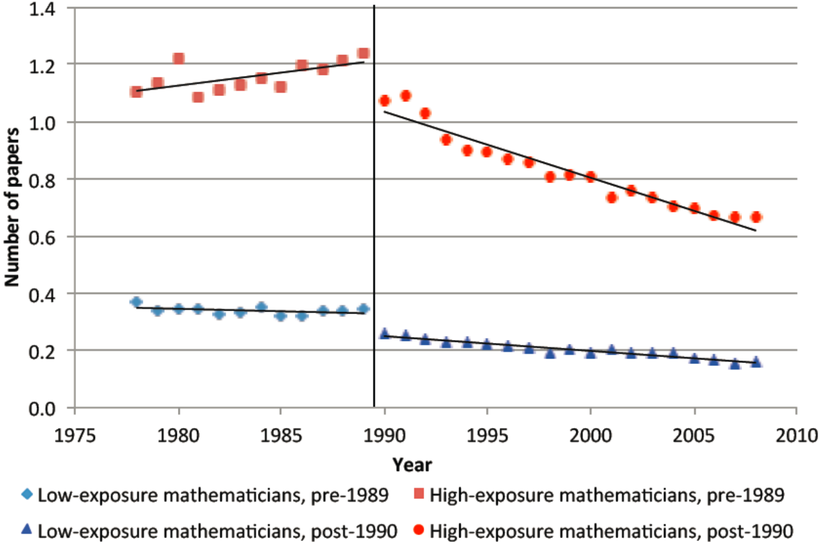
| Variable: | Group of mathematicians: Americans | Soviet émigrés to US | Soviet émigrés elsewhere | All other Soviets |
|---|---|---|---|---|
| Number of mathematicians | 29392 | 336 | 715 | 11173 |
| Papers published, 1978-1991 | | | | |
| Mean papers per mathematician | 6.7 | 17.8 | 14.6 | 8.1 |
| Median papers | 3.0 | 13.0 | 10.0 | 5.0 |
| Maximum number of papers | 232.0 | 104.0 | 152.0 | 180.0 |
| Papers published, 1992-2008 | | | | |
| Mean papers per mathematician | 6.8 | 27.2 | 28.8 | 7.6 |
| Median papers | 1.0 | 21.0 | 22.0 | 1.0 |
| Maximum number of papers | 768.0 | 128.0 | 317.0 | 311.0 |

# Share of Output Published By Soviet Emigres in the US




Note: Emigres are mathematicians who were at some point affiliated in the Soviet Union and are later observed with a US affiliation

# Productivity of US Mathematicians Working in Soviet vs. Other Fields



# Estimating the Effect of the Soviet Influx

- They estimate the effect of potential Soviet immigration on the productivity of American mathematicians as follows:

  $$y_{it} = IndvidualFE_i + YearFE_t + X_i(t) + \theta(Post92 * Index_i) + \varepsilon_i$$

  - Index measures the overlap of an individual's research fields with the pre-1992 research fields of all Soviet mathematicians (independently of whether they migrated to the US)
  - Standard errors are clustered at the individual level

# Main Results: The Effect of Emigres on the Productivity of US Mathematicians

| | Mathematicians predominantly in U.S. | | Mathematicians always in U.S. | |
|---|---|---|---|---|
| Specification/regressor | Number of papers | Number of citations | Number of papers | Number of Citations |
| A. Author-year regressions | | | | |
| Correlation coefficient | -0.133 | -19.577 | -0.116 | -16.298 |
| | (0.036) | (1.576) | (0.034) | (1.540) |
| Index of intensity | -0.047 | -14.845 | -0.042 | -12.293 |
| | (0.028) | (1.293) | (0.027) | (1.261) |
| Index of similarity | -1.523 | -69.155 | -1.419 | -58.494 |
| | (0.113) | (4.645) | (0.108) | (4.655) |

# Does the Inflow Lead to Exit of Exposed Mathematicians?

**Impact of Soviet supply shock on probability of "retirement" from publishing (Cox proportional hazard models)**

| | Measure of overlap | | |
|---|---|---|---|
| Sample | Correlation coefficient | Index of intensity | Index of similarity |
| All pre-existing mathematicians | 0.410 | 0.230 | 5.571 |
| | (0.090) | (0.084) | (0.298) |
| Less than 10 years of experience | 1.099 | 0.653 | 10.340 |
| | (0.229) | (0.176) | (0.962) |
| 10-19 years of experience | 0.166 | 0.299 | 0.232 |
| | (0.192) | (0.175) | (0.645) |
| At least 20 years of experience | 0.099 | 0.101 | 1.433 |
| | (0.181) | (0.183) | (0.491) |

# Do Exposed Scientists Move To a Lower Ranked University?

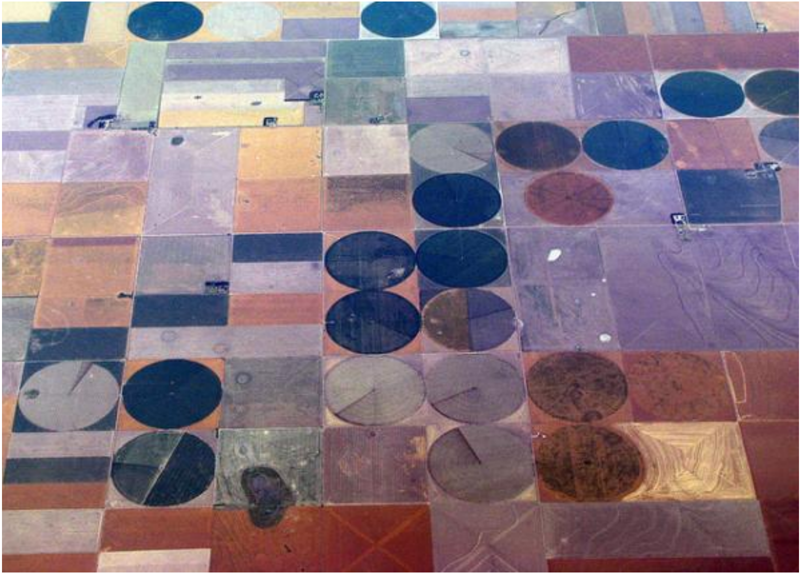
| | Measure of overlap/Dependent variable | | | | | |
|---|---|---|---|---|---|---|
| | Correlation coefficient | | Index of intensity | | Index of similarity | |
| Sample/regressor | Moved | Δ Quality | Moved | Δ Quality | Moved | Δ Quality |
| A. All mathematicians | | | | | | |
| Institution hired émigré | 0.046 | -2.382 | 0.046 | -2.383 | 0.047 | -2.385 |
| | (0.013) | (.122) | (0.013) | (.122) | (0.013) | (.122) |
| Overlap index | 0.172 | -0.415 | 0.158 | -0.282 | 0.321 | -1.329 |
| | (0.025) | (0.308) | (0.022) | (0.252) | (0.066) | (.997) |

# Summary Peer Effects in the Workplace

- The well-identfied literature that estimates peer effects within firms usually finds:
  - positive effects for low-skilled workers
  - 0 or very small effects for high-skilled workers
- See also recent paper by Cornelissen, Dustmann, and Schoenberg (2015) who confirm these findings
- What could explain this?
  - Is the effect of peer pressure less important for high-skilled individuals?
  - Are localized knowledge spillovers less important than economists think?
- Note: 0 effects for high-skilled workers does not mean that hiring them makes no difference!
  - They affect colleagues in joint production (e.g. publishing or patenting, see Azoulay, Zivin, and Wang 2010, Jaravel, Petkova, and Bell, 2015, Waldinger, 2016b)
  - They affect hiring of other high-quality workers (e.g. Waldinger, 2016a)
  - They affect training of students (e.g. Waldinger, 2010)

# Why do we observe something like the Silicon Valley?

# And on the other hand something like this?



# What Causes Industry Agglomeration?

- A large literature in urban economics analyzes industry agglomeration. Why do we observe agglomeration of industries?
  1. Random chance
  2. Natural advantages
  3. Industry-specific spillovers
- Marshall (1890) highlighted the importance of localized industry spillovers because industries share:
  1. goods: inputs may be cheaper if other firms in an area also buy them.
  2. people: thicker labor markets lead to more productive worker-firm matches; insurance effect for workers and firms (should not affect productivity)
  3. ideas (*"the mysteries of the trade become no mystery, but are, as it were, in the air."*)

# Ellison, Glaeser, and Kerr (2010)

- EGK (2010) use coagglomeration patterns of different US manufacturing industries to test for the relative importance of these factors for industry agglomeration.
- They measure coagglomeration of industry $i$ with industry $j$ using the Ellison and Glaeser (1997) index:

$$\gamma_{ij}^{c} = \frac{\sum_{m=1}^{M}(s_{mi}-x_m)(s_{mj}-x_m)}{1-\sum_{m=1}^{M} x_m^2}$$

  - $m$ indexes geographical areas
  - $s_{mi}$ = share of industry $i$'s employment contained in area $m$.
  - $x_m$ = aggregate size of area $m$ (measured as mean employment share in the region across manufacturing industries)

- They also use a second (more complicated) agglomeration metric developed by Duranton and Overman (2005).

# Highest Coagglomeration Industries

| Rank | Industry 1 | Industry 2 | Coagglomeration |
|---|---|---|---|
| *Panel A. EG index using 1987 state total employments* | | | |
| 1 | Broadwoven mills, cotton (221) | Yarn and thread mills (228) | 0.207 |
| 2 | Knitting mills (225) | Yarn and thread mills (228) | 0.187 |
| 3 | Broadwoven mills, fiber (222) | Textile finishing (226) | 0.178 |
| 4 | Broadwoven mills, cotton (221) | Broadwoven mills, fiber (222) | 0.171 |
| 5 | Broadwoven mills, fiber (222) | Yarn and thread mills (228) | 0.164 |
| 6 | Handbags (317) | Photographic equipment (386) | 0.155 |
| 7 | Broadwoven mills, wool (223) | Carpets and rugs (227) | 0.149 |
| 8 | Carpets and rugs (227) | Yarn and thread mills (228) | 0.142 |
| 9 | Photographic equipment (386) | Jewelry, silverware, plated ware (391) | 0.139 |
| 10 | Textile finishing (226) | Yarn and thread mills (228) | 0.138 |
| 11 | Broadwoven mills, cotton (221) | Textile finishing (226) | 0.137 |
| 12 | Broadwoven mills, cotton (221) | Carpets and rugs (227) | 0.137 |
| 13 | Broadwoven mills, cotton (221) | Knitting mills (225) | 0.136 |
| 14 | Carpets and rugs (227) | Pulp mills (261) | 0.110 |
| 15 | Jewelry, silverware, plated ware (391) | Costume jewelry and notions (396) | 0.107 |

# Estimation Strategy

- Baseline regression:

$$Coagg_{ij} = \alpha + \beta_{NA} Coagg_{ij}^{NA} + \beta_L LaborCorrelation_{ij}$$
$$+\beta_{IO} InputOutput_{ij} + \beta_T Tech_{ij} + \varepsilon_{ij}$$

- $Coagg_{ij}$ measures pairwise coagglomeration between industries $i$ and $j$.
- $Coagg_{ij}^{NA}$ = predicted coagglomeration of industries $i$ and $j$ due to natural advantages.
- $LaborCorrelation_{ij}$ = correlation of shares of people in certain occupations across industries $i$ and $j$.
- $InputOutput_{ij} = \max\{Input_{ij}, Output_{ji}\}$ where $Input_{ij} = \max\{Input_{i \leftarrow j}, Input_{j \leftarrow i}\}$; $Output_{ij} = \max\{Output_{i \leftarrow j}, Output_{j \leftarrow i}\}$
- $Tech_{ij}$ = Scherer's (1984) technology matrix that captures how R&D activity in industry $i$ benefit industry $j$.

# OLS Results

| | EG coaggl. index with state total emp. | | | |
|---|---|---|---|---|
| | Base estimation | Exclude natural advantages | Separate input & output | Exclude pairs in same SIC2 |
| | (1) | (2) | (3) | (4) |
| Natural advantages [DV specific] | 0.163 (0.017) | | 0.162 (0.017) | 0.172 (0.016) |
| Labor correlation | 0.118 (0.011) | 0.146 (0.012) | 0.114 (0.011) | 0.085 (0.012) |
| Input-output | 0.146 (0.032) | 0.149 (0.032) | | 0.110 (0.022) |
| Input | | | 0.106 (0.029) | |
| Output | | | 0.093 (0.039) | |
| Technology flows Scherer R&D | 0.096 (0.035) | 0.112 (0.035) | 0.079 (0.035) | 0.046 (0.019) |
| $R^2$ | 0.103 | 0.077 | 0.110 | 0.059 |
| Observations | 7,381 | 7,381 | 7,381 | 7,000 |

# Potential Problems of OLS Results

- Reverse causality: coagglomeration may cause more labor, input-output, and ideas flows and not vice-versa.
- Omitted variables: unobserved factors that lead to coagglomeration and are correlated with some of the Marshallian factors (e.g. co-located universities).
  $\Rightarrow$ They use an IV strategy to address these concerns.
- Instruments:
  1. input-output and labour patterns of UK industries
  2. input-output and labor patterns in US areas where the other industry is rare.

# IV Results

| | EG coaggl. index with state total emp. | | |
|---|---|---|---|
| | Base OLS | UK IV | US spatial IV |
| | (1) | (2) | (3) |
| Natural advantages | 0.173 | 0.173 | 0.171 |
| [DV specific] | (0.016) | (0.019) | (0.016) |
| Labor correlation | 0.083 | 0.079 | 0.091 |
| | (0.012) | (0.060) | (0.023) |
| Input-output | 0.122 | 0.191 | 0.185 |
| | (0.023) | (0.048) | (0.036) |
| Observations | 7,000 | 7,000 | 7,000 |

# Summary of Results

- Natural advantages are important drivers of agglomeration.
- Sharing goods and labour also seems important (both OLS and IV)
- Sharing ideas is significant in the OLS but they do not address endogeneity.

# Identifying Agglomeration Spillovers - Evidence from Large Plant Openings

- Greenstone, Hornbeck, and Moretti (2010) analyze agglomeration spillovers using large plant openings.
- They compare counties that received a new large plant to counties that were considered as alternative site but were not chosen.
- Example: BMW plant in Greenville-Spartanburg, South Carolina:

# Summary Statistics Million Dollar Plants

| | (1) |
|---|---|
| Sample MDP openings:[a] | |
| Across all industries | 47 |
| Within same two-digit SIC | 16 |
| Across all industries: | |
| Number of loser counties per winner county: | |
| 1 | 31 |
| 2+ | 16 |
| Reported year − matched year:[b] | |
| −2 to −1 | 20 |
| 0 | 15 |
| 1 to 3 | 12 |
| Reported year of MDP location: | |
| 1981–85 | 11 |
| 1986–89 | 18 |
| 1990–93 | 18 |
| MDP characteristics, 5 years after opening:[c] | |
| Output ($1,000s) | 452,801 |
| | (901,690) |
| Output, relative to county output 1 year prior | .086 |
| | (.109) |
| Hours of labor (1,000s) | 2,986 |
| | (6,789) |

# Summary Statistics Winning vs. Losing Counties

| | All Plants | | | | |
|---|---|---|---|---|---|
| | Winning Counties (1) | Losing Counties (2) | All U.S. Counties (3) | *t*-Statistic (Col. 1 − Col. 2) (4) | *t*-Statistic (Col. 1 − Col. 3) (5) |
| | | | | | A. County Ch |
| No. of counties | 47 | 73 | | | |
| Total per capita earnings ($) | 17,418 | 20,628 | 11,259 | **−2.05** | **5.79** |
| % change, over last 6 years | .074 | .096 | .037 | −.81 | 1.67 |
| Population | 322,745 | 447,876 | 82,381 | −1.61 | **4.33** |
| % change, over last 6 years | .102 | .051 | .036 | **2.06** | **3.22** |
| Employment-population ratio | .535 | .579 | .461 | −1.41 | **3.49** |
| Change, over last 6 years | .041 | .047 | .023 | −.68 | **2.54** |
| Manufacturing labor share | .314 | .251 | .252 | **2.35** | **3.12** |
| Change, over last 6 years | −.014 | −.031 | −.008 | 1.52 | −.64 |
| | | | | | B. Plant Cha |
| No. of sample plants | 18.8 | 25.6 | 7.98 | −1.35 | **3.02** |
| Output ($1,000s) | 190,039 | 181,454 | 123,187 | .25 | **2.14** |
| % change, over last 6 years | .082 | .082 | .118 | .01 | −.97 |
| Hours of labor (1,000s) | 1,508 | 1,168 | 877 | 1.52 | **2.43** |
| % change, over last 6 years | .122 | .081 | .115 | .81 | .14 |

# Estimation Equations

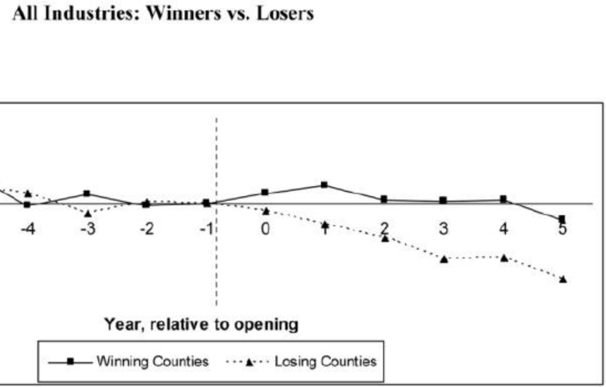
1. Mean shifts:

$$\ln(Y_{pijt}) = \beta_1 \ln(L_{pijt}) + \beta_2 \ln(K^B_{pijt}) + \beta_3 \ln(K^E_{pijt}) + \beta_4 \ln(M_{pijt})$$
$$+\delta_1 WinnerCounty_{pj}$$
$$+\kappa_1 Post_{jt}$$
$$+\theta_1 WinnerCounty_{pj} * Post_{jt}$$
$$+PlantFE_p + Industry * TimeFE_{it} + CaseFE_j + \varepsilon_{pijt}$$

2. Allow for plant specific trends and trend breaks:

$$\ln(Y_{pijt}) = \beta_1 \ln(L_{pijt}) + \beta_2 \ln(K^B_{pijt}) + \beta_3 \ln(K^E_{pijt}) + \beta_4 \ln(M_{pijt})$$
$$+\delta_1 WinnerCounty_{pj} + \psi Trend_{jt} + \Omega[Trend_{jt} \times Winner_{pj}]$$
$$+\kappa_1 Post_{jt} + \gamma[Trend_{jt} \times Post_{jt}]$$
$$+\theta_1 WinnerCounty_{pj} * Post_{jt}$$
$$+\theta_2[Trend_{jt} \times WinnerCounty_{pj} \times Post_{jt}]$$
$$+PlantFE_p + Industry * TimeFE_{it} + CaseFE_j + \varepsilon_{pijt}$$

# Graphical Evidence: Incumbent Firms' Productivity



# Regression Results: Effect on Incumbents' TFP

| | All Counties: MDP Winners − MDP Losers | | MDP Counties: MDP Winners − MDP Losers | | All Counties: Random Winners |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | A. Model 1 | | | | |
| Mean shift | .0442* | .0435* | .0524** | .0477** | − 0.0496*** |
| | (.0233) | (.0235) | (.0225) | (.0231) | (.0174) |
| | | | | [$170 m] | |
| $R^2$ | .9811 | .9812 | .9812 | .9860 | ~0.98 |
| Observations (plant by year) | 418,064 | 418,064 | 50,842 | 28,732 | ~400,000 |
| | B. Model 2 | | | | |
| Effect after 5 years | .1301** | .1324** | .1355*** | .1203** | −.0296 |
| | (.0533) | (.0529) | (.0477) | (.0517) | (.0434) |
| | | | | [$429 m] | |
| Level change | .0277 | .0251 | .0255 | .0290 | .0073 |
| | (.0241) | (.0221) | (.0186) | (.0210) | (.0223) |
| Trend break | .0171* | .0179** | .0183** | .0152* | − 0.0062 |
| | (.0091) | (.0088) | (.0078) | (.0079) | (.0063) |
| Pre-trend | −.0057 | −.0058 | −.0048 | −.0044 | −.0048 |
| | (.0046) | (.0046) | (.0046) | (.0044) | (.0040) |
| $R^2$ | .9811 | .9812 | .9813 | .9861 | ~.98 |
| Observations (plant by year) | 418,064 | 418,064 | 50,842 | 28,732 | ~400,000 |
| Plant and industry by year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Case fixed effects | No | Yes | Yes | Yes | NA |
| Years included | All | All | All | $-7 \leq \tau \leq 5$ | All |

# Regression Results: Effect on Other Outcomes

| | Output (1) | Worker Hours (2) | Machinery Capital (3) | Building Capital (4) | Materials (5) |
|---|---|---|---|---|---|
| Model 1: mean shift | .1200*** | .0789** | .0401 | .1327* | .0911*** |
| | (.0354) | (.0357) | (.0348) | (.0691) | (.0302) |
| Model 2: after 5 years | .0826* | .0562 | −.0089 | −.0077 | .0509 |
| | (.0478) | (.0469) | (.0300) | (.0375) | (.0541) |

# Where Do The TFP Increases Come From? - Looking at Interactions

- To understand how new firms affect TFP of incumbent firms they interact their Winner*Post coefficient with measures for the Marshallian factors.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| CPS worker transitions | .0701*** | | | | | | .0374 |
| | (.0237) | | | | | | (.0260) |
| Citation pattern | | .0545*** | | | | | .0256 |
| | | (.0192) | | | | | (.0208) |
| Technology input | | | .0320* | | | | .0501 |
| | | | (.0173) | | | | (.0421) |
| Technology output | | | | .0596*** | | | .0004 |
| | | | | (.0216) | | | (.0434) |
| Manufacturing input | | | | | .0060 | | −.0473 |
| | | | | | (.0123) | | (.0289) |
| Manufacturing output | | | | | | .0150 | −.0145 |
| | | | | | | (.0196) | (.0230) |
| $R^2$ | .9852 | .9852 | .9851 | .9852 | .9851 | .9852 | .9853 |
| Observations | 23,397 | 23,397 | 23,397 | 23,397 | 23,397 | 23,397 | 23,397 |

# Where Do The TFP Increases Come From? - Looking at Interactions

- Spillovers seem to occur between firms that share workers and ideas (measured by patent citations or R&D flows).
- Input and output flows between firms seem to be less important (this is quite different from the Ellison, Glaeser, and Kerr results).
- Broad conclusion from this literature: spillovers and localized knowledge flows are quite important for firms.

# Do Firms Necessarily Benefit From Other Firms' R&D?

## Knowledge Spillovers vs. Product Market Rivalry

- Many previous papers have found that knowledge spillovers seem to be important among firms.
- Does R&D spending of other firms necessarily benefit similar firms?
- Bloom, Schankerman, and Van Reenen (2012) investigate two potentially opposite effects of R&D:
  1. Technology spillovers
  2. Product market rivalry
- Their main analysis does not consider spillovers in geographic space. Instead, they exploit that firms differ in how much they overlap according to their
  1. Technology space (i.e. patents)
  2. Product market space (sales activity across 4-digit industries)

# Summary of Model Predictions

| (1) | (2) | (3) | (7) | (8) | (9) |
|---|---|---|---|---|---|
| | | | Technology Spillovers | | |
| Equation | Comparative static prediction | Empirical counterpart | No Product Market Rivalry | Strategic Complements | Strategic Substitutes |
| Market value | $\partial V_0/\partial r_\tau$ | Market value with SPILLTECH | Positive | Positive | Positive |
| Market value | $\partial V_0/\partial r_m$ | Market value with SPILLSIC | Zero | Negative | Negative |
| Patents (or productivity) | $\partial k_0/\partial r_\tau$ | Patents with SPILLTECH | Positive | Positive | Positive |
| Patents (or productivity) | $\partial k_0/\partial r_m$ | Patents with SPILLSIC | Zero | Zero | Zero |
| R&D | $\partial r_0/\partial r_\tau$ | R&D with SPILLTECH | Ambiguous | Ambiguous | Ambiguous |
| R&D | $\partial r_0/\partial r_m$ | R&D with SPILLSIC | Zero | Positive | Negative |

$\partial r_\tau$ =changes in R&D expenditure by firms sharing technology space
$\partial r_m$ =changes in R&D expenditure by firms sharing product space

# Measuring Technology and Product Market Spillovers

- Following Jaffe (1986) they measure technology spillovers flowing to firm $i$ in year $t$ as:

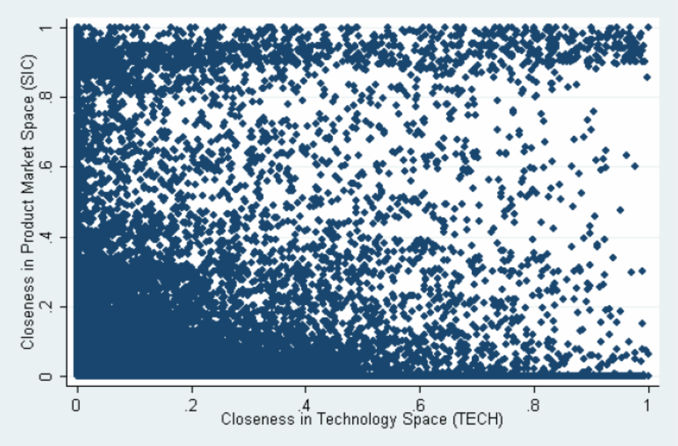
$$SPILLTECH_{it} = \sum_{j \neq i} TECH_{ij} G_{jt}$$

- Where:
  - $TECH_{ij}$ measures the uncentered correlation between the patenting activity of firm $i$ and firm $j$ ranging from 0 to 1. $TECH_{ij} = \frac{(T_i T_j')}{(T_i T_i)^{1/2} (T_j T_j)^{1/2}}$ where $T_i = (T_{i1}, T_{i2}, ..., T_{i426})$ measures share of patenting activity of firm $i$ in 426 USPTO technology classes.
  - $G_{jt}$ is firm $j$'s stock of R&D
- Similarly product market proximity is defined using the overlap of sales that are classified within 597 industries (firms sell on avg. in 5.2 industries):

$$SPILLSIC_{it} = \sum_{j \neq i} SIC_{ij} G_{jt}$$

# Within Firm Variation in Spillover Measures

- To be able to separately identify the effects of technology spillovers and product market rivalry they need within-firm variation in the two measures:



# Examples

| | Correlation | *IBM* | *Apple* | *Motorola* | *Intel* |
|---|---|---|---|---|---|
| *IBM* | SIC Compustat | 1 | 0.65 | 0.01 | 0.01 |
| | SIC BVD | 1 | 0.55 | 0.02 | 0.07 |
| | *TECH* | *1* | *0.64* | *0.46* | *0.76* |
| *Apple* | SIC Compustat | | 1 | 0.02 | 0.00 |
| | SIC BVD | | 1 | 0.01 | 0.03 |
| | *TECH* | | *1* | *0.17* | *0.47* |
| *Motorola* | SIC Compustat | | | 1 | 0.34 |
| | SIC BVD | | | 1 | 0.47 |
| | *TECH* | | | *1* | *0.46* |
| *Intel* | SIC Compustat | | | | 1 |
| | SIC BVD | | | | 1 |
| | *TECH* | | | | *1* |

# Addressing the Endogeneity of R&D

- They are interested in estimating (for different outcomes):

$$\ln Outcome_{it} = \phi(Own\ R\&D\ Stock\,/\,Non - R\&D\ assets)_{it-1}$$
$$+\gamma_2 \ln SPILLTECH_{it-1} + \gamma_3 \ln SPILLSIC_{it-1} + \beta_4 X_{it} + u_{it}$$

- They model $u_{it} = firmFE_i + YearFE_t + \nu_{it}$
- R&D expenditure (and therefore *SPILLTECH* and *SPILLSIC*) is likely endogenous if new technological opportunities lead all firms in an area to invest more in R&D.
- They address this concern by instrumenting for R&D expenditures using tax induced changes to the user cost of R&D. User costs are different because
  - different states have different levels of R&D tax credits and corporation tax
  - Federal rules affect different firms differently

# Results: Tobin's Q

| | (1) | (2) | (5) | (6) |
|---|---|---|---|---|
| Specification: | OLS | OLS | OLS | IV 2nd stage |
| Distance measure: | Jaffe | Jaffe | Mahalanobis | Jaffe |
| $Ln(SPILLTECH_{t-1})$ | -0.064 | 0.381 | 0.903 | 1.079 |
| | (0.013) | (0.113) | (0.105) | (0.192) |
| $Ln(SPILLSIC_{t-1})$ | 0.053 | -0.083 | -0.136 | -0.235 |
| | (0.007) | (0.032) | (0.031) | (0.109) |
| $Ln(R\&D\ Stock/Capital\ Stock)_{t-1}$ | 0.859 | 0.806 | 0.835 | 0.831 |
| | (0.154) | (0.197) | (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 |
| No. Observations | 9,944 | 9,944 | 9,944 | 9,944 |

# Results: Patenting

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

# The Role of Geography

- To investigate whether geography matters for knowledge spillovers and product market competition they construct proximity variables that further consider geography (50 U.S. states plus locations abroad).
- They then reestimate their model by including both measures.

# The Role of Geography

| Dependent Variable: | (1) Tobin's Q | (2) Cite Weighted Patents | (3) Real Sales | (4) R&D/Sales |
|---|---|---|---|---|
| C. Geographically Based Measure of Spillovers | | | | |
| $\ln(SPILLTECH^{\text{GEOG}})_{t-1}$ | 1.314 | 0.037 | 0.117 | |
| | (0.176) | (0.053) | (0.066) | |
| $\ln(SPILLTECH)_{t-1}$ | −0.559 | 0.391 | 0.101 | |
| | (0.163) | (0.069) | (0.060) | |
| $\ln(SPILLSIC^{\text{GEOG}})_{t-1}$ | 0.110 | | | −0.041 |
| | (0.078) | | | (0.094) |
| $\ln(SPILLSIC)_{t-1}$ | −0.175 | | | 0.135 |
| | (0.062) | | | (0.086) |
| Observations | 9,944 | 9,122 | 10,018 | 8,579 |

# Summary of Results

- They give a detailed summary of their results and how they conform with the model predictions (they do very well!).
- Very nice link of theory and empirics.
- An important insight if we think about spillovers: competition effects may affect the interpretation of estimated effects (depending on the context of the paper, of course).
- Geograpy seems to matter for Tobin's Q and sales but not not for patents (where we think that knowledge spillovers are particularly important).

# Bringing All Results Together

- The well-identfied literature that estimates localized spillovers *within* firms usually finds:
  - positive effects for low-skilled workers
  - 0 or very small effects for high-skilled workers
- The literature that analyzes localized spillovers *across* firms usually finds:
  - positive effects but they are driven by different factors
- What could drive these differences?
  - Firm level studies mostly estimate spillovers encompassing many different channels (labor sharing, input-output linkages, knowledge spillovers) but studies on high-skilled individuals focus much more on knowledge spillovers, only.
  - Firm level studies do not have "quasi-experimental" variation that can isolate effects of different spillover channels.
  - Knowledge that is valuable for firms is very different from academic knowledge: academics try to disseminate their findings to a broad public but firms benefit from exclusive use of knowledge.