Peer Effects

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Lecture Content

1. Localized (within-firm) peer effects among low skilled workers:
   Mas and Moretti (2009)
2. Peer effects among high-skilled workers:
   Waldinger (2012)
   See also (next week): Borjas and Doran (2012) and Moser, Voena, and Waldinger (2014)
3. Peer effects for both high and low skilled:
   Cornelissen, Dustmann and Schoenberg (2015)

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 productivty of other 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:

$$\begin{aligned} y_{itcs} &= \theta_i + \beta\bar{\theta}_{-itcs} + \pi \,\#\, workers_{tcs} \\ &+ \tau \; register\ locationFE_{ics} + \gamma \; time * day * storeFE_{tds} + e_{itcs} \end{aligned}$$

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

$$\Delta y_{itcs} = \alpha + \beta\Delta\bar{\theta}_{-itcs} + \pi \; \Delta\# \; workers_{tcs} + e_{itcs}$$

Estimation Details

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

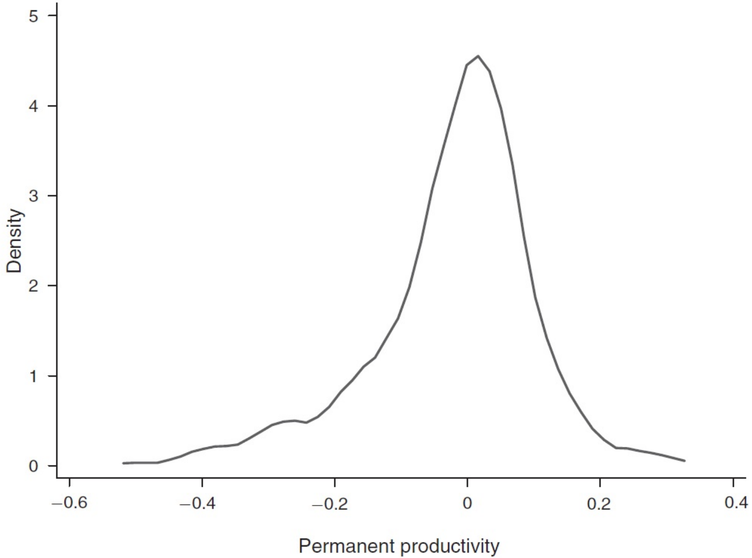
$$\begin{aligned} y_{itcs} &= \theta_i + M'\varphi_{Ci} + \pi \# \, workers_{tcs} \\ &+ \tau \; register \; locationFE_{ics} + \gamma \; time * day * storeFE_{tds} + e_{itcs} \end{aligned}$$

     - where φ_{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 θ_is and calculate $\bar{\theta}_{-itcs}$ 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 (i.e. θ_i) Differs Across Workers

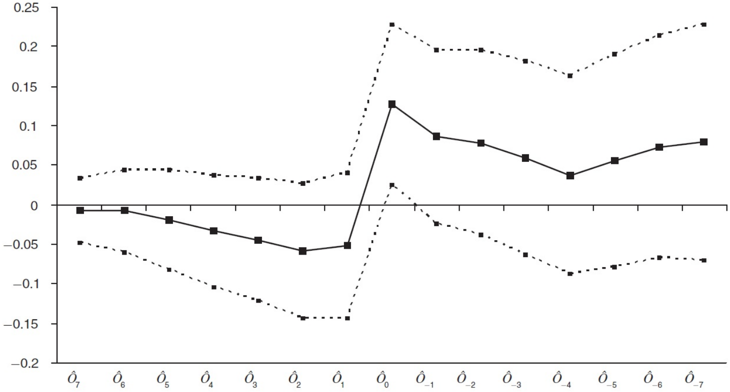


10% Increase in Co-Worker Quality Increases Prod. by 1.5%

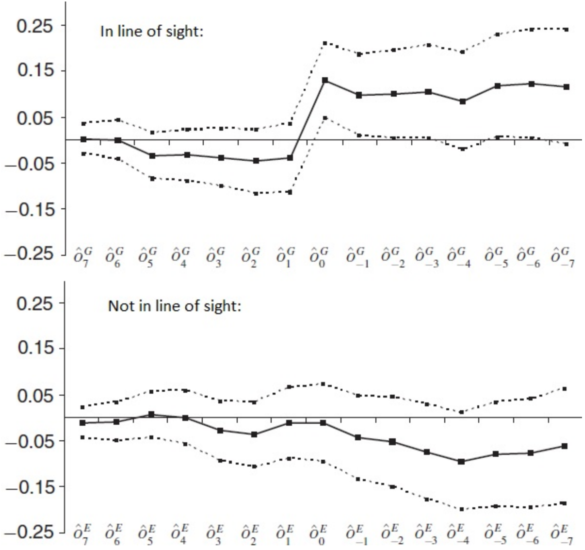
	(1)	(2)	(3)	(4)
Δ Average coworker permanent productivity	0.15 (0.02)	0.15 (0.02)	0.13 (0.03)	−0.03 (0.03)
Δ Average coworker permanent productivity $\times$ positive Δ indicator				0.24 (0.05)
Positive Δ indicator				0.004 (0.001)
Entry of above average productivity worker				
Exit of an above average 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



Clean Evidence on Peer Effects

- Very clean evidence on peer effects
- Results only valid if workers are indeed randomly assigned
- Results on line of sight are not only consistent with peer pressure as the main channel but also support random assignment

Methodology: Instrumental Variables

- Instrumental Variables can solve many endogeneity problems encountered in economics:
    1. Simultaneity
    2. Measurement Error
    3. Omitted Variable Bias.
- Look at an example from the returns to education literature
- Suppose the true model is:

$$ln(y) = \beta_1 + \beta_2 S + \beta_3 A + \varepsilon_1$$

- But we estimate:

$$ln(y) = \beta_1 + \beta_2 S + \varepsilon_2$$

- where $\varepsilon_2 = \beta_3 A + \varepsilon_1$

Methodology: Instrumental Variables

- The OLS estimator would then be:

$$\hat{\beta}_2^{OLS} = \frac{Cov(Y,S)}{Var(S)}$$

- We can show that $plim\,\hat{\beta}_2^{OLS} = \beta_2 + \beta_3 \frac{Cov(A,S)}{Var(s)}$
- Suppose we can use Z as an instrument for S. Two conditions for a valid IV:
  1. Z is uncorrelated with $\varepsilon_2 \Rightarrow Cov(Z,\varepsilon_2) = 0$ (Exclusion Restriction)
  2. Z correlated with S $\Rightarrow$ $Cov(Z,S) \neq 0$ (First Stage exists)

If there is only one endogenous regressor and one instrument the IV estimator is:

$$\hat{\beta}_2^{IV} = \frac{Cov(Y,Z)}{Cov(S,Z)}$$

Methodology: Instrumental Variables

- The IV estimator is consistent.
- Substitute true model for Y:

$$\hat{\beta}_2^{IV} = \frac{Cov([\beta_1 + \beta_2 S + \beta_3 A + \varepsilon_1], Z)}{Cov(S, Z)}$$

$$= \beta_2 \frac{Cov([S], Z)}{Cov(S, Z)} + \beta_3 \frac{Cov([A], Z)}{Cov(S, Z)} + \frac{Cov([\varepsilon_1], Z)}{Cov(S, Z)}$$

- $plim\, \hat{\beta}_2^{OLS} = \beta_2$
- because $Cov([A], Z) = 0$ and $Cov([\varepsilon_1], Z = 0$ due to the exclusion restriction, and $Cov(S, Z) \neq 0$ if a first stage exists.

Methodology: Instrumental Variables Jargon

- Estimated Model:

$$ln(y) = \beta_1 + \beta_2 S + \varepsilon_1$$

  S is the endogenous regressor.
- One way to estimate IV is two-stage-least squares (2SLS):
- First Stage Regression:

$$S = \gamma_1 + \gamma_2 Z + \mu$$

- Second Stage Regression:

$$ln(y) = \beta_1 + \beta_2 \hat{S} + \varepsilon_3$$

- Reduced Form:

$$ln(y) = \delta_1 + \delta_2 Z + \varepsilon_4$$

Methodology: IV with Heterogenous Treatment Effects

- With heterogeneity in returns one can potentially estimate different parameters
  1. Average Treatment Effect (ATE)
     (the average effect in the population. E.g. What would be the average increase in earnings if you increase schooling of everybody by one year
  2. Treatment Effect on the Treated
     How does the outcome change for those who received a certain treatment?
  3. Treatment Effect on the Untreated
     How would the outcome change if the untreated received the treatment?
  4. Local average treatment effect (LATE)
     How does the outcome change for those who were induced by the instrument to obtain treatment

Methodology: IV with Heterogenous Treatment Effects

- With heterogeneous treatment effects IV does not estimate the average treatment effect but the LATE. (see Imbens and Angrist 1995)
- Their framework is developed for a binary instrument and a binary treatment but the results generalize to non-binary setups
- With heterogeneous treatment effects IV will estimate the treatment effect of the so-called compliers

Methodology: IV with Heterogenous Treatment Effects

- The LATE framework partitions any population with an instrument into 3 instrument-dependent subgroups:
  1. Compliers: The subpopulation which only receives the treatment if the instrument is equal to 1.
  2. Always-takers: The subpopulation that always receives treatment independently of the value of the instrument
  3. Never-takers: The subpopulation that never receives treatment independently of the value of the instrument

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

Year of dismissal	Physics: Number of dismissals	Physics: % of all physicists in 1933	Chemistry: Number of dismissals	Chemistry: % of all chemists in 1933	Mathematics: Number of dismissals	Mathematics: % 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

	Physics			
University	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

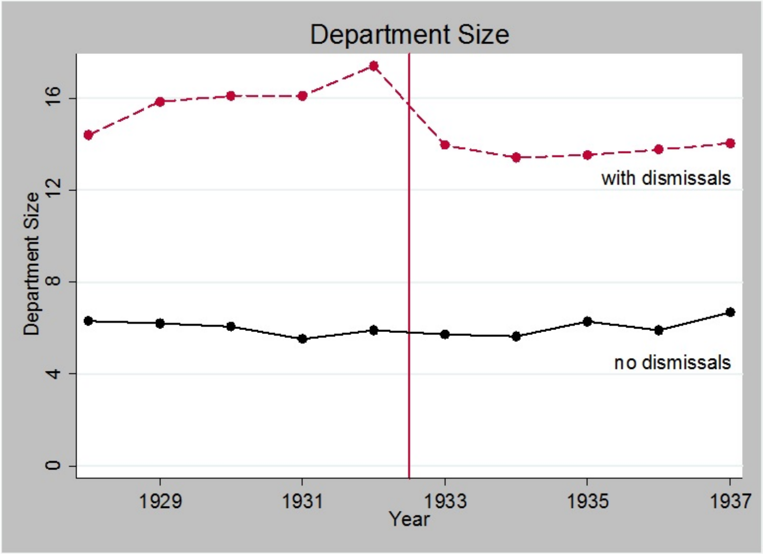
Dismissal Across Different Universities

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

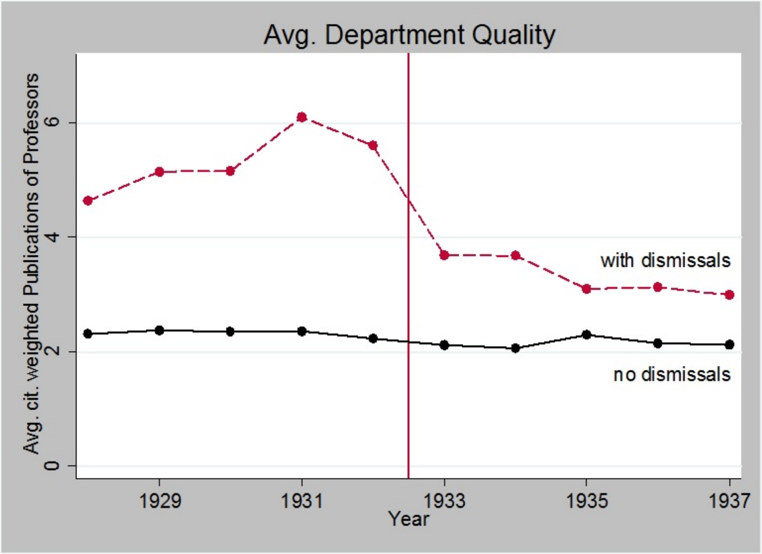
Summary Statistics Dismissed vs. Stayers

	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

Effect on Department Size



Effect on Peer Quality



- OLS model to estimate peer effects among university researchers:

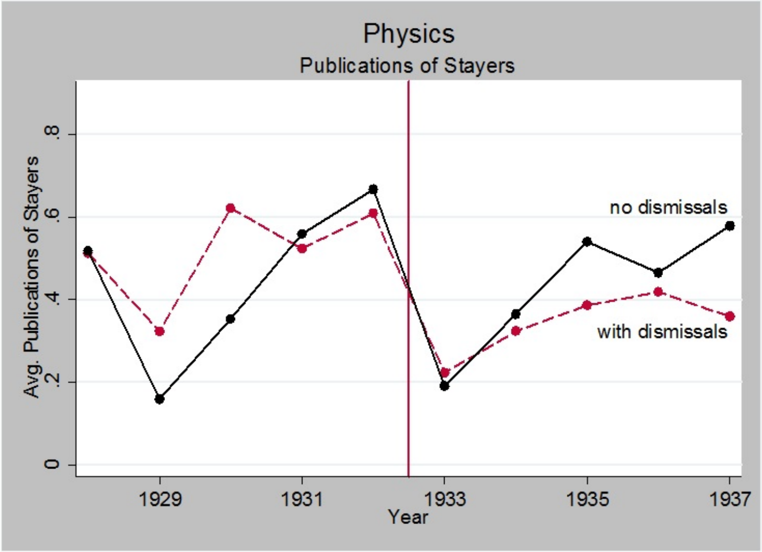
$$\begin{aligned} Pub_{iut} = & \quad \beta_1 + \beta_2 (Avg.\ Peer\ Quality)_{ut-1} + \beta_3 (\#\ of\ Peers)_{ut-1} \\ + & \quad \beta_4 Age\ Dummies_{iut} + \beta_5 YearFE_t + \beta_6 IndividualFE_i + \varepsilon_{iut} \end{aligned}$$

- Using the dismissals to instrument for the two endogenous variables. The 2 first stages are:

$$\begin{aligned} (Avg.\ Peer\ Quality)_{dt} = & \quad \gamma_1 + \gamma_2 (DismissalInduced \downarrow inPeerQualit \\ + & \quad \gamma_3 (\#Dismissec \\ + & \quad \gamma_4 Age\ Dummies_{iut} + \gamma_5 YearFE_t + \gamma_6 IndividualFE_i + \end{aligned}$$

$$\begin{aligned} (\#\ of\ Peers)_{ut-1} = & \quad \delta_1 + \gamma_2 (DismissalInduced \downarrow inPeerQua \\ + & \quad \gamma_3 (\#Dismiss \\ + & \quad \gamma_4 Age\ Dummies_{iut} + \gamma_5 YearFE_t + \gamma_6 IndividualFE_i \end{aligned}$$

Reduced Form - Graph



Reduced Form - Regression

	Physics	
Dependent variable	Publications	Cit. weighted publications
Dismissal induced fall in peer quality	0·029	0·312
	(0·015)	(0·235)
Number dismissed	−0·021	−0·017
	(0·017)	(0·302)
Age dummies	Yes	Yes
Year dummies	Yes	Yes
Individual FE	Yes	Yes
Observations	*2261*	*2261*
No. of researchers	*258*	*258*
R-squared	0·39	0·25

First Stages

	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

	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 Right Peer Group? - Specialization Level Results

	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*

How Do the Two Sets of Results Go Together?

- Cornelissen, Dustmann, and Schoenberg (2015) analyze peer effects for both low and high-skilled workers in the same context
- While they cannot rely on quasi-experimental variation to identify peer effects they use worker movement across firms to identify peer effects for a very large sample of workers
- Unlike the two previous papers they investigate how wages of peers affect the focal worker's wages
- Sample: all workers in a large local labor market in GermanyVery nice evidence that effective patent length (as measured by expected survival) affects innovation incentives

Summary Statistics

No. of workers	2,115,544
No. of firms	89,581
Number of peer groups (occupations within firm-years)	1,387,216
Average number of time periods per worker	6.07
Number of peer groups per firm-year	2.30
Average number of employers per worker	1.60
Average number of occupations per worker	1.40
Share of mobility group with identified firm fixed effects	0.995
Share of mobility group with identified firm-time fixed effects	0.994
Share of mobility group with identified firm-occupation fixed effects	0.983
St. dev. worker fixed effect	0.32
St. dev. average peer fixed effect	0.24

Estimating Equation

- They estimate the following regression model:

$$
\begin{aligned}
n(w)_{iojt} = & \quad a_i + \gamma \bar{a}_{-iojt} + Controls \\
+ & \quad Occ \times YearFE_{ot} + Firm \times YearFE_{jt} + Occ \times FirmFE_{oj} + \varepsilon_{iojt}
\end{aligned}
$$

- Where i indexes the worker, o the occupation, j the establishment, and t the year
- Like Mas and Moretti (2009) they need to first consistently estimate the individual FE and then include them in the model (they estimate them slightly differently than Mas and Moretti)

Results Full Sample

	(1) outside option and firm fixed effects	(2) plus firm-occupation fixed effects	(3) plus firm-occupation and firm-year fixed effects
Average peer fixed effect	0.148	0.066	0.011
	(0.002)	(0.002)	(0.001)
Worker Fixed Effects	Yes	Yes	Yes
Occupation X Year Effects	Yes	Yes	Yes
Firm Effects	Yes	-	-
Occupation X Firm Effects	-	Yes	Yes
Firm X Year Effects	-	-	Yes

High Versus Low-Skill Occupations

	(1)	(2)	(3)
Panel A: Peer Effects for Sub-Samples of Low Skilled Occupations			
	5% most repetitive occupations	As in case studies	Low learning content
Average peer fixed effect	0.064	0.067	0.052
	(0.0070)	(0.0116)	(0.0031)
Panel B: Peer Effects for Sub-Samples of High Skilled Occupations			
	10% most skilled occupations	10% most innovative occupations	High learning content
Average peer fixed effect	0.013	0.007	0.017
	(0.0039)	(0.0044)	(0.0028)

Overview of Results

- 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
- What could explain the diverging findings?
  - Is the effect of peer pressure less important for high-skilled individuals?
  - Are localized knowledge spillovers less important than economists think?
  - Do the high-skilled collaborate outside firm boundaries?

Comparing Within-Firm Results to Across Firm Spillovers

- It is striking that within-firm results usually do not find evidence for peer effects among the high-skilled
- Literature on spillovers across firms (see last week) find externalties (albeit driven by different factors depending on the paper)
- What is going on?
    - Are across firm spillovers more important than within-firm ones?
    - Are within-firm papers better identified?
    - A lot of open questions...