

# **Schools and Learning Inequalities**

## A Theoretical Model of Quantitative and Qualitative School Effects

Said Hassan    Richard Breen

Nuffield College, University of Oxford



# Roadmap

**Do schools contribute to inequalities in learning outcomes?**

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5. School *quality* versus *exposure*

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4. Natural experiment: school quality  $\rightarrow$  test score gaps
5. School *quality* versus *exposure*
6. Do our results hold in other contexts?



# Schools and Inequality: Two conflicting narratives

## Reproduction

### ► Class analyses and cultural capital

(Bowles and Gintis, 1976; Bourdieu and Passeron, 1977)

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💡 within and between school differences  
in **quality**

**Investing in schools → less inequality**

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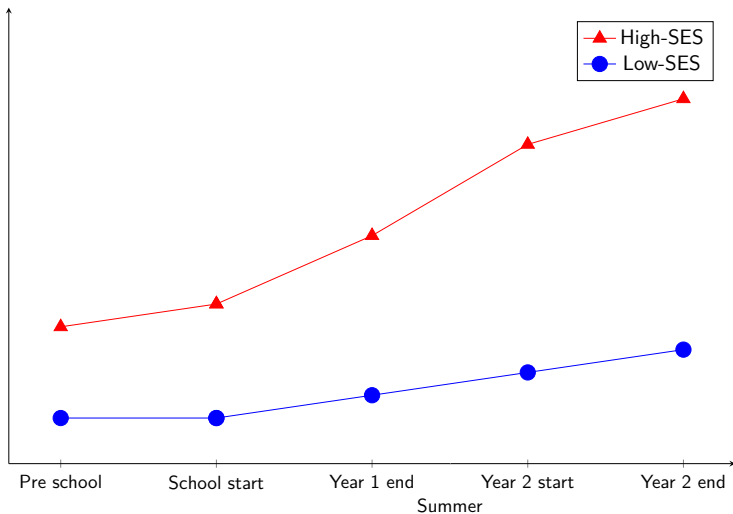
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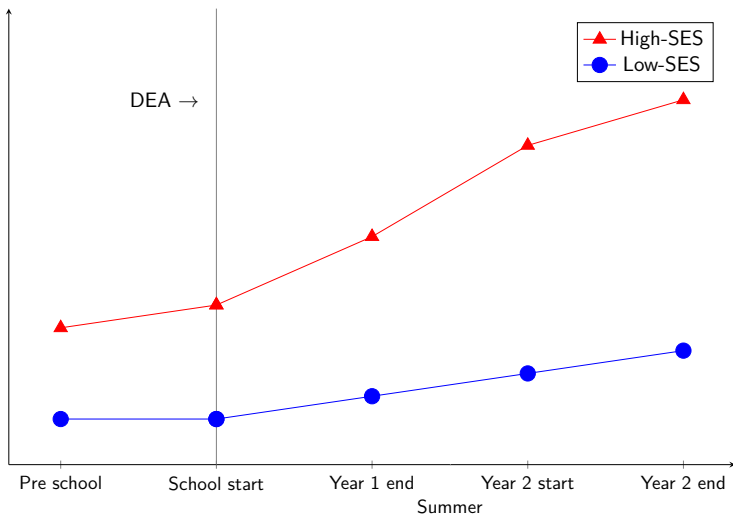
💡 School **exposures** ineffective because  
home environments more unequal

**Intervening in schools ineffective**

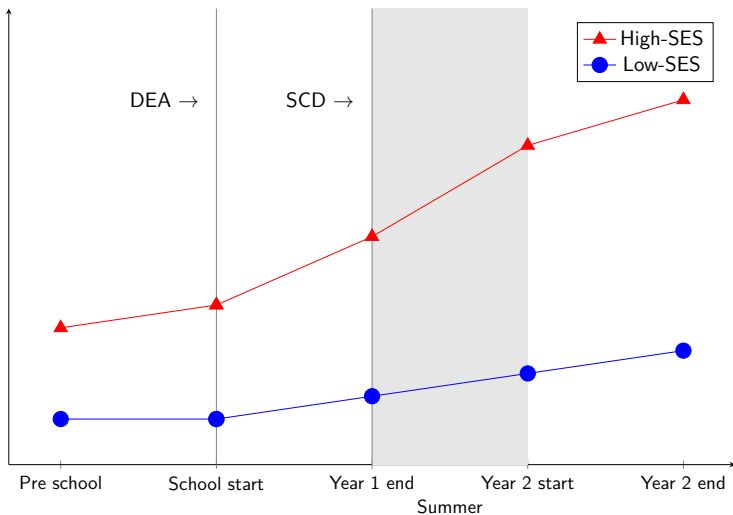
## Different counterfactuals



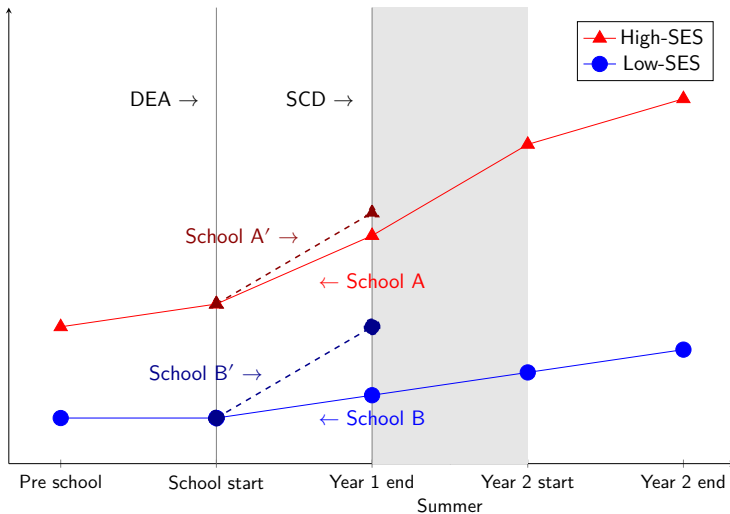
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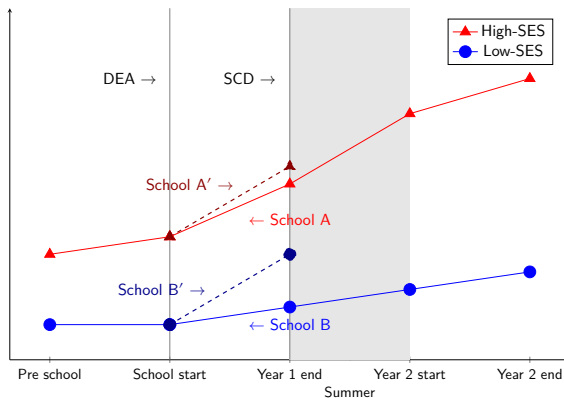
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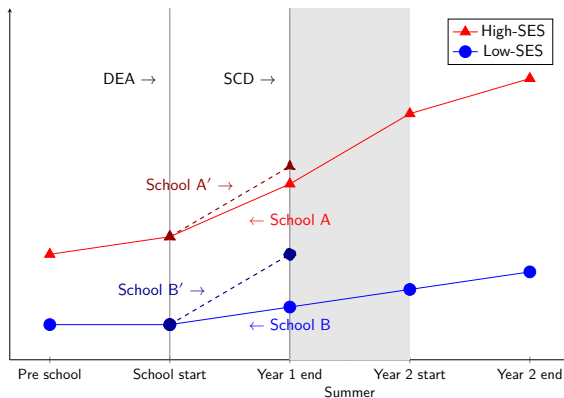
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Three **different** counterfactuals

1. DEA: shortening pre-school
2. SCD: Shortening summer break
3. Investing in quality

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*Quantitative vs qualitative effects*

# Formal model

## Goals:

1. Explains why increasing exposure has **minor** impacts on inequality

(Downey et al., 2004,; Downey et al., 2019; Workman et al., 2023; Passaretta and Skopek 2023)



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(Lareau, 2003; Calarco, 2011,2014)
4. Predicts that investments in quality more equitable than investments in exposure  
(Raudenbush and Eschmann, 2015)

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$$y = A \cdot Q \cdot E$$

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**Assumption 1:** Marginal diminishing returns

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$$y_L = A Q_L^\alpha E^\beta \qquad y_H = A Q_H^\alpha E^\beta$$

**Assumption 1:** Marginal diminishing returns

**Assumption 2:** Selection into school quality (but not exposure)



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**Assumption 1:** Marginal diminishing returns

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**Assumption 3:** Flexibility (differential returns between groups)

## Formal model: Quantitative (exposure) effects

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(Relative gains–inequality of increasing  $E$ )

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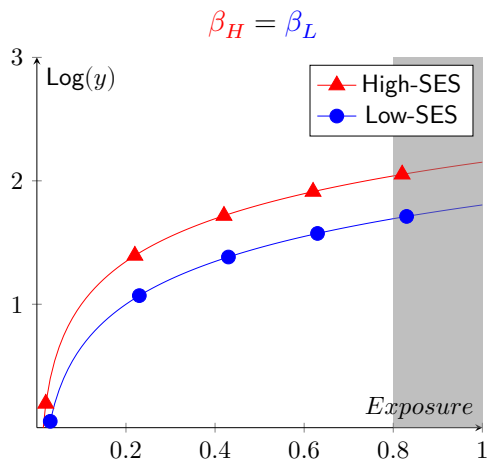
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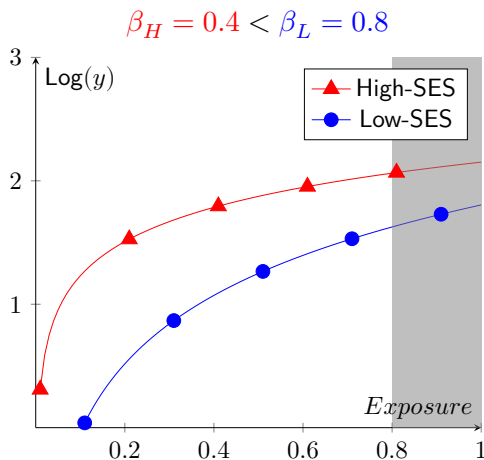
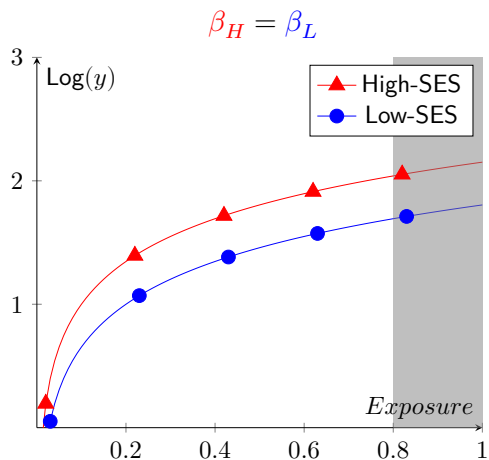
$$\Theta_E = \begin{cases} 1 & \text{if } \beta_H = \beta_L \text{ (Preserves inequality)} \\ < 1 & \text{if } \beta_H < \beta_L \text{ (Reduces inequality)} \\ > 1 & \text{if } \beta_H > \beta_L \text{ (Increases inequality)} \end{cases}$$

## Formal model: Quantitative effects





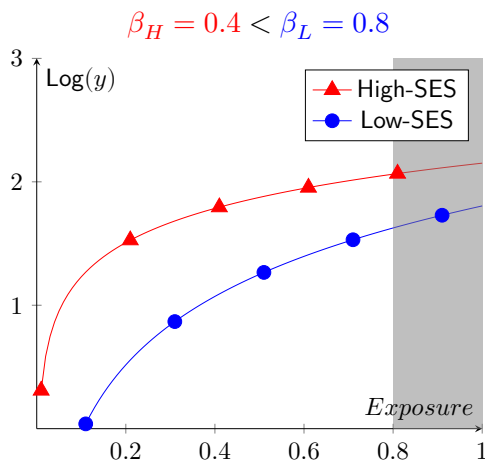
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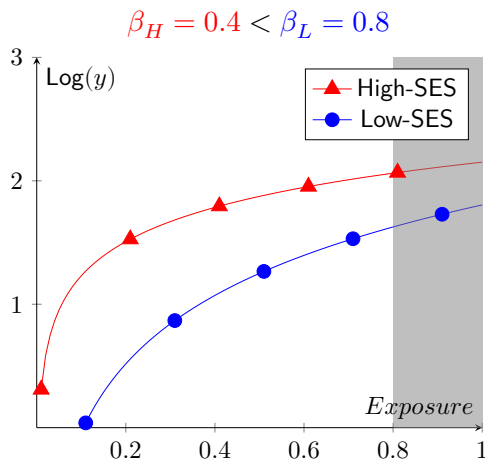
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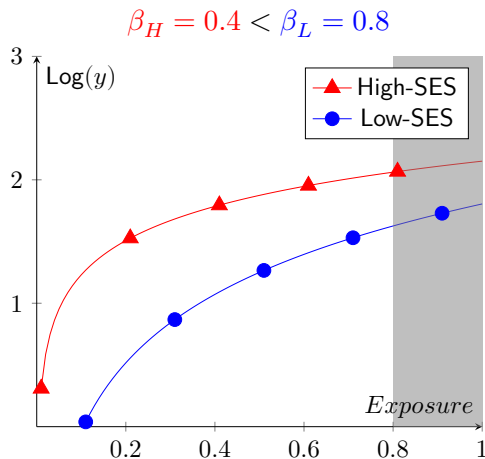
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## Formal model: Quantitative effects

### 💡 Takeaways:

- Limited gains to exposure investments even if low-SES children benefit *more* from exposure
- Exposure is hard to scale up!
- Selection into quality  $\Rightarrow$  low-SES children get more low quality schooling vs high-SES children get more high quality schooling



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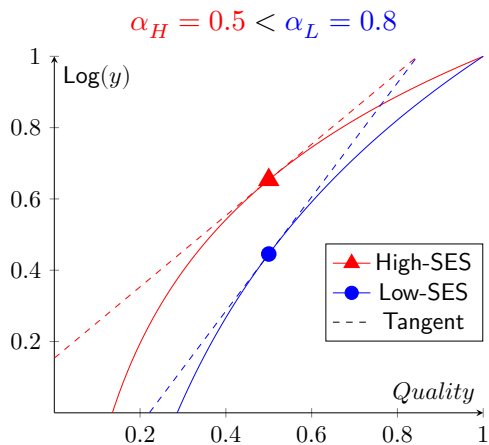
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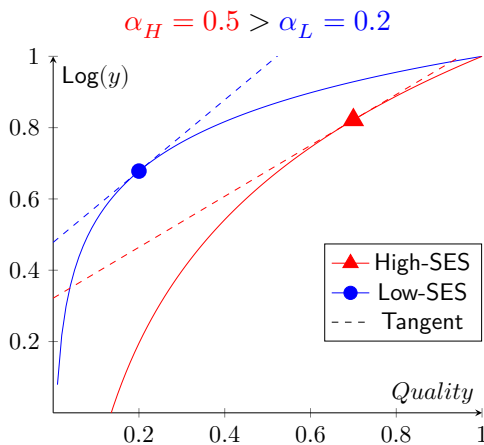
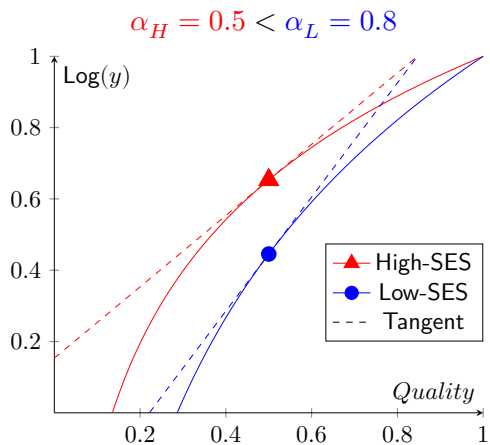
**Intuition:**

$$\Theta_Q = \begin{cases} 1 & \text{if } \alpha_H = \alpha_L \text{ (Inequality by } Q \text{ only)} \\ < 1 & \text{if } \alpha_H < \alpha_L \text{ (Less inequality at any } Q\text{)} \\ > 1 & \text{if } \alpha_H > \alpha_L \text{ (Less inequality at lower } Q\text{)} \end{cases}$$

# Formal model: Qualitative effects



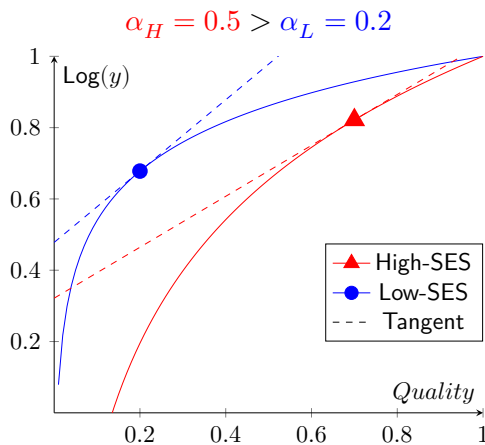
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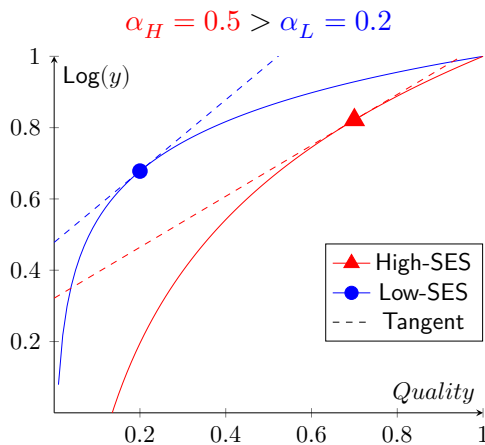
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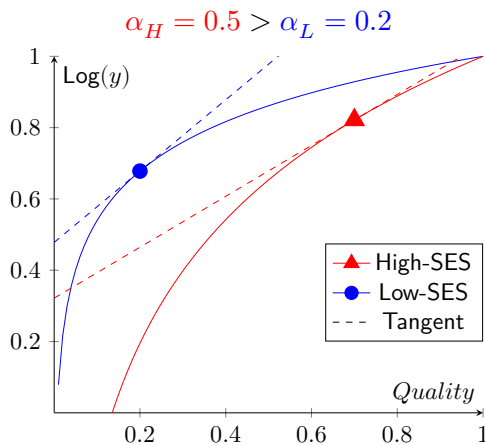
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## Formal model: Qualitative effects

### 💡 Takeaways:

- Quality investments more effective at reducing inequality
- If selection into quality strong, gains even higher among low-SES children
- Even if low-SES children have low returns, investing in quality still leads to more equality because of selection



## Empirical setup

How do schools contribute to learning inequalities?



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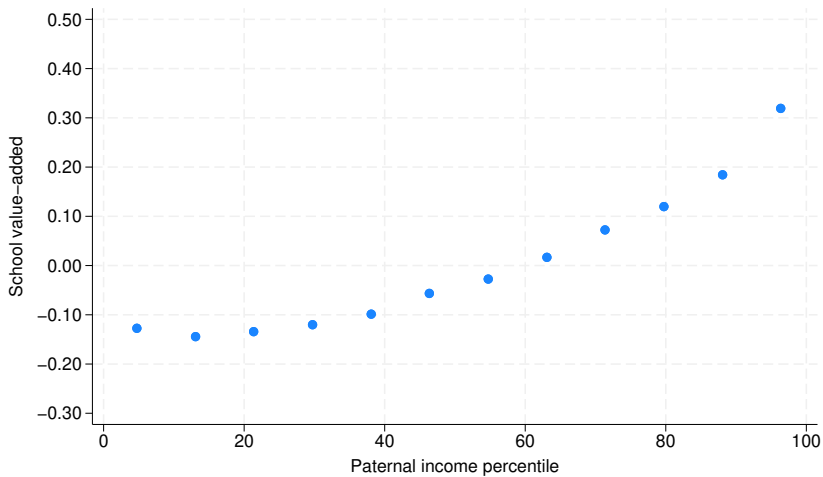
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- School quality measured as value-added
- Standardized test scores in reading and mathematics
- Detailed information on parents' SES

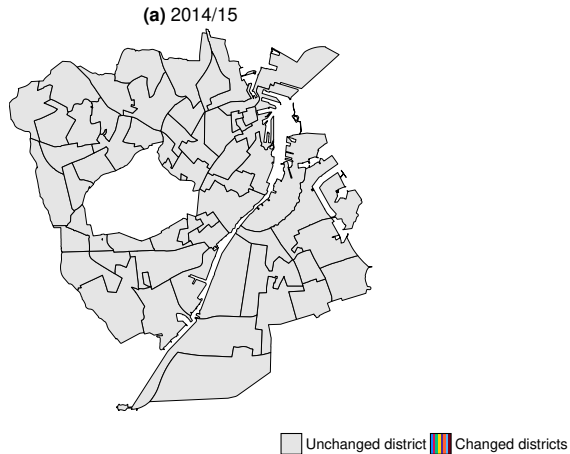
# School Quality

► Value-added

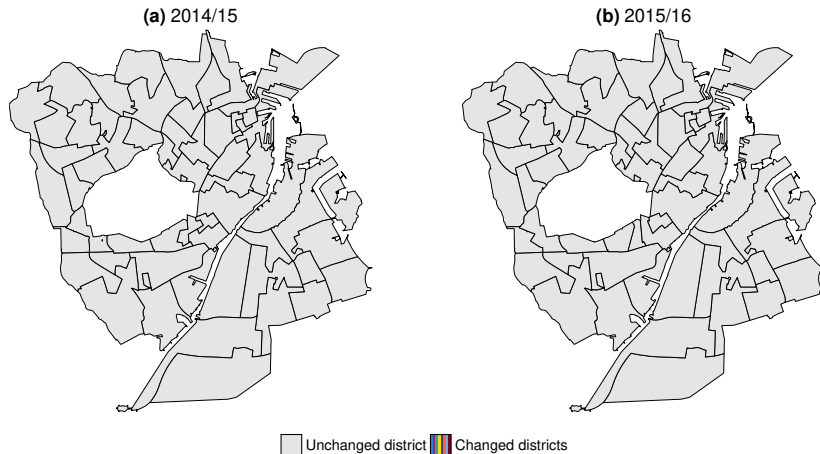




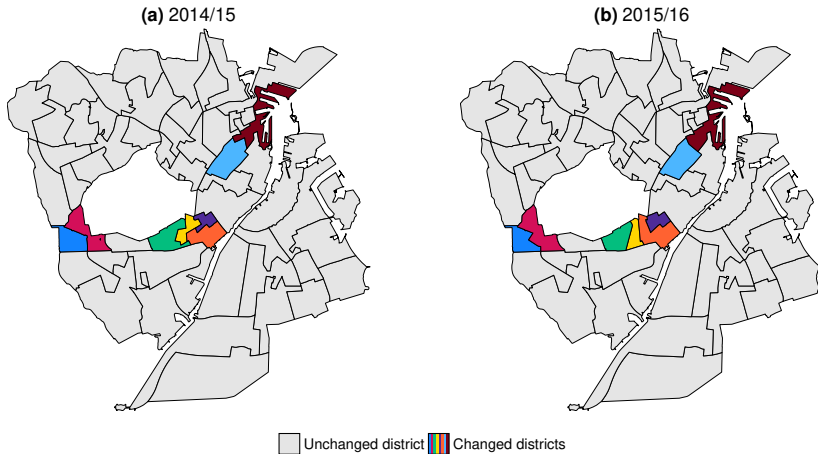
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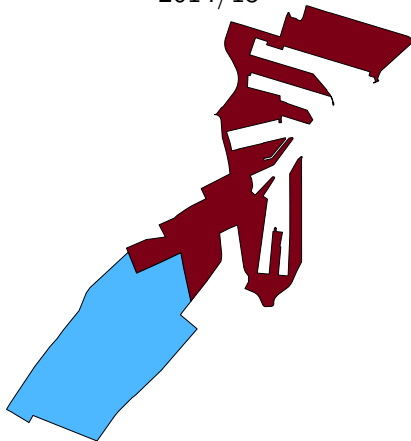


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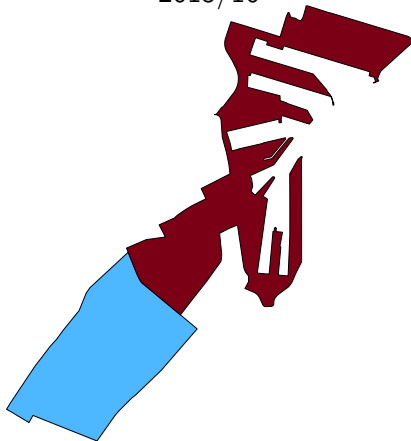
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2014/15

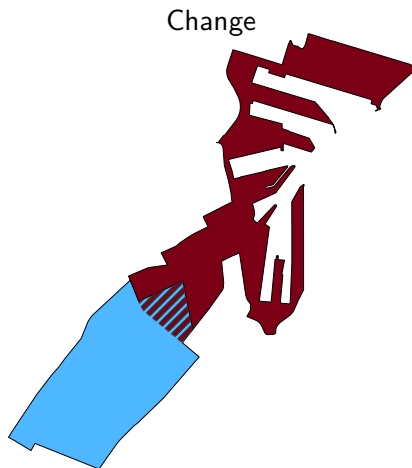


## School district changes

2015/16

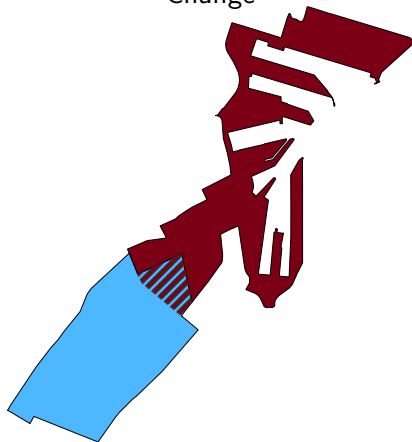


# School district changes



# School district changes

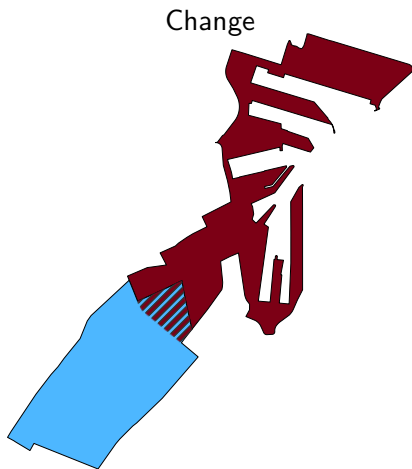
Change



➤ Exactly 1 school per district

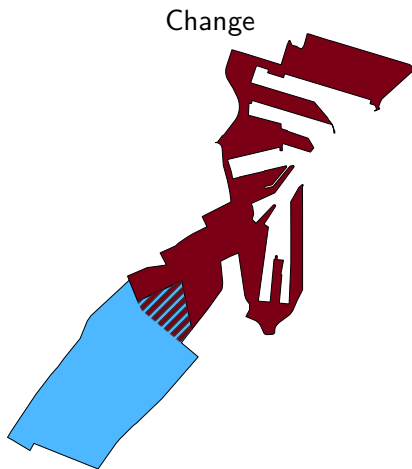
## School district changes

- Exactly 1 school per district
- Assigned at child age 5



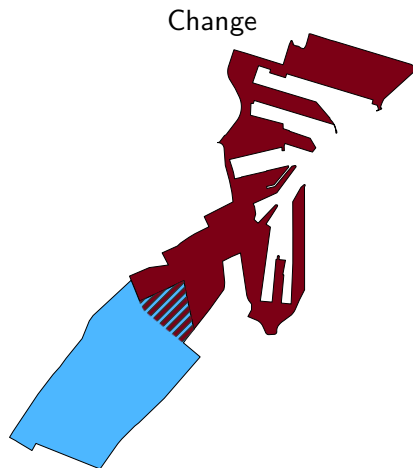


## School district changes



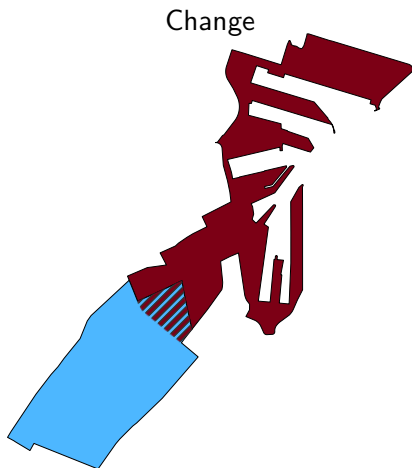
- Exactly 1 school per district
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# School district changes



- Exactly 1 school per district
- Assigned at child age 5
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- Outside options exist ▶ Robust

# School district changes

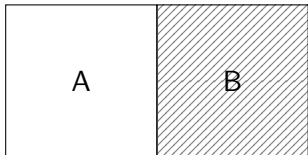


- Exactly 1 school per district
- Assigned at child age 5
- Unanticipated to parents
- Outside options exist ▶ Robust
- $\approx 85$  attend assigned district school

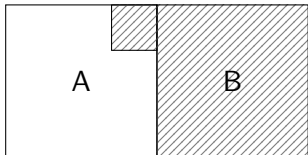
## School district changes

Year	N(Obs.)	N(Changes)	% Any change	% Positive	% Negative
2009	34,319	358	1.04	0.52	0.53
2010	37,703	218	0.58	0.33	0.25
2011	36,405	452	1.24	0.69	0.55
2012	38,247	609	1.59	0.44	1.15
2013	36,793	201	0.55	0.40	0.15
2014	37,403	429	1.15	0.38	0.76
2015	33,532	574	1.71	1.01	0.70
Total	254,402	2,841	1.12	0.53	0.59

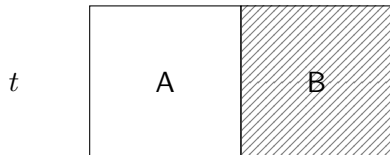
# Does school quality impact test scores?

 $t$ 

$$y_{ijt} = \rho Q_{jt} + \gamma L_i + \delta(Q_{jt} \times L_i) + \mathbf{x}_i' \beta + (\eta_{j'} \times \lambda_t) + \varepsilon_{ijt}$$

 $t + 1$ 

## Does school quality impact test scores?



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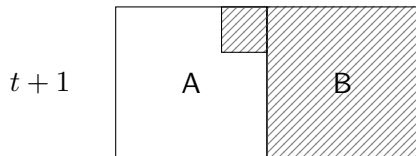
where:

$y_{ijt}$  student test score in reading (grade 2)

$\eta_j'$  old school FE

$Q_{jt}$  school quality (post-redistricting)

$L_i$  low-SES dummy (no parent with university degree)



## Fixed effects results

	No controls		Controls	
	Coef	(SE)	Coef	(SE)
SVA	0.021	(0.027)	0.026	(0.025)
Low-SES	-0.462***	(0.007)	-0.440***	(0.006)
Low-SES $\times$ SVA	0.037***	(0.007)	0.035***	(0.006)
$N$ (obs.)	254,397			
$N$ (identifying obs.)	2,841			
$R^2$	0.143		0.177	

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Total impact for low-SES  $\approx 0.06\sigma$

# School quality versus exposure

## School quality versus exposure

Let  $Z_j$  be a dummy instrument for every school district change  $j = 1, \dots, 81$ .

$$Q_{it} = \alpha_0 + \sum_{j=1}^K \alpha_j \cdot 1(Z_i = j) + \lambda_{1,t} + e_{it}$$

$$E_{it} = \beta_0 + \sum_{j=1}^K \beta_j \cdot 1(Z_i = j) + \lambda_{2,t} + u_{it}$$

$$A_{it} = \gamma_0 + \sum_{j=1}^K \gamma_j \cdot 1(Z_i = j) + \lambda_{3,t} + v_{it}$$

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School quality  $\rightarrow Q_{it} = \alpha_0 + \sum_{j=1}^K \alpha_j \cdot 1(Z_i = j) + \lambda_{1,t} + e_{it}$

Exposure  $\rightarrow E_{it} = \beta_0 + \sum_{j=1}^K \beta_j \cdot 1(Z_i = j) + \lambda_{2,t} + u_{it}$

Age at test  $\rightarrow A_{it} = \gamma_0 + \sum_{j=1}^K \gamma_j \cdot 1(Z_i = j) + \lambda_{3,t} + v_{it}$

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$$\text{Age at test} \rightarrow A_{it} = \gamma_0 + \sum_{j=1}^K \gamma_j \cdot 1(Z_i = j) + \lambda_{3,t} + v_{it}$$

Use to estimate the second stage Eq:

$$y_{it} = \delta_1 \hat{Q}_i + \delta_2 \hat{E}_i + \delta_3 \hat{A}_i + \varphi_t + \epsilon_i$$

## School quality versus exposure

	Full Sample	Low-SES	High-SES
	(1)	(2)	(3)
Quality	0.126* (0.055)	0.103* (0.044)	0.048 (0.073)
Exposure	0.036 (0.096)	0.044 (0.081)	-0.010 (0.089)
Observations	199,690	149,120	50,570



## School quality versus exposure

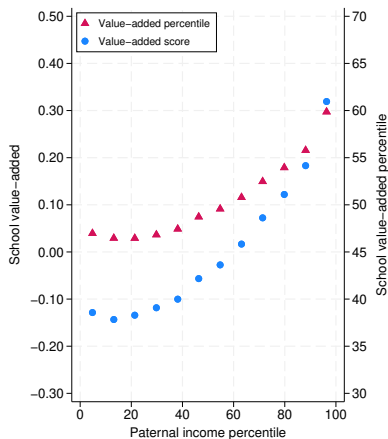
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Observations	199,690	149,120	50,570

Differential impact for low-SES:  $\approx 0.05\sigma$

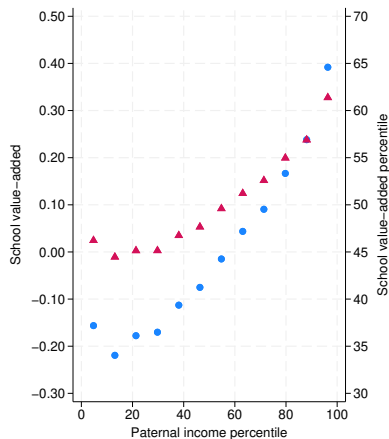
## Results for Copenhagen

How would these results look in a more unequal setting?

# Results for Copenhagen



(a) Full sample



(b) Copenhagen

## Results for Copenhagen

	Full sample		Copenhagen	
	Coef	(SE)	Coef	(SE)
SVA	0.026	(0.025)	0.028	(0.021)
Low-SES	−0.440***	(0.006)	−0.455***	(0.010)
Low-SES × SVA	0.035***	(0.006)	0.044***	(0.009)
$N$ ( <i>obs.</i> )	254,397		67,851	
$N$ ( <i>identifying obs.</i> )	2,841		1,444	
$R^2$	0.177		0.189	

# Summary

**Consistent effect of  $\approx 6\text{--}7\%$  SD**

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## School effectiveness literature:

- 1 year of schooling effect  $\approx 1/3\sigma\text{--}1/4\sigma$  (Woessmann, 2016)



# Summary

## Consistent effect of $\approx 6\text{--}7\%$ SD

- Total SES gap  $\approx 45\%$  SD—similar in US (Reardon, 2016)
- About  $1/6$  of total SES gap

## School effectiveness literature:

- 1 year of schooling effect  $\approx 1/3\sigma\text{--}1/4\sigma$  (Woessmann, 2016)
- Re-allocating low-SES kids to higher quality schools  $\approx 1/4$  school year

# Conclusion

## Theoretical contributions

1. Model that makes sense of contradictory findings

# Conclusion

## **Theoretical contributions**

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# Conclusion

## Theoretical contributions

1. Model that makes sense of contradictory findings
2. Explains why improvements in exposure ineffective
3. ... and why quality investments have an equalizing potential

## Empirical contributions

4. Large inequalities in quality even in Denmark
5. Quality improvements especially important for low-SES kids
6. Investments in quality have larger returns in unequal settings

**Thank You!**

`said.hassan@nuffield.ox.ac.uk`



## Derivation $\Theta_Q$ , Low-SES

We start with the production function for the Low-SES group:

$$y_L = A Q_L^{\alpha_L} E^{\beta_L}$$

**Step 1: Compute the Partial Derivative with Respect to  $Q$**

$$\frac{\partial y_L}{\partial Q} = \frac{\partial}{\partial Q} (A Q_L^{\alpha_L} E^{\beta_L}) = A \alpha_L Q_L^{\alpha_L - 1} E^{\beta_L}$$

**Step 2: Divide by  $y_L$  to Find the Marginal Effect Relative to  $y_L$**

$$\frac{1}{y_L} \frac{\partial y_L}{\partial Q} = \frac{A \alpha_L Q_L^{\alpha_L - 1} E^{\beta_L}}{A Q_L^{\alpha_L} E^{\beta_L}} = \frac{\alpha_L}{Q_L}$$

Thus, for the Low-SES group, we have:

$$\frac{1}{y_L} \frac{\partial y_L}{\partial Q} = \frac{\alpha_L}{Q_L}$$

## Derivation $\Theta_Q$ , High-SES

$$y_H = AQ_H^{\alpha_H} E^{\beta_H}$$

**Step 1: Compute the Partial Derivative with Respect to  $Q$**

$$\frac{\partial y_H}{\partial Q} = \frac{\partial}{\partial Q} (AQ_H^{\alpha_H} E^{\beta_H}) = A\alpha_H Q_H^{\alpha_H-1} E^{\beta_H}$$

**Step 2: Divide by  $y_H$  to Find the Marginal Effect Relative to  $y_H$**

$$\frac{1}{y_H} \frac{\partial y_H}{\partial Q} = \frac{A\alpha_H Q_H^{\alpha_H-1} E^{\beta_H}}{AQ_H^{\alpha_H} E^{\beta_H}} = \frac{\alpha_H}{Q_H}$$

Thus, for the High-SES group, we have:

$$\frac{1}{y_H} \frac{\partial y_H}{\partial Q} = \frac{\alpha_H}{Q_H}$$

## Relative Ratio between Marginal Effects

Now, we form the relative ratio between the derivatives for the High-SES and Low-SES groups:

$$\Theta_Q = \frac{\frac{1}{y_H} \frac{\partial y_H}{\partial Q}}{\frac{1}{y_L} \frac{\partial y_L}{\partial Q}}$$

Substituting the expressions derived for each group:

$$\Theta_Q = \frac{\frac{\alpha_H}{Q_H}}{\frac{\alpha_L}{Q_L}}$$

### Simplifying the Ratio

$$\Theta_Q = \frac{\alpha_H}{\alpha_L} \cdot \frac{Q_H}{Q_L}$$

Thus, the relative ratio between the derivatives is:

$$\Theta_Q = \frac{\alpha_H}{\alpha_L} \cdot \frac{Q_H}{Q_L}$$

## Theoretical model - assumptions

$$\text{Government problem: } \max_{E, Q} \int Y_1(Q, E, H; \theta) \partial F(\theta) \quad (1)$$

Assume concavity in returns to  $E$  and  $Q$ :

$$Y_1 = Q^{\alpha_0} E^{\alpha_1} H^{1-\alpha_0-\alpha_1} \theta \quad (2)$$

and a budget constraint:

$$P_E E + P_Q Q \leq G \quad (3)$$

$$\max_{E, Q} \int Q^{\alpha_0} E^{\alpha_1} H^{1-\alpha_0-\alpha_1} \theta \partial F(\theta) \quad \text{s.t.} \quad P_E E + P_Q Q \leq G \quad (4)$$

# Theoretical model - Optimal investments

Apply a Lagrange multiplier ( $\lambda(\cdot)$ ) to the problem in (4) and optimize :

$$\max_{E, Q} \int Q^{\alpha_0} E^{\alpha_1} H^{1-\alpha_0-\alpha_1} \theta \partial F(\theta) + \lambda[G - P_E E - P_Q Q] \quad (5)$$

$$\text{w.r.t. to } Q: \quad (6)$$

$$\int \alpha_0 Q^{\alpha_0-1} E^{\alpha_1} H^{1-\alpha_0-\alpha_1} \theta \partial F(\theta) - \lambda[P_Q] = 0 \quad (7)$$

$$\text{w.r.t. to } E: \quad (8)$$

$$\int \alpha_1 E^{\alpha_1-1} Q^{\alpha_0} H^{1-\alpha_0-\alpha_1} \theta \partial F(\theta) - \lambda(P_E) = 0 \quad (9)$$

So we get:

$$\lambda P_Q = \alpha_0 \mathbb{E}_{Q^{-1}Y_1(\theta)} \quad (10)$$

$$\lambda P_E = \alpha_1 \mathbb{E}_{E^{-1}Y_1(\theta)} \quad (11)$$

# Theoretical model - Optimal investments results 1

1. The optimal investment in  $E$  relative to  $Q$  is:

$$E = \frac{P_Q \alpha_1}{P_E \alpha_0} Q \quad (12)$$

2. A budget constraint of:

$$G = P_Q Q + P_E E \quad (13)$$

$$= P_Q Q + P_E \frac{P_Q \alpha_1}{P_E \alpha_0} Q \quad (14)$$

$$= P_Q Q + \frac{P_Q \alpha_1}{\alpha_0} Q \quad (15)$$

$$= \left[1 + \frac{\alpha_1}{\alpha_0}\right] P_Q Q \quad (16)$$

## Theoretical model - Optimal investments results 2

Now re-arrange, to get how much we should spend on quality (here, let  $Q^*$  denote the optimal  $Q$ ):

$$G = [1 + \frac{\alpha_1}{\alpha_0}] P_Q Q \quad (17)$$

$$Q^* = \frac{G}{P_Q} \frac{\alpha_0}{\alpha_0 + \alpha_1} \quad (18)$$

Symmetrically, we can derive the same for the optimal  $E$ ,  $E^*$ :

$$E^* = \frac{G}{P_E} \frac{\alpha_1}{\alpha_0 + \alpha_1} \quad (19)$$

## Theoretical model - Experiment 1: Targeted investments

$$\mathbb{E}(Y_1(\theta)) = \mathbb{P}(\theta)Y(\theta) + \mathbb{P}(\theta')Y(\theta') \quad (20)$$

where  $\mathbb{P}(\theta)$  is the probability (here, share) of individuals in the population with low initial skills ( $\theta$ ), and  $\mathbb{P}(\theta')$  is for high initial skills.

Now consider a policy that increases  $Q(\theta) \forall \theta$  holding constant home environment  $H$  and exposure to schooling  $E$ . This policy satisfies  $P_E E + P_Q Q = G$  such that  $Q_N = Q + \delta(\theta)$ . Here,  $Q_N$  denotes the “new” quality level after the investment.

The effect of this policy is given by:

$$Y_1^N(\theta) = \theta(Q + \delta(\theta))^{\alpha_0} E(\theta)^{\alpha_1} H^{1-\alpha_0-\alpha_1} \quad (21)$$

$$Y_1^N(\theta') = \theta'(Q + \delta(\theta'))^{\alpha_0} E(\theta')^{\alpha_1} H^{1-\alpha_0-\alpha_1} \quad (22)$$

$$E(Y_1^N) = \mathbb{P}(\theta)Y_1^N(\theta) + \mathbb{P}(\theta')Y_1^N(\theta') \quad (23)$$



# Theoretical model - Experiment 1: Targeted investments

Now we can ask suppose we want to choose  $\mathbb{E}(Y_1^N)$  (the attained skill after the investment) to be larger, how should we choose  $\delta_\theta$  (the amount of additional quality we invest in low-skill individuals) and  $\delta_\theta^1$  (the amount of additional quality we invest in high-skill individuals):

$$\max_{\{\delta_\theta, \delta_\theta^1\}} \mathbb{E}(Y_1^N) \Leftrightarrow \max_{\{\delta_\theta, \delta_\theta^1\}} \mathbb{P}(\theta)Y_1^N(\theta) + \mathbb{P}(\theta')Y_1^N(\theta') \quad (24)$$

The benefit from raising  $\delta_\theta$  for low-skill individuals:

$$\mathbb{P}(\theta) \frac{\partial Y_1^N(\theta)}{\partial \delta_\theta} = P\alpha_0 \frac{Y_1^N(\theta)}{Q(\theta) + \delta(\theta)} \quad (25)$$

The benefit from raising  $\delta_{\theta'}$  for high skill individuals:

$$(1 - \mathbb{P})\alpha_0 \frac{Y_1^N(\theta')}{Q(\theta')} + \delta(\theta') \quad (26)$$

Because of concavity of  $Y_1(Q)$ , then  $\forall \theta < \theta'$ :

$$\frac{Y_1^N(\theta)}{Q(\theta) + \delta(\theta)} > \frac{Y_1^N(\theta')}{Q(\theta') + \delta(\theta')} \quad (27)$$

## Theoretical model - Experiment 2: Indiscriminate investments

I.e.,  $Q^N = Q + \delta$ :

$$\max_{\delta} \mathbb{E}(Y_1) \quad (28)$$

$$\max_{\delta} \mathbb{P}(\theta)Y_1(\theta) + \mathbb{P}(\theta')Y_1(\theta') \quad (29)$$

Then we have:

$$\frac{\mathbb{P}(\theta)Y_1(\theta)}{Q(\theta) + \delta} + \frac{\mathbb{P}(\theta')Y_1(\theta')}{Q(\theta) + \delta'} > 0 \quad (30)$$

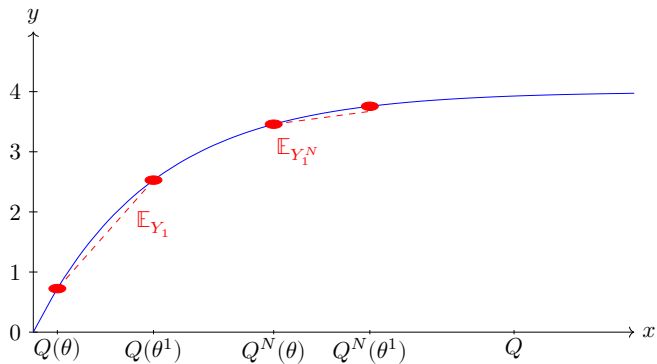
Assuming that

$$\frac{\partial Y}{\partial Q} > 0$$

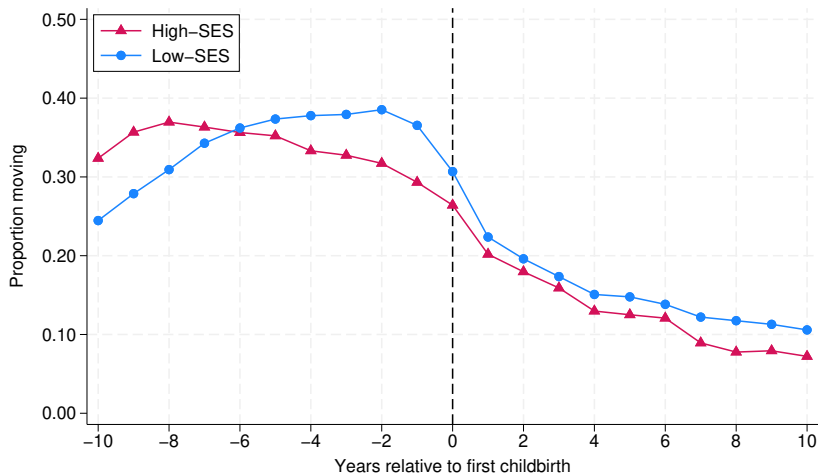
we would rather choose the highest change in quality in order to increase the  $\mathbb{E}(Y_1)$ , this is because  $Y_1(\theta)$  and  $Y_1(\theta')$

## Theoretical model - Experiment 2: Indiscriminate investments

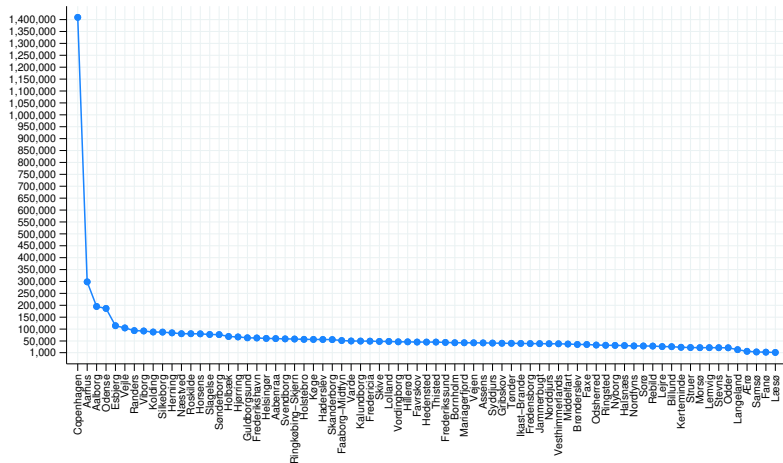
Figure: Illustration



## Robustness check: Anticipation of district changes



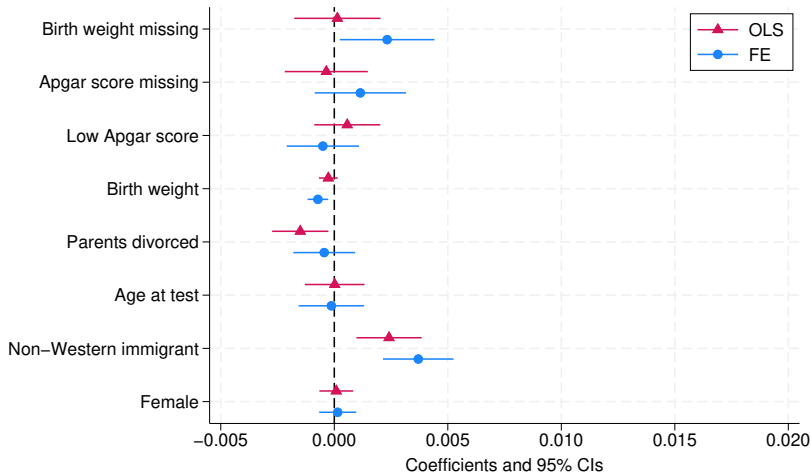
## Population size



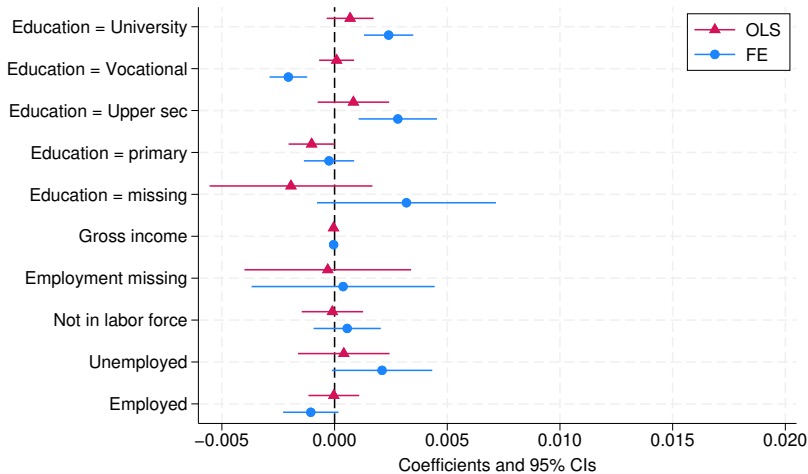
# Summary stats by district change

	No			
	District Change		District Change	
	Mean	(SD)	Mean	(SD)
<i>Demographic variables</i>				
Female	0.494	(0.500)	0.497	(0.500)
Non-Western immigrant or descendant	0.074	(0.262)	0.097	(0.296)
Age at test	8.088	(0.283)	8.087	(0.283)
Parents divorced	0.100	(0.300)	0.096	(0.295)
Copenhagen	0.264	(0.441)	0.508	(0.500)
Large city <sup>a</sup>	0.375	(0.484)	0.522	(0.500)
<i>Health at birth</i>				
Birth weight (kg)	3.349	(0.899)	3.296	(0.952)
Low Apgar score (< 10)	0.071	(0.256)	0.068	(0.251)
Apgar score missing	0.043	(0.203)	0.048	(0.213)
Birth weight missing	0.040	(0.195)	0.048	(0.214)
<i>Paternal characteristics</i>				
Employed	0.873	(0.333)	0.863	(0.344)
Unemployed	0.035	(0.183)	0.041	(0.199)
Not in labor force	0.082	(0.274)	0.086	(0.280)
Employment missing	0.010	(0.101)	0.011	(0.102)
Gross income (10,000s) <sup>b</sup>	7.145	(7.572)	6.928	(4.838)
Education missing	0.011	(0.103)	0.014	(0.116)
Primary education	0.160	(0.366)	0.157	(0.364)
Upper secondary	0.058	(0.235)	0.073	(0.259)
Vocational	0.604	(0.489)	0.559	(0.497)
University	0.167	(0.373)	0.198	(0.398)

## Balance test: Demographics

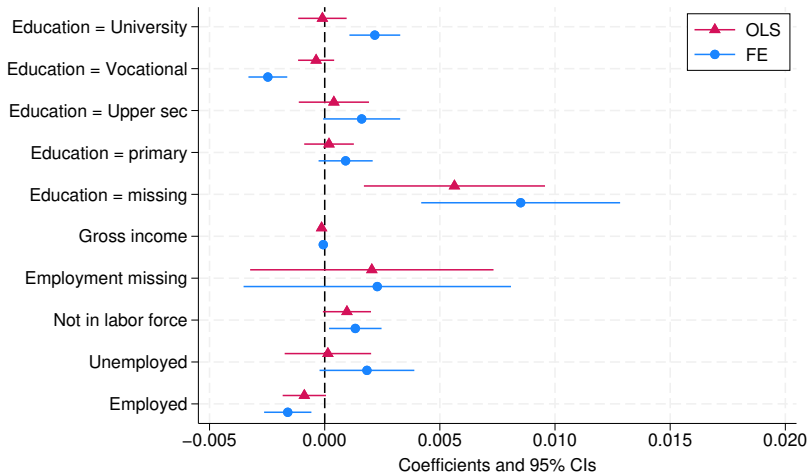


## Balance test: Paternal variables





## Balance test: Maternal variables



## School district changes by SES

Year	% Any change		% Positive		% Negative	
	Low-SES	High-SES	Low-SES	High-SES	Low-SES	High-SES
2009	1.01	1.18	0.49	0.62	0.52	0.55
2010	0.52	0.76	0.32	0.36	0.21	0.40
2011	1.14	1.58	0.67	0.75	0.47	0.83
2012	1.39	2.20	0.35	0.71	1.04	1.49
2013	0.63	0.28	0.47	0.19	0.17	0.09
2014	0.98	1.63	0.28	0.67	0.70	0.95
2015	1.87	1.30	1.10	0.76	0.76	0.54
Total	1.06	1.29	0.51	0.58	0.55	0.71

## FE results: Different SVA measures

	(1) Main results (Jackknife SVA)	(2) Alternative 1 (Chetty et al., 2014)	(3) Alternative 2 (Simple FEs)
SVA	0.026 (0.025)	0.027 (0.026)	0.006 (0.021)
Low-SES	−0.440*** (0.006)	−0.439*** (0.006)	−0.435*** (0.006)
Low-SES × SVA	0.035*** (0.006)	0.030*** (0.006)	0.022*** (0.005)
N(Obs.)	254, 397	252, 637	254, 690
N(Changers)	2, 841	2, 781	2, 879
$R^2$	0.177	0.177	0.176
Controls	Yes	Yes	Yes

## FE results: Different SEs

	(1) Main (pre school)	(2) Pre school $\times t$	(3) Actual school	(4) Actual school $\times t$	(5) Bootstrap
SVA	0.026 (0.025)	0.026 (0.026)	0.026 (0.027)	0.026 (0.027)	0.026 (0.026)
Low-SES	-0.440*** (0.006)	-0.440*** (0.005)	-0.440*** (0.006)	-0.440*** (0.005)	-0.440*** (0.005)
Low-SES $\times$ SVA	0.035*** (0.006)	0.035*** (0.005)	0.035*** (0.006)	0.035*** (0.005)	0.035*** (0.003)
N(Obs.)	254, 397	254, 397	254, 397	254, 397	254, 402
N(Changers)	2, 841	2, 841	2, 841	2, 841	2, 841
$R^2$	0.177	0.177	0.177	0.177	0.075
Controls	Yes	Yes	Yes	Yes	Yes

## FE results: Different SES measures (1)

	(1) Main results	(2) SES index < p90	(3) Ses index < p75	(4) Ses index < p50
SVA	0.026 (0.025)	0.022 (0.027)	0.027 (0.026)	0.042 (0.026)
Low-SES	-0.440*** (0.006)	-0.334*** (0.009)	-0.403*** (0.006)	-0.364*** (0.005)
Low-SES × SVA	0.035*** (0.006)	0.035*** (0.008)	0.032*** (0.006)	0.008 (0.006)
N(Obs.)	254, 397	254, 397	254, 397	254, 397
N(Changers)	2, 841	2, 841	2, 841	2, 841
$R^2$	0.177	0.156	0.173	0.176
Controls	Yes	Yes	Yes	Yes

## FE results: Different SES measures (2)

	(1) Main results	(2) Income < p90	(3) Income < p75	(4) Income < p50	(5) Unemployed
SVA	0.026 (0.025)	0.026 (0.028)	0.036 (0.027)	0.040 (0.026)	0.043 (0.027)
Low-SES	-0.440*** (0.006)	-0.216*** (0.008)	-0.256*** (0.006)	-0.285*** (0.005)	-0.249*** (0.005)
Low-SES × SVA	0.035*** (0.006)	0.028*** (0.008)	0.023*** (0.006)	0.015** (0.005)	0.014** (0.005)
N(Obs.)	254, 397	254, 397	254, 397	254, 397	254, 397
N(Changers)	2, 841	2, 841	2, 841	2, 841	2, 841
$R^2$	0.177	0.151	0.158	0.165	0.158
Controls	Yes	Yes	Yes	Yes	Yes

## Robustness check compliance: Same school, first borns

	(1) Main results	(2) Firstborns only	(3) Same school
SVA	0.026 (0.025)	0.039 (0.046)	−0.000 (0.026)
Low-SES	−0.440*** (0.006)	−0.418*** (0.008)	−0.426*** (0.006)
Low-SES × SVA	0.035*** (0.006)	0.024** (0.008)	0.034*** (0.006)
N(Obs.)	254,397	101,537	227,165
N(Changers)	2,841	1,190	2,206
$R^2$	0.177	0.201	0.182
Controls	Yes	Yes	Yes

# School quality measure

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## Standard school value-added model (Koedel et al., 2015)

$$A_{ijt} = \omega A_{ij,t-1} + \mathbf{x}'_{ijt}\beta + \alpha_{jt} + \epsilon_{ijt}$$



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► net of student characteristics

# School quality measure

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- net of student characteristics
- captures (unobserved) school factors

# School quality measure

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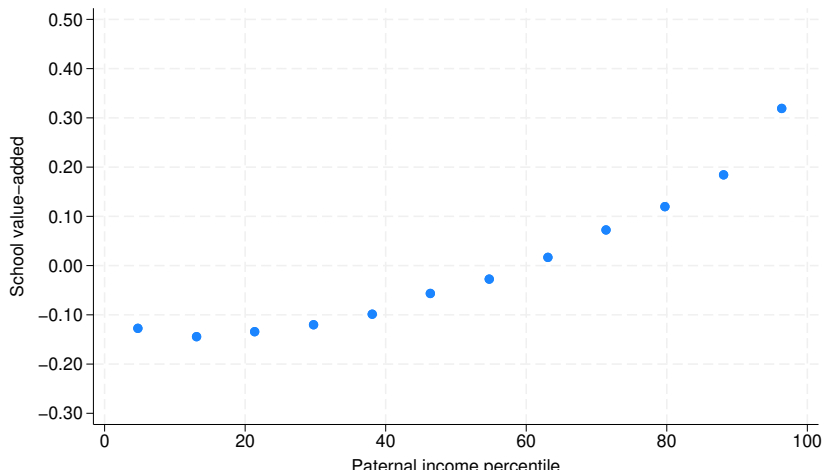
## Standard school value-added model (Koedel et al., 2015)

$$A_{ijt} = \omega A_{ij,t-1} + \mathbf{x}'_{ijt}\beta + \alpha_{jt} + \epsilon_{ijt}$$

$\hat{\alpha}_{jt}$  : contribution of school  $j$  to  $\bar{A}_{jt}$

- net of student characteristics
- captures (unobserved) school factors
- very high autocorrelation ( $\hat{\alpha}_{j,t}, \hat{\alpha}_{j,s>t}$ )

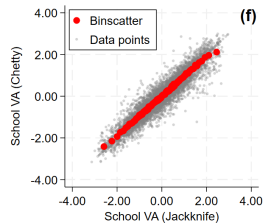
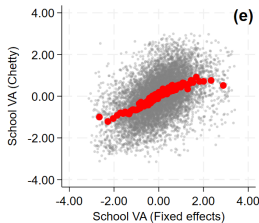
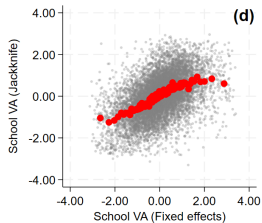
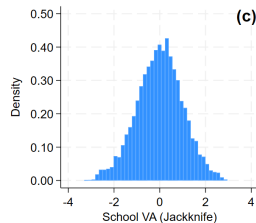
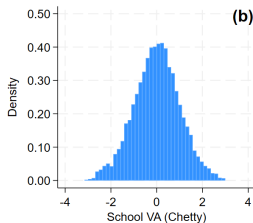
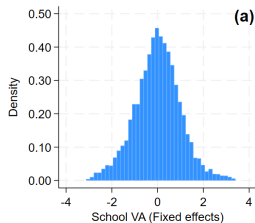
# School quality measure

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## Correlation between SVAs

	SVA Fixed Effects	SVA Jackknife	SVA Chetty
SVA Fixed Effects	1.000		
SVA Jackknife	0.486	1.000	
SVA Chetty	0.467	0.947	1.000

# Comparing SVA measures



## Autocorrelations in SVA over time

**Table:** Correlation between SVA in  $t$  and lagged SVA measures.

Variables	SVA in $t$	$t - 1$	$t - 2$	$t - 3$	$t - 4$	$t - 5$	$t - 6$	$t - 7$	$t - 8$
SVA in $t$	1.000								
$t - 1$	0.881	1.000							
$t - 2$	0.859	0.895	1.000						
$t - 3$	0.831	0.862	0.897	1.000					
$t - 4$	0.798	0.824	0.860	0.894	1.000				
$t - 5$	0.701	0.791	0.826	0.863	0.892	1.000			
$t - 6$	0.606	0.690	0.788	0.829	0.861	0.886	1.000		
$t - 7$	0.546	0.597	0.694	0.794	0.833	0.862	0.877	1.000	
$t - 8$	0.528	0.550	0.611	0.708	0.810	0.847	0.867	0.858	1.000



# Autocorrelation in SVA over time

