7. Education Quality

KAT.TAL.322 Advanced Course in Labour Economics

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Education quality

Knowledge/productivity doesn’t rise linearly with years of education.

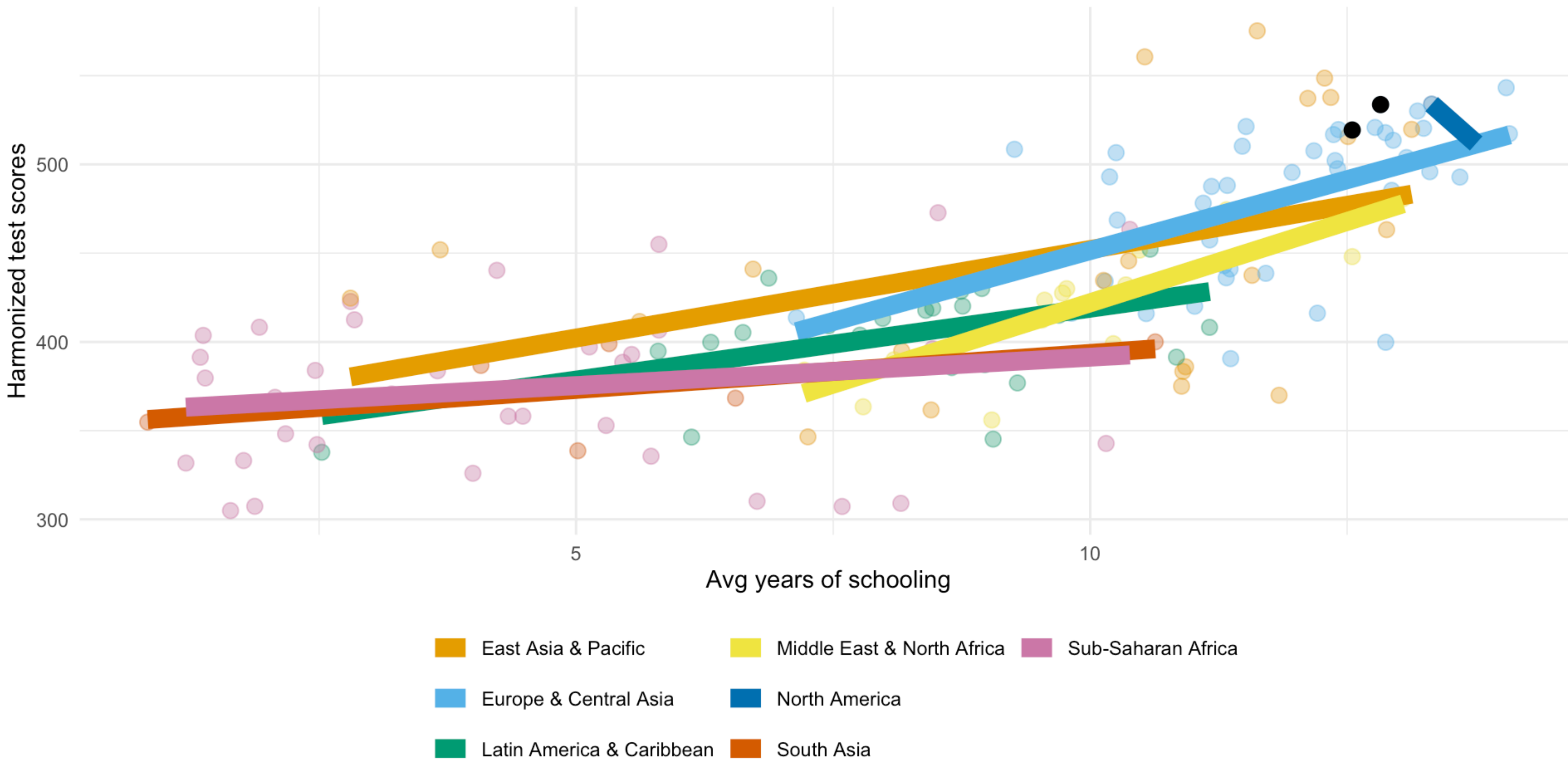
Production process that takes inputs and develops skills.

Today

- Stylised facts
- Education production function
- (Quasi-)Experimental estimations

Stylised facts

Education quantity vs quality



Source: World Bank

Education production function

Education production function

Simple framework

Education output of pupil i in school j in community k

$$q_{ijk} = q(P_i, S_{ij}, C_{ik})$$

$$\text{where} \quad \begin{array}{rl} P_i & \text{are pupil characteristics} \\ S_{ij} & \text{are school inputs} \\ C_{ik} & \text{are non-school inputs} \end{array}$$

Education production function

Measures

Output

Years of schooling, standardised test scores, noncognitive skills

Student inputs

Effort, patience, genetics, parental characteristics, family income, family size

School inputs

Teacher characteristics, class sizes, teacher-student ratio, school expenditures, school facilities

Non-school inputs

Peers, local economic conditions, national curricula, regulations, certification rules

Education production function

*Todd and Wolpin (**2003**)*

Achievement of student i in family j at age a

$$q_{ija} = q_a\left(\mathbf{F}_{ij}(a), \mathbf{S}_{ij}(a), \mu_{ij0}, \varepsilon_{ija}\right)$$

$\mathbf{F}_{ij}(a)$ history of family inputs up to age a

$\mathbf{S}_{ij}(a)$ history of school inputs up to age a

μ_{ij0} initial skill endowment

ε_{ija} measurement error in output

$q_a(\cdot)$ age-dependent production function

Education production function

*Todd and Wolpin (**2003**): Contemporaneous specification*

$$q_{ija} = q_a(F_{ija}, S_{ija}) + \nu_{ija}$$

Strong assumptions:

1. Only current inputs are relevant **OR** inputs are stable over time
2. Inputs are uncorrelated with μ_{ij0} or ε_{ija}

Education production function

*Todd and Wolpin (**2003**): Value-added specification*

$$q_{ija} = q_a \left(F_{ija}, S_{ija}, q_{a-1} \left[F_{ij}(a-1), S_{ij}(a-1), \mu_{ij0}, \varepsilon_{ij,a-1} \right], \varepsilon_{ija} \right)$$

Typical empirical estimation assumes linear separability and $q_a(\cdot) = q(\cdot)$:

$$q_{ija} = F_{ija}\alpha_F + S_{ija}\alpha_S + \gamma q_{ij,a-1} + \nu_{ija}$$

Additional assumptions implied:

1. Past input effects decay at the same rate γ
2. Shocks ε_{ija} are serially correlated with persistence γ

Education production function

*Todd and Wolpin (**2003**): Cumulative specification*

Still assume linear separability:

$$q_{ija} = \sum_{t=1}^{a} X_{ijt}\alpha_{a-t+1}^{a} + \beta_a \mu_{ij0} + \varepsilon_{ij}(a)$$

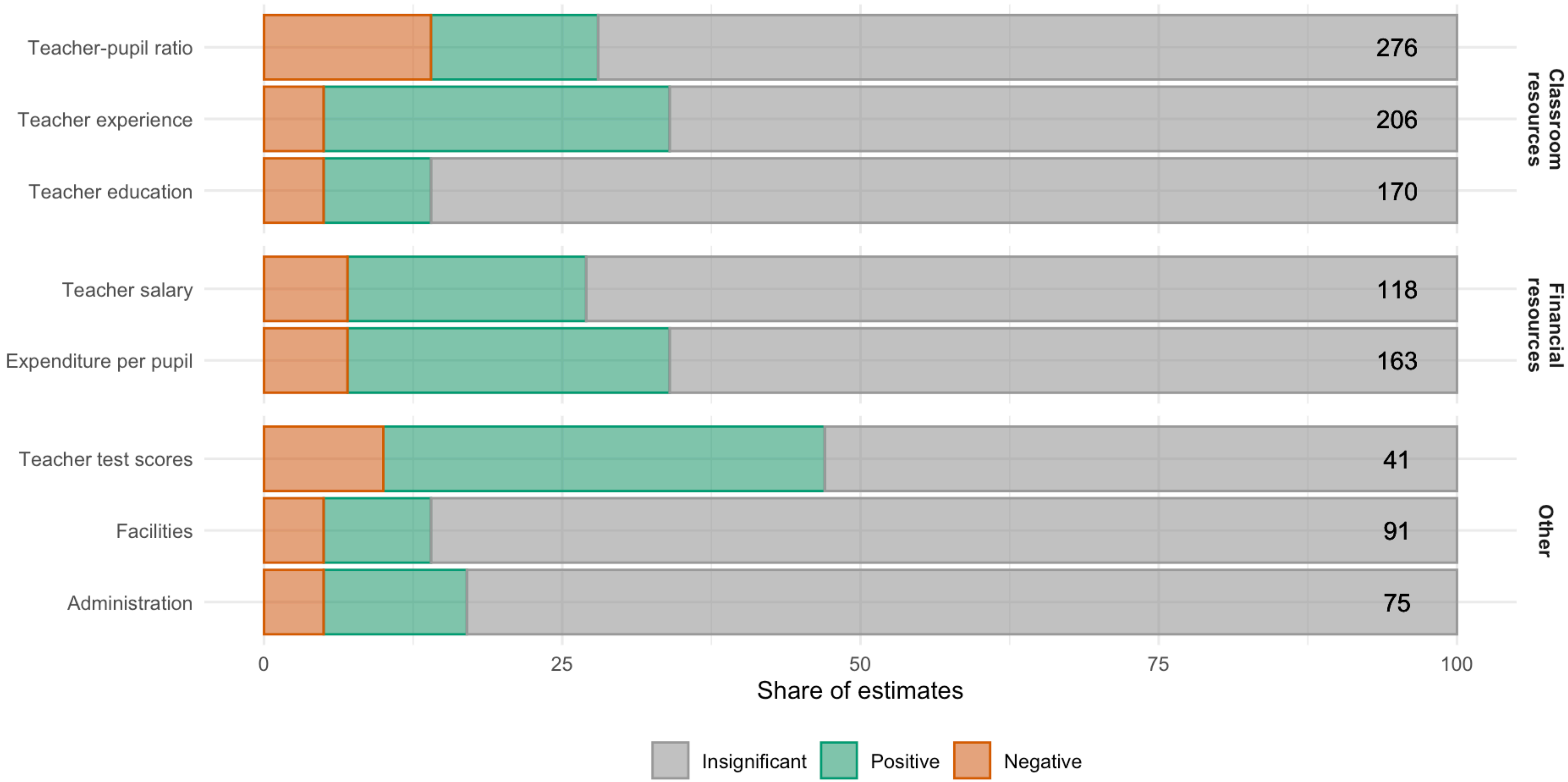
Estimation strategies:

1. Within-child: $q_{ija} - q_{ija'}$ for ages a and a'
2. Within-family: $q_{ija} - q_{i'ja}$ for siblings i and i'

Each with their own caveats

Early estimates of school inputs (prior to 1995)

*"resources are not closely related to student performance" (**Hanushek 2003**)*



Source: Hanushek (2003), Table 3

Education production function

Non-experimental estimations

- Require strong assumptions
  → Some can be relaxed
- Require rich data
- Endogenous allocation of resources

Quasi-experimental estimations

- May not recover structural parameters
- Ignore general equilibrium
- Issues with scaling List (2022)

(Quasi-)Experimental estimations

Productivity of student inputs

Student inputs: nature vs nurture

Twin models (ACDE)

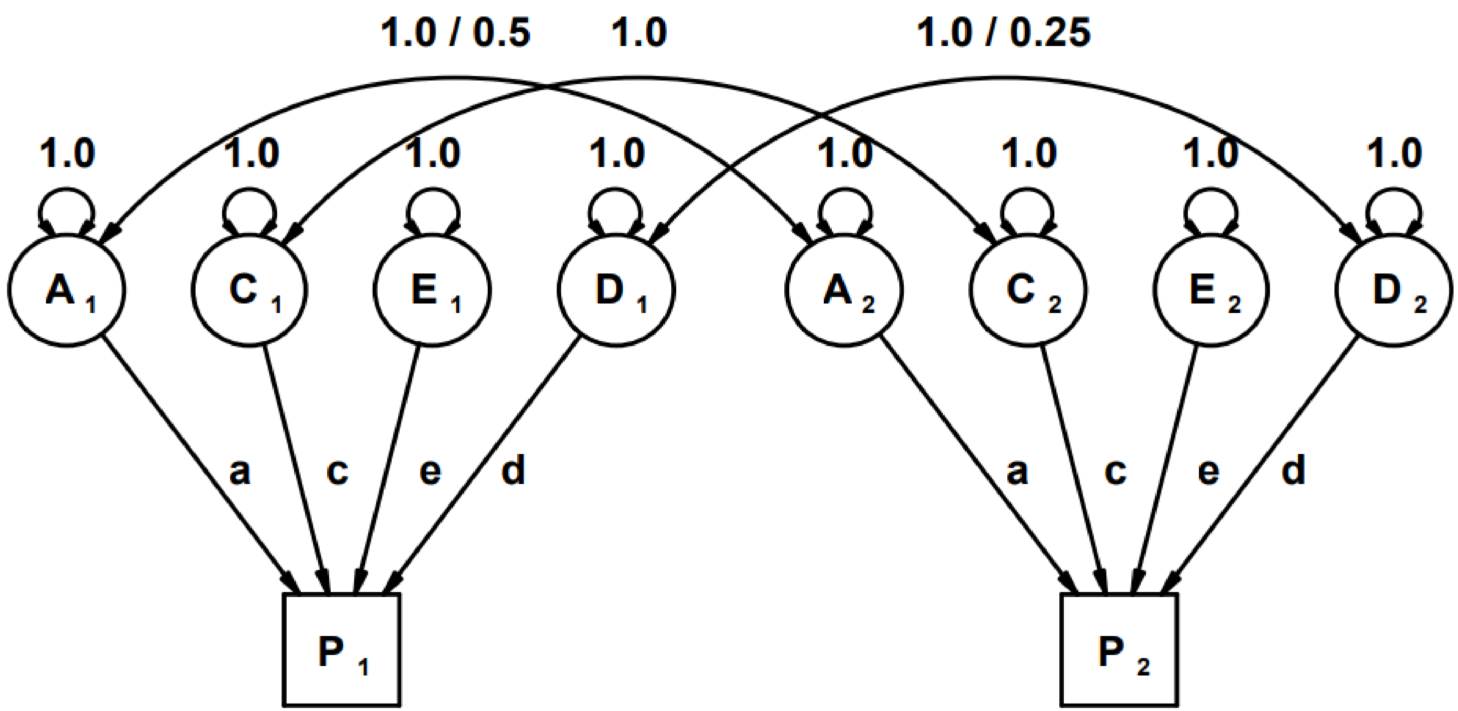


Figure 6.1: Univariate genetic model for data from monozygotic (MZ) or dizygotic (DZ) twins reared together. Genetic and environmental latent variables cause the phenotypes P_1 and P_2. The correlation between A_1 and A_2 is 1.0 for MZ and 0.5 for DZ twins. The correlation between D_1 and D_2 is 1.0 for MZ and 0.25 for DZ twins.

Source: Neale and Maes (2004)

Student inputs: nature vs nurture

*Twin models: Polderman et al. (**2015**)*

Meta-analysis of >17,000 twin-analyses (>1,500 **cognitive traits**)

- 47% of variation due to genetic factors
- 18% of variation due to shared environment

Adoption studies

Fagereng, Mogstad, and Rønning (2021): Korean Norwegian

- Wealth: $a^2 \approx 58$% and $c^2 \approx 37$%
- Education: $a^2 \approx 49$% and $c^2 \approx 6$%

Sacerdote (2007): Korean American

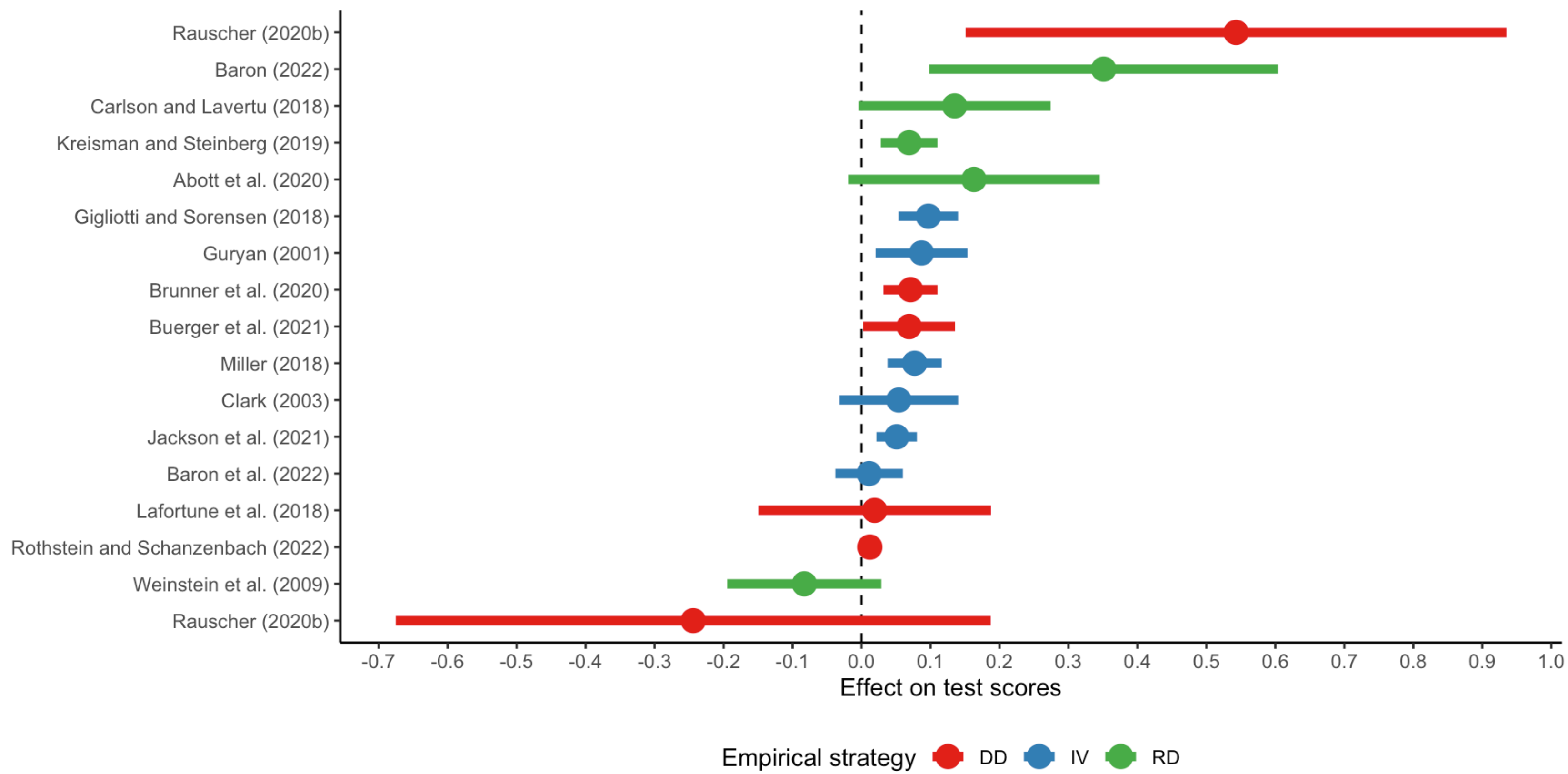
- College: $a^2 \approx 41$% and $c^2 \approx 16$%

Productivity of school inputs

Productivity of school inputs

*School expenditures: review by Handel and Hanushek (**2023**)*

Exogenous variation due to court decisions or legislative action



Source: Table 10 (Handel and Hanushek 2023)

Productivity of school inputs

*School spending: review by Handel and Hanushek (**2023**)*

- Large variation of spending effects on test scores
- Not clear how money was used
- Role of differences in regulatory environments
- Similar results for participation rates are all positive (mostly significant)

Productivity of school inputs

*Class size: Joshua D. Angrist and Lavy (**1999**)*

Quasi-experimental variation in Israel: **Maimonides rule**

Rule from Babylonian Talmud, interpreted by Maimonides in XII century:

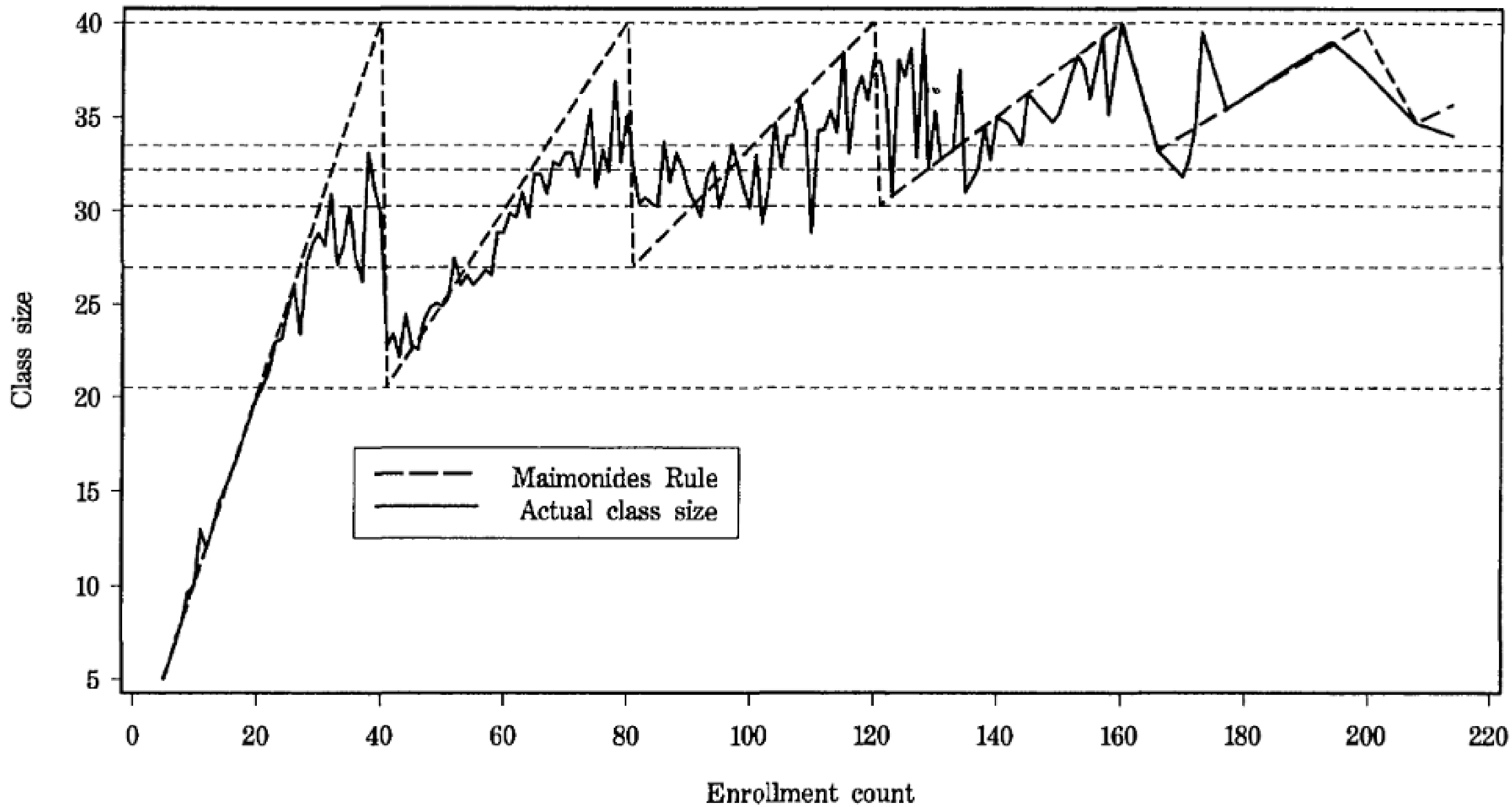
> If there are more than forty [students], two teachers must be appointed

Sharp drops in class sizes with 41, 81, … cohort sizes in schools

Regression discontinuity design (RDD)

Productivity of school inputs

*Class size: Joshua D. Angrist and Lavy (**1999**)*



Source: Figure I (Joshua D. Angrist and Lavy 1999)

Productivity of school inputs

*Class size: Joshua D. Angrist and Lavy (**1999**)*

Maimonides rule: $f_{sc} = \dfrac{E_s}{\text{int}\left(\frac{E_s - 1}{40}\right) + 1}$

“Fuzzy” RDD

First stage: $n_{sc} = X_{sc}\pi_0 + f_{sc}\pi_1 + \xi_{sc}$

Second stage: $y_{sc} = X_s\beta + n_{sc}\alpha + \eta_s + \mu_c + \epsilon_{sc}$

Productivity of school inputs

Class size

Source: Angrist and Lavy 1999

	Grade 4		Grade 5	
	Reading	**Math**	**Reading**	**Math**
Class size	-0.150	0.023	-0.582	-0.443
	(0.128)	(0.160)	(0.181)	(0.236)
Mean score	72.5	68.7	74.5	67.0
SD score	7.8	9.1	8.2	10.2
Obs.	415	415	471	471

Source: Angrist et al. 2019

	Grade 5	
	Reading	**Math**
Class size	-0.006	-0.062
	(0.066)	(0.088)
Mean score	72.1	68.1
SD score	17.4	20.6
Obs.	225 108	226 832

Productivity of school inputs

*Class size: Krueger (**1999**), Chetty et al. (**2011**)*

Project STAR: 79 schools, 6323 children in 1985-86 cohort in Tennessee

Randomly assigned students and teachers into

- small class (13-17 students)
- regular class (22-25 students)
- regular class + teacher's aide (22-25 students)

$$Y = \alpha + \beta_S SMALL + \beta_A AIDE + X\delta + \varepsilon$$

Randomization means students between classes are on average similar

$\Rightarrow$ β_S and β_A are causal

Productivity of school inputs

Class size

SOURCE: TABLE V (KRUEGER 1999)

	Test scores			
	Kindergarten	**Grade 1**	**Grade 2**	**Grade 3**
SMALL	5.370	6.370	5.260	5.240
	(1.190)	(1.110)	(1.100)	(1.040)

SOURCE: TABLE V (CHETTY ET AL. 2011)

	Test score, %	**College by age 27, %**	**College quality, $**	**Wage earnings, $**
SMALL	4.760	1.570	109.000	-124.000
	(0.990)	(1.070)	(92.600)	(336.000)
Avg dep var	48.67	45.5	27 115	15 912
Obs.	9 939	10 992	10 992	10 992

Productivity of school inputs

*Class quality: Chetty et al. (**2011**)*

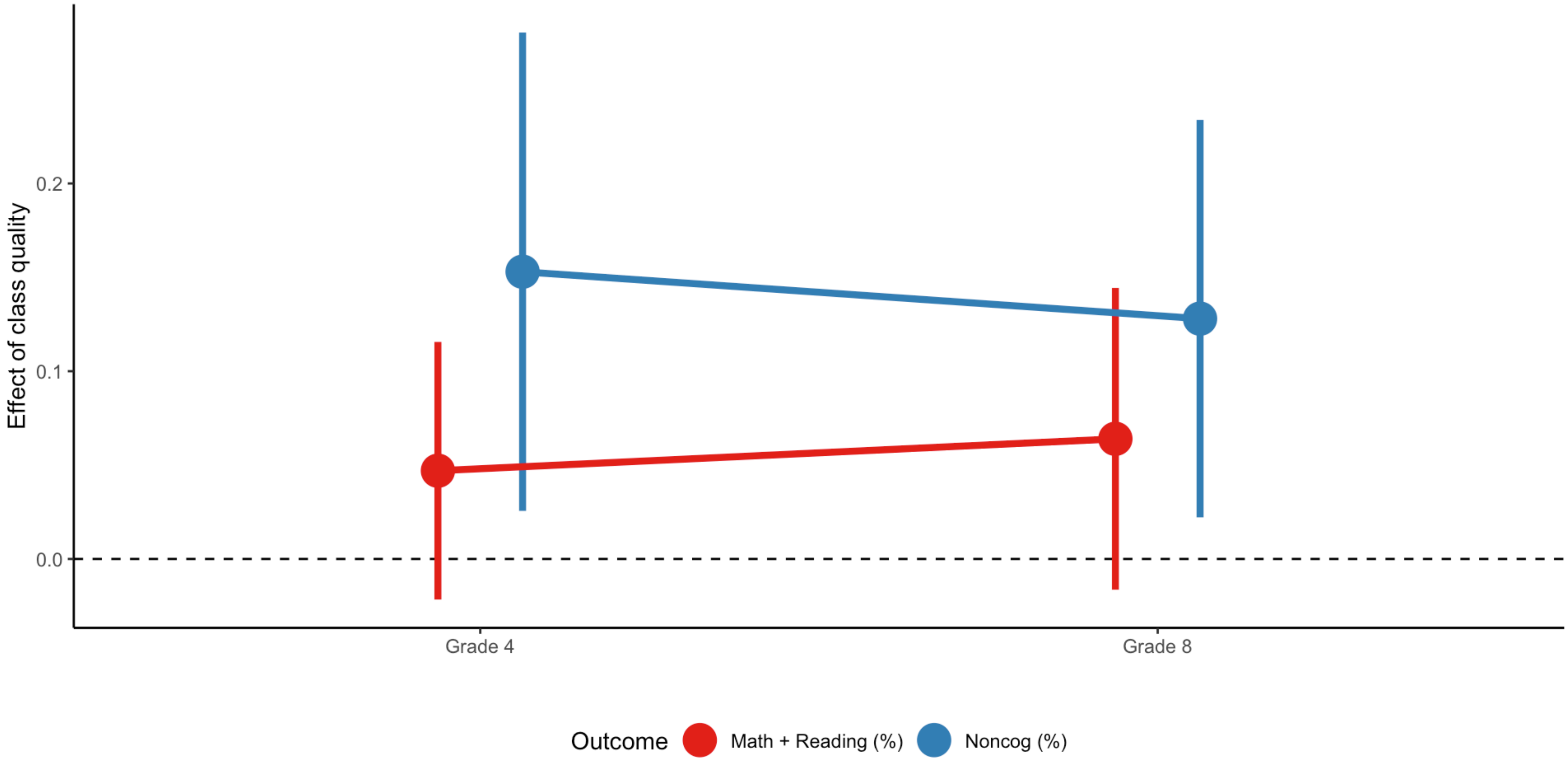
Notice: random assignments of peers ($QUAL$)

Source: Table VIII (Chetty et al. 2011)

	Test score, %	College by age 27, %	College quality, $	Wage earnings, $
QUAL	0.662	0.108	9.328	50.610
	(0.024)	(0.053)	(4.573)	(17.450)
Obs.	9 939	10 959	10 959	10 959

Productivity of school inputs

*Class quality and noncognitive skills: Chetty et al. (**2011**)*



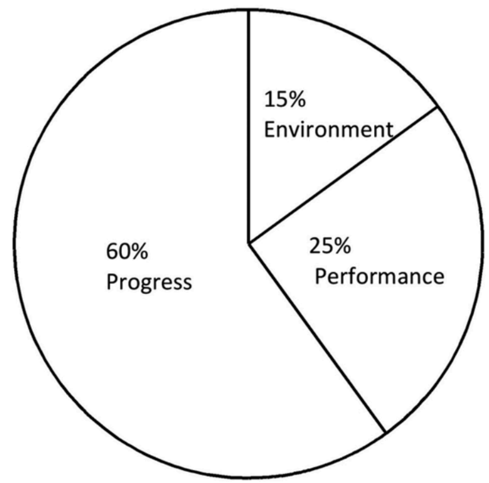
Source: Table IX (Chetty et al. 2011)

Productivity of school inputs

*Teacher incentives: Fryer (**2013**)*

2-year pilot program in 2007 among lowest-performing schools in NYC

- 438 eligible schools, 233 offered treatment, 198 accepted, 163 control
- Relative rank of schools in each subscore
- Bonus sizes:
  - → $3,000/teacher if 100% target
  - → $1,500/teacher if 75% target



Subscore	Criteria
Environment	5% Attendance, 10% Learning Environment Survey results
Progress	Elementary/Middle schools: Average change in state exam proficiency ratings among level 1 and 2 students, average change in state exam proficiency ratings among level 3 and 4 students, percentage of students making a year of progress among the bottom third High schools: Percentage of students earning more than 10 credits among the bottom third, weighted Regents pass rates, average completion rates of remaining Regents
Performance	Elementary/middle schools: Proportion of students at state ELA and math exam performance level 3 or 4, state exam median proficiency ratings High schools: 4-and 6-year graduation rates, diploma-weighted graduation rates

FIG. 1.—Progress report card metrics

Productivity of school inputs

*Teacher incentives: Fryer (**2013**)*

Instrumental variable approach (LATE = ATT):

$$\begin{aligned} Y &= \alpha_2 + \beta_2 X + \pi_2 \text{ incentive} + \epsilon \\ \text{incentive} &= \alpha_1 + \beta_1 X + \pi_1 \text{ treatment} + \xi \end{aligned}$$

Productivity of school inputs

Teacher incentives: Fryer (2013)

SOURCE: TABLES 4 AND 5 (FRYER 2013)

	Elementary	**Middle**	**High**
English	-0.010 (0.015)	-0.026 (0.010)	-0.003 (0.043)
Math	-0.014 (0.018)	-0.040 (0.016)	-0.018 (0.029)

- Incentives too small and too complex
- Bonuses to schools (not teachers)
- Effort of existing teachers vs selection into teaching

Productivity of school inputs

*Teacher incentives: Biasi (**2021**)*

Change in teacher pay scheme in Wisconsin in 2011:

- seniority pay (SP): **collective** scheme based on seniority and quals
- flexible pay (FP): bargaining with **individual** teachers

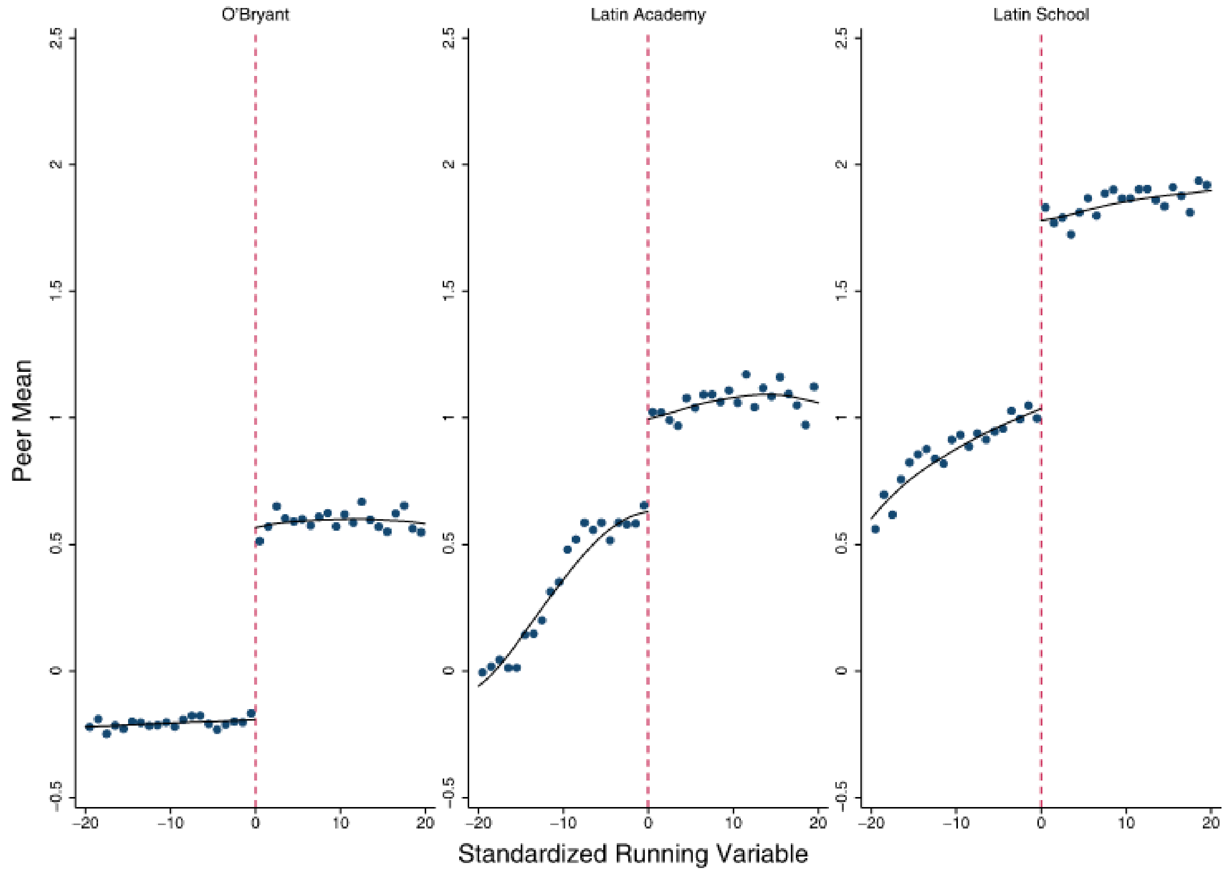
Main results:

- FP $\uparrow$ salary of high-quality teachers relative to low-quality
- high-quality teachers moved to FP districts (low-quality to SP)
- teacher effort $\uparrow$ in FP districts relative to SP
- student test scores $\uparrow$ 0.06σ (1/3 of effect of $\downarrow$ class size by 5)

Productivity of non-school inputs

*Peer effects: Abdulkadiroğlu, Angrist, and Pathak (**2014**)*

Admission to elite high school in Boston



Peer math scores, Figure 2 (Abdulkadiroğlu, Angrist, and Pathak 2014)

Productivity of school inputs

*Peer effects: Abdulkadiroğlu, Angrist, and Pathak (**2014**)*

SOURCE: TABLE VI (ABDULKADIROĞLU, ANGRIST, AND PATHAK 2014)

	Parametric	**Nonparametric**
Attended any college	0.010	0.031
	(0.032)	(0.019)
Attended 4-year college	0.003	0.013
	(0.041)	(0.026)
Attended competitive college	-0.011	-0.004
	(0.051)	(0.029)
Attended highly competitive college	-0.009	-0.014
	(0.032)	(0.017)

Productivity of school inputs

Peer effects

Dale and Krueger (2002) study admission into selective colleges in the US

- No effect on average earnings
- ↑ earnings of students from low-income families

Kanninen, Kortelainen, and Tervonen (2023): selective schools in Finland

- ↑ university enrolment and graduation rates
- No impact on income
- Change edu preferences, not skills!

Pop-Eleches and Urquiola (2013): selective schools and tracks in Romania

- ↑ university admission exam score
- ↓ parental investments
- ↑ marginalisation and negative interactions with peers

Productivity of non-school inputs

Productivity of non-school inputs

*Curriculum: Alan, Boneva, and Ertac (**2019**)*

RCT among schools in remote areas of Istanbul

Carefully designed curriculum promoting **grit** (≥ 2h/week for 12 weeks)

Treated students are more likely to

- set challenging goals
- exert effort to improve their skills
- accumulate more skills
- have higher standardised test scores

These effects persist 2.5 years after the intervention

Productivity of non-school inputs

Curriculum: other evidence

Squicciarini (2020): adoption of technical education in France in 1870-1914

- higher resistance in religious areas, led to lower economic development

Machin and McNally (2008): 'literacy hour' introduced in UK in 1998/99

- highly structured framework for teaching
- $\uparrow$ English and reading skills of primary schoolchildren

Summary

- Academic achievement is complex function of student, parent, school and non-school inputs
- Measuring achievement can also be difficult
- Genetic and environmental factors from twin studies almost 50/50
- Large variation in school resource effects (from $\ll 0$ to $\gg 0$)
  - → How resources are used?
  - → Which resources are most effective?
- Studies of class size, teacher incentives, peer effects and curricula
- Another (often overlooked) step is scaling up to the population

Next lecture: Technological shift and labour markets on 17 Sep

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