

# The impact of elite high schools on academic performance in Hungary

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# Why?

- 1 Debated topic in literature with mixed results
- 2 Subject to planned reforms in Hungary

# Our methodology

- We define elite schools as schools with selective early tracking
- Non-parametric bounds from Charles Manski
  - Partial identification: less restrictive assumptions
  - Key advantage: statements for the entire treatment group
- (Yet) unable to restrict the bound on the effect to get a relevant result (e.g. exclude zero)

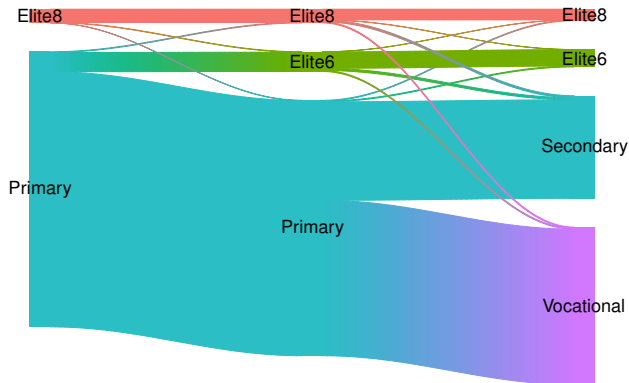
# What is an "elite" school?

- Exclusive schools Abdulkadiroglu et al. (2014), Dobbie&Fryer (2014)
- Early tracking Duflo et al. (2011)
- Selective tracks Pop-Eleches&Urquiola (2013), Lucas&Mbiti (2014)
- Gifted and talented programs Bui et al. (2013), Card&Giuliano (2014)
- Hungary: selective early tracking

# Institutional background: "elite" schools in Hungary

- Schools with 8/6 year academic track
  - about 10% of schools offer such option
- Complex treatment
  - early tracking (from age 10/12)
  - offering special curriculum tailored to the needs of the talented
  - highly selective: good teachers (Varga 2009), good peers

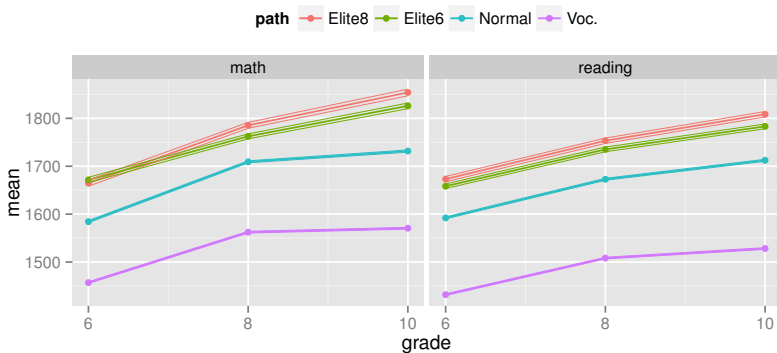
# The flow of students between school types (2010)



# Data

- National Assessment of Basic Competencies (NABC) ~ PISA
- Standardized test for grade 6/8/10 - literacy and numeracy
- Bw 2008 - 2014 - individual identifier: panel structure
- Background questionnaire: parental information
  - voluntary: missing data ~ 15-20%
- Size of a cohort: ~ 90,000 - 100,000 students
  - Data available for ~ 75,000 - 80,000 students

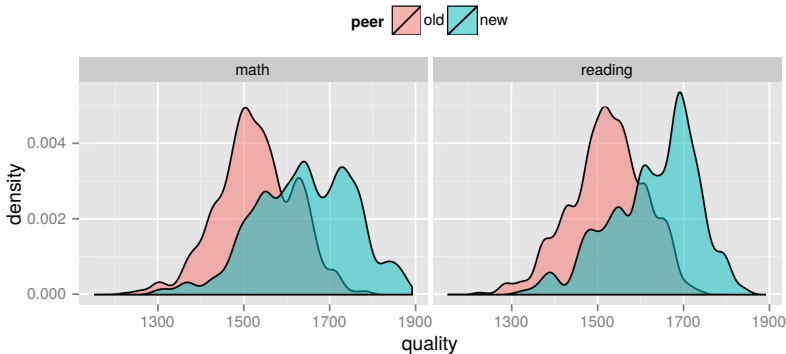
# School path





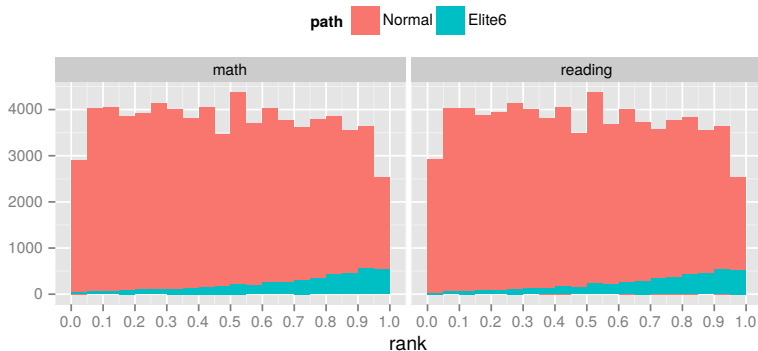
# Elite school students study among better peers

Grade-6 scores of grade-6 versus grade-8 peers for switchers



# Elite students were top-performers in their ex-schools

## Rank distribution



# Method

- Current literature
  - Classic endogeneity problem: disentangle selection and effect
  - Usually uses IV or RD techniques Abdulkadiroglu et al. 2014, Dobbie&Fryer 2014, Card&Guiliano 2014, ...
  - Mainly finds no effect (on a subpopulation...)
- We apply Charles Manski's non-parametric bound framework
  - in a slightly adjusted way

# Parameter of interest: ATET

$$ATET = \mathbb{E}[y(1)|d = 1] - \mathbb{E}[y(0)|d = 1]$$

- Average Treatment Effect on the Treated

# A1: Monotone Treatment Selection (MTS)

$$\mathbb{E}[y(0)|d = 1] \geq \mathbb{E}[y(0)|d = 0]$$

- On average, more able students select into the program
  - defined by the untreated potential outcome

## A2: Monotone Treatment Response (MTR)

$$\mathbb{E}[y(1)|d=1] \geq \mathbb{E}[y(0)|d=1]$$

- On average, the program does not hurt the treated

# MTS & MTR

- The combination of MTS and MTR assumptions yield the following result:

$$0 \leq ATET \leq \mathbb{E}[y(1)|d=1] - \mathbb{E}[y(0)|d=0]$$

- Bounds the effect between 0 and the OLS estimate

## A3: Monotone Instrumental Variable (MIV)

$$z_0 \leq z_1 \Rightarrow \mathbb{E}[y(s)|z = z_0] \leq \mathbb{E}[y(s)|z = z_1], s = 0, 1$$

- The potential outcomes are monotonically increasing between certain subgroups
- Classical IV requires the equality of expected values
- Candidates: Number of books at home, parental schooling



# MTR & MTS & MIV

- For the combination of the assumptions, we need the MTR and MTS to hold for each values of the monotone instrument
- This results in the following bound for the group-specific untreated potential outcome:

$$\mathbb{E}[y(0)|d=0, z=z_i] \leq \mathbb{E}[y(0)|z=z_i] \leq \mathbb{E}[y|z=z_i]$$

- Then, we can derive bounds for ATET by aggregating the group-specific bounds (estimatable from sample averages)

# Mechanics of MIV

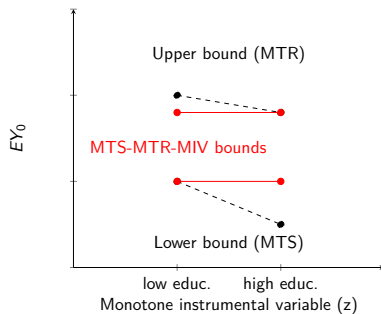


Figure: Binding MIV

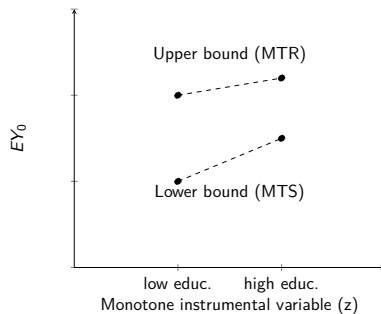


Figure: Non-binding MIV

# When does an MIV bind? Case 1

- if distribution of MIV-groups differs in the untreated population relative to the whole population (selection)

$$\mathbb{E}[y(0)|d=0, z=z_i] \leq \mathbb{E}[y(0)|z=z_i] \leq \mathbb{E}[y|z=z_i]$$

- sharpens the lower bound of  $\mathbb{E}[y(0)] \Rightarrow$  upper bound of ATET

## When does an MIV bind? Case 2

- if conditional means relate in the opposite (counter-intuitive) direction (Richey, 2014)
  - for some  $z_0 \leq z_1$

$$\mathbb{E}[y|z = z_0] \geq \mathbb{E}[y|z = z_1]$$

- Recall, MIV

$$\mathbb{E}[y(s)|z = z_0] \leq \mathbb{E}[y(s)|z = z_1], s = 0, 1$$

- sharpens the upper bound of  $\mathbb{E}[y(0)] \Rightarrow$  lower bound of ATET

# The method in practice

- Step 1 Bound  $\mathbb{E}[y(0)]$  based on the MTS-MTR-MIV assumptions
- Step 2 Transform the bounds for  $\mathbb{E}[y(0)|d = 1]$
- Step 3 Derive bounds on the ATET parameter

# Selection on MIV

Elite school attendance by MIV: 6-year vs primary

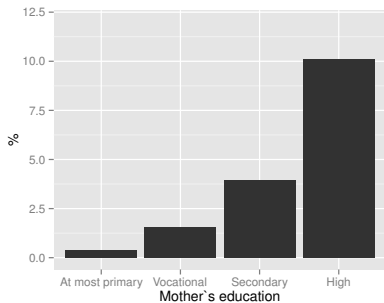


Figure: Mother's education

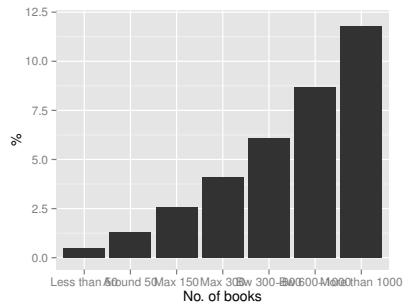


Figure: Number of books

# Bounds on the untreated outcome - single MIV

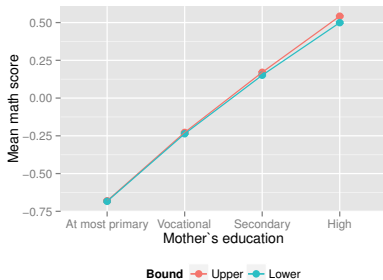


Figure: Mother's education

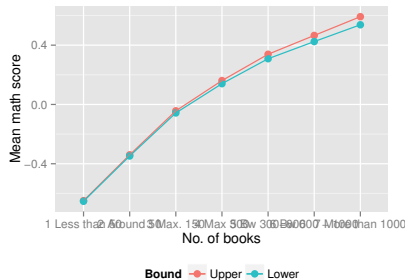


Figure: Number of books

# Results for grade 6

		Mathematics		Reading	
		Lower/upper bound		Lower/upper bound	
A. MTS - MTR					
	Conventional	0.000	0.803	0.000	0.883
	95% CI	0.000	0.813	0.000	0.892
B. Single monotone instrument (MTR - MTS - MIV)					
Father's education	Conventional	0.000	0.482	0.000	0.534
	Bias corr.	0.000	0.482	0.000	0.534
	95% CI	0.000	0.491	0.000	0.543
Mother's education	Conventional	0.000	0.464	0.000	0.516
	Bias corr.	0.000	0.464	0.000	0.516
	95% CI	0.000	0.474	0.000	0.525
Number of books	Conventional	0.000	0.505	0.000	0.547
	Bias corr.	0.000	0.505	0.000	0.547
	95% CI	0.000	0.514	0.000	0.556
# observations		569,758			

Notes: The 95% confidence interval is calculated using robust standard errors and it is based on Imbens & Manski (2004). 1,000 bootstrap replications.



# Combination of MIVs: number of books and mother's education

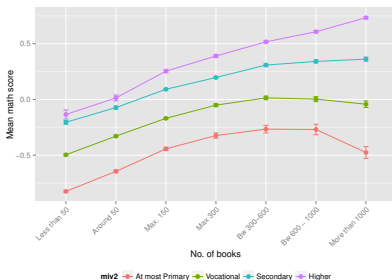


Figure: Lower bound

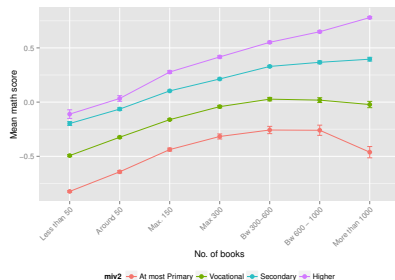


Figure: Upper bound

# Results for grade 6 - combined MIV

		Mathematics		Reading	
		Lower/upper bound		Lower/upper bound	
<i>C. Two monotone instruments (MTS - MTR - MIV)</i>					
Father's education - number of books	Conventional	0.057	0.376	0.084	0.401
	Bias corr.	0.056	0.378	0.081	0.401
	95% CI	0.023	0.391	0.048	0.414
Mother's education - number of books	Conventional	0.108	0.370	0.138	0.406
	Bias corr.	0.099	0.372	0.131	0.408
	95% CI	0.052	0.384	0.080	0.419
# observations		569,758			

*Notes:* The 95% confidence interval is calculated using robust standard errors and it is based on Imbens & Manski (2004). 1,000 bootstrap replications.

# Key findings

- Both the education of the parents and the number of books are key predictors of school choice and educational achievements
- A single MIV can exclude large treatment effects, however, it does not lift the lower bound on the treatment effect
- The combination of MIVs yields impossible results (invalidates the MIV assumption)

# Further plans

- Experiment with other MIVs
  - distance to school
- Focus on subgroups for which selection is stronger
- Go into a "how-to" direction
  - it would have helped us to have some kind of checklist

Thank you for your attention!