Early and Later-life Stimulation: How Retirement Shapes the Effect of Education on Old-age Cognitive Abilities

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EEA Annual Meeting Barcelona

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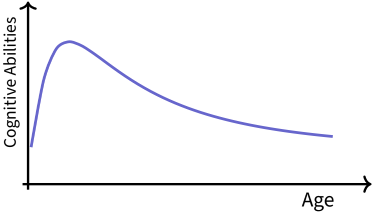
Motivation

Evidence from neuroscience and economic research let it appear irrevocable that cognitive abilities decline with age.



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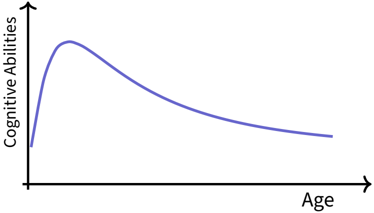

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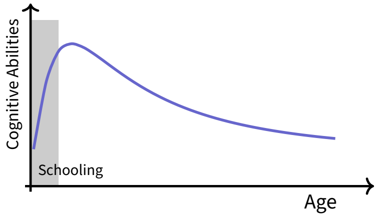

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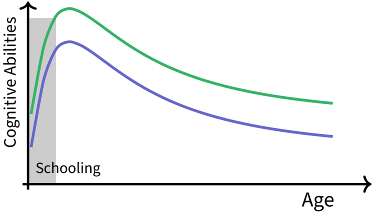

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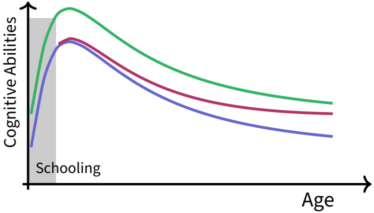

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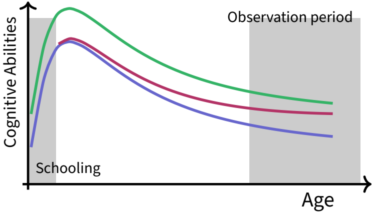

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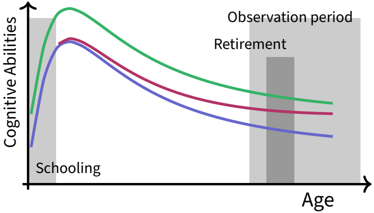

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Research question:

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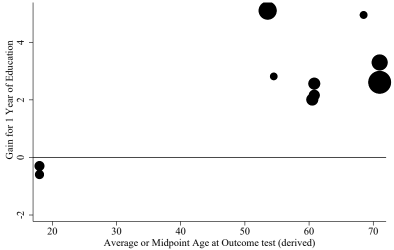
Education has many downstream implications over the life course: is retirement a mechanism?

Meta-analysis by Ritchie and Tucker-Drob (2018, Psychological Science):



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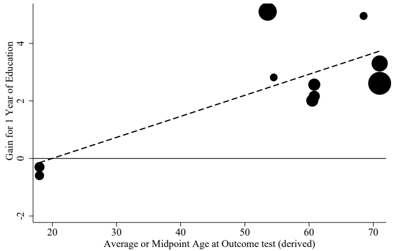

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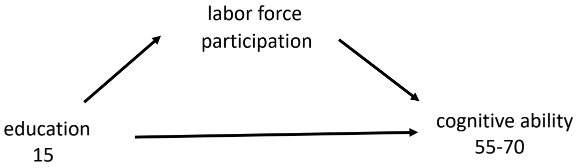

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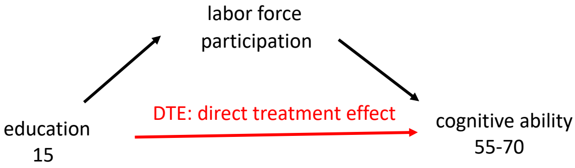

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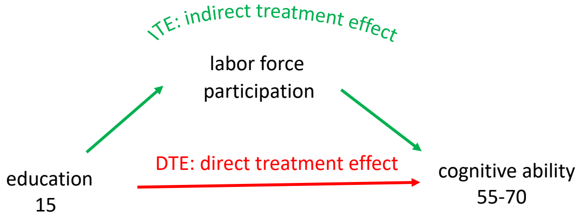

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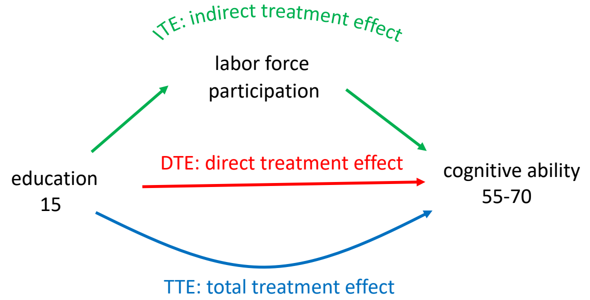

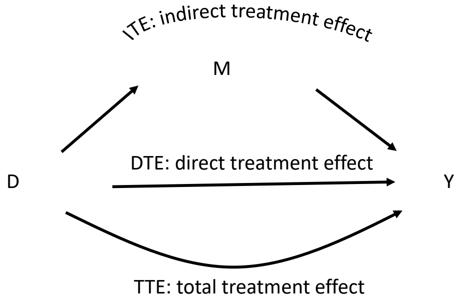

Contribution:

1. We develop of novel estimator for causal mediation analysis that is directly based on IV estimation.
   - Except for Frölich and Huber [2017] (based on a control function approach), no estimator exists that incorporates endogeneity of treatment and mediator and heterogeneous treatment effects.
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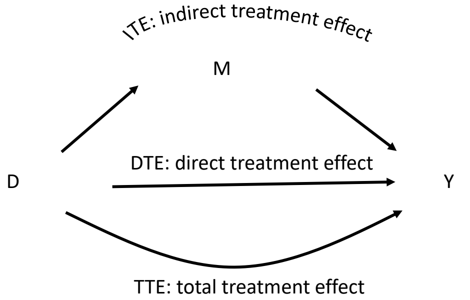

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2. First to test whether labor force causes emerging effects of education on old-age cognitive abilities

Agenda:

- Data
- Baseline Results
- Causal Mediation Analysis
- Causal Mediation Analysis—Results
- Summary & Conclusion

Data

Pool representative survey data from 17 countries on population aged 50+

- Survey of Health Ageing, and Retirement (SHARE), ELSA (UK)
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- Individuals around the age of 50 to 70
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Measure of **cognitive abilities**: *Word recall* test: interviewer reads ten words, respondent is asked to repeat the words

- directly after words are read (*immediate recall*)
- 5 minutes later (*delayed recall*)
- both together add up to word recall test score (range: 0-20)
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Celidoni et al. (2017): Strong reduction (minus 20 per cent) **predict dementia** in the HRS in 70%

Retirement ages and compulsory schooling

- Schooling is endogenous

Austria
Czech Republic
England
France
Germany
HH
SH
HB
NI
SL
BW, HE, NRW, RP
BY
Greece
Italy
Netherlands
Spain

Retirement ages and compulsory schooling

- Schooling is endogenous
- We define $D = \mathbb{1}(\text{years of schooling} \geq \text{new level of compulsory schooling})$

	Compulsory schooling (Z_D)	
	change in years	pivotal cohort
Austria	8-9	1951
Czech Republic	8-9	1934
	9-8	1939
	8-9	1947
England	10-11	1957
France	7-8	1923
	8-10	1953
Germany		
HH	8-9	1934
SH	8-9	1941
HB	8-9	1943
NI	8-9	1947
SL	8-9	1949
BW, HE, NRW, RP	8-9	1953
BY	8-9	1955
Greece	6	1963
Italy	5-8	1949
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Spain	6-8	1957

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	ERA (Z_M)		Compulsory schooling (Z_D)	
	men	women	change in years	pivotal cohort
Austria	60-65	55-60	8-9	1951
Czech Republic	57-60	54-60	8-9	1934
			9-8	1939
			8-9	1947
England	65-66	60-66	10-11	1957
France	60	60	7-8	1923
			8-10	1953
Germany	63	62-63		
HH			8-9	1934
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BW, HE, NRW, RP			8-9	1953
BY			8-9	1955
Greece	58-60	55-60	6	1963
Italy	57-58	57-58	5-8	1949
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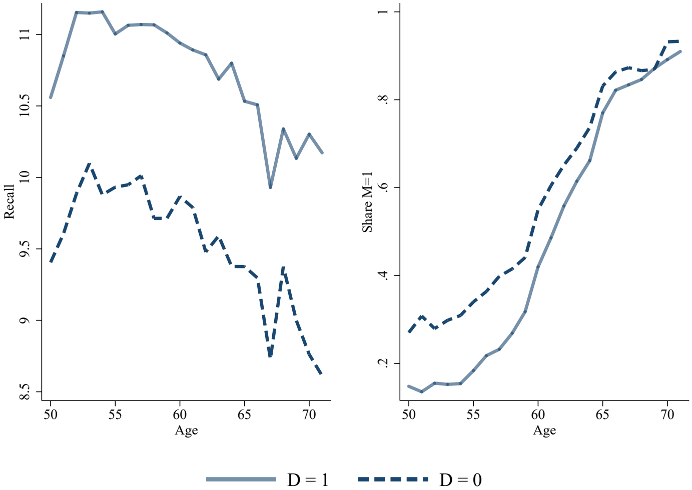
Recall by age and treatment status

73% have $D = 1$.

55% have $M = 1$ (not in the labor force)



Regression results: total treatment effect

$$y_{it} = \beta D_{it} + \gamma_c + \lambda_t + \delta_b + \tau_c(t - b) + \varepsilon_{it}$$

	Treatment: More education		
	OLS (1)	First stage (2)	2SLS (3)
More education (D)	1.485^{***} (0.0483)		0.811^{***} (0.306)
Post CS-reform (Z_1)		0.244^{***} (0.0220)	
Control variables	yes	yes	yes

Number of observations in each regression: 80,164. Additional control variables are birth year fixed effects, interview wave fixed effects, country fixed effects, country-specific linear age trends, test repetition fixed effects and male. Standard errors in parentheses clustered on birth year-country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Regression results: Effect of D on M

	OLS (1)	2SLS (2)
More education (D)	-0.082*** (0.008)	-0.177*** (0.05)
Control variables	yes	yes

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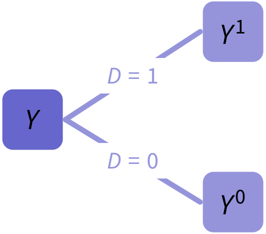
Causal Mediation Analysis

Steps: **Choice about the treatment** **Choice about the mediator**



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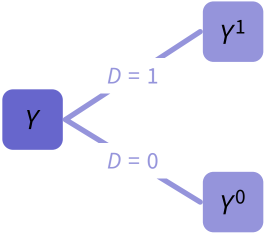

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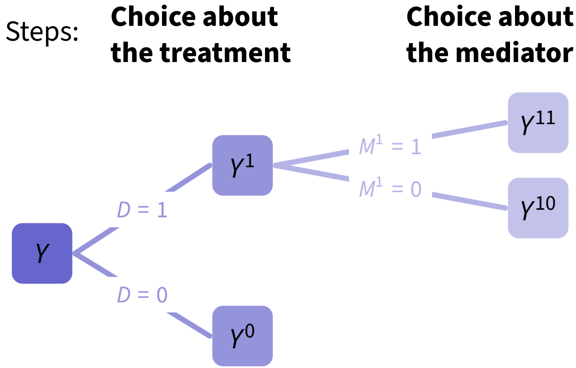

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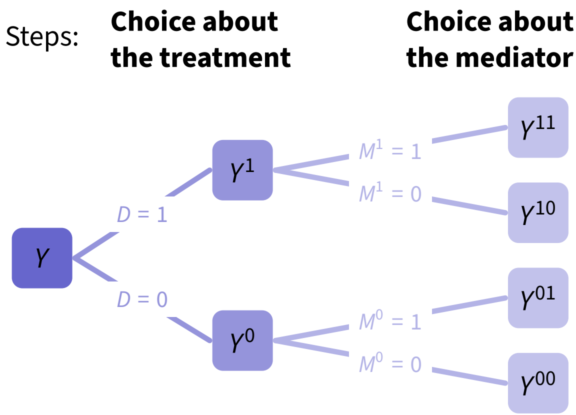

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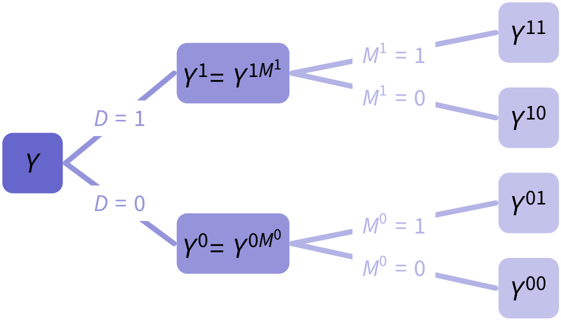

Mediated Outcomes:

$$Y^{1M^1} := Y^{11}M^1 + Y^{10}(1 - M^1)$$

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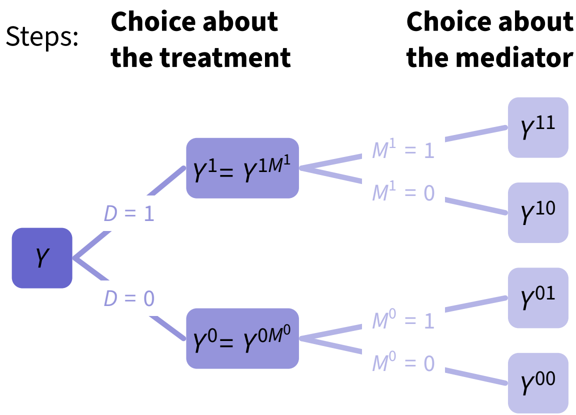

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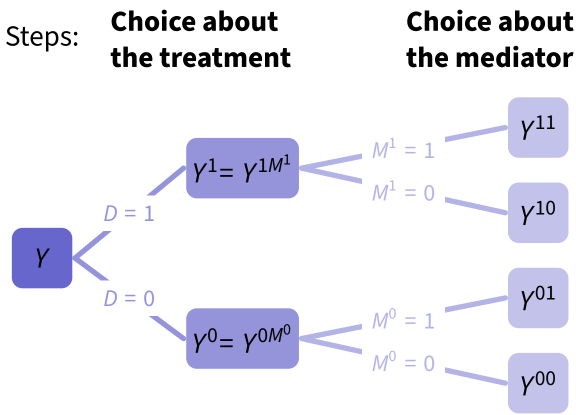

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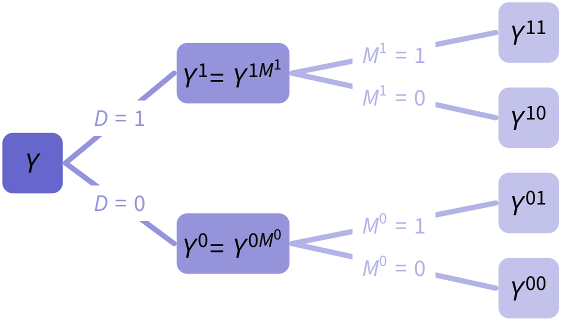

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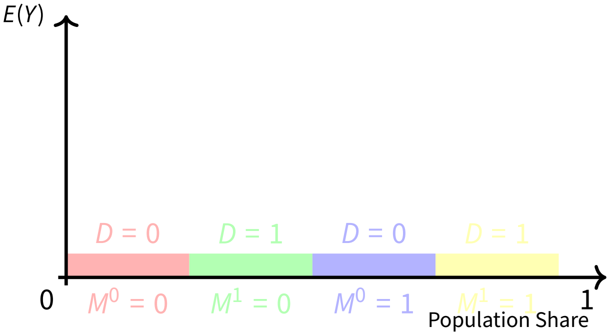

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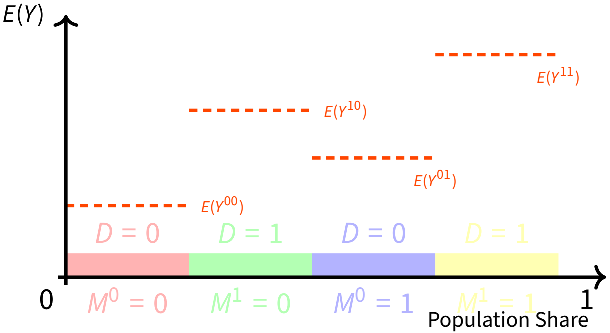

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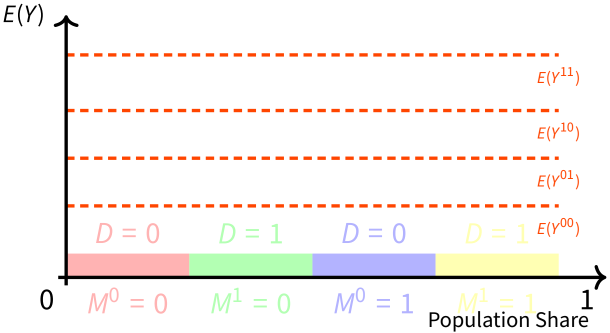

- Because of the random assignment, we can extrapolate the means to the other groups

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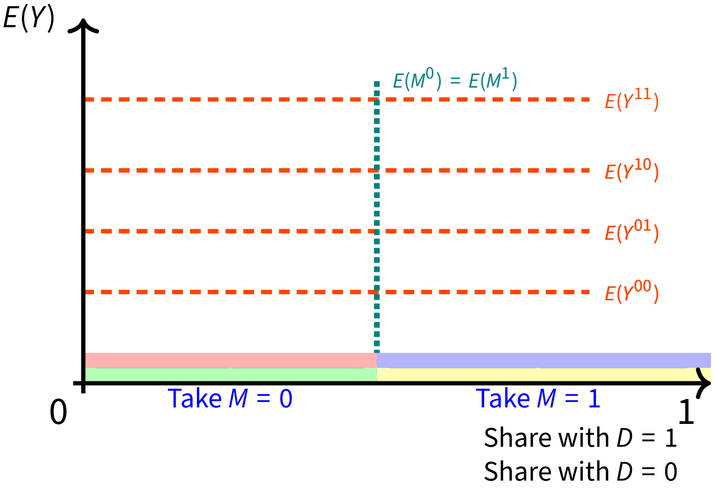
To study the ITEs, we stack the populations with $D = 1$ and $D = 0$ on top of each other:



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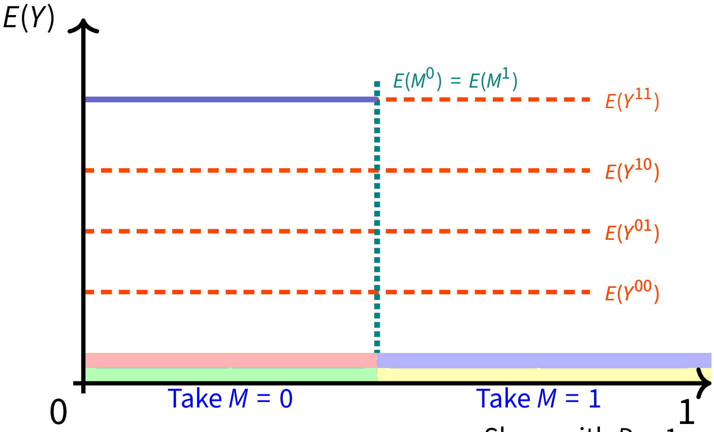

Share with $D = 1$
Share with $D = 0$

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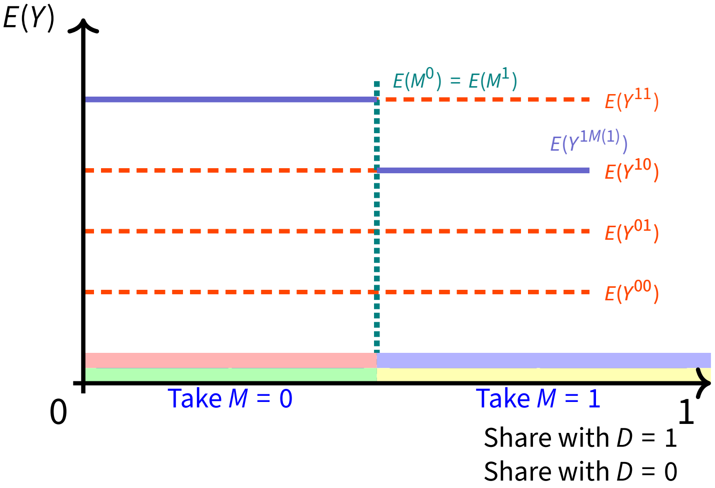

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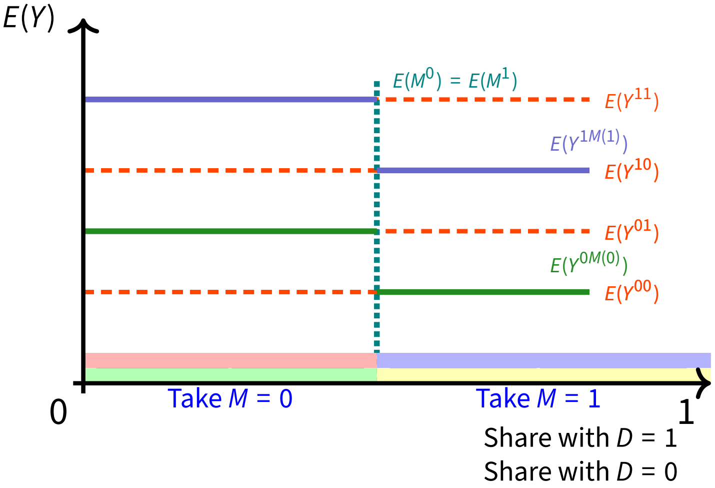

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- $Y^0 = Y^{0M^0} = Y^{01}M^0 + Y^{00}(1 - M^0)$
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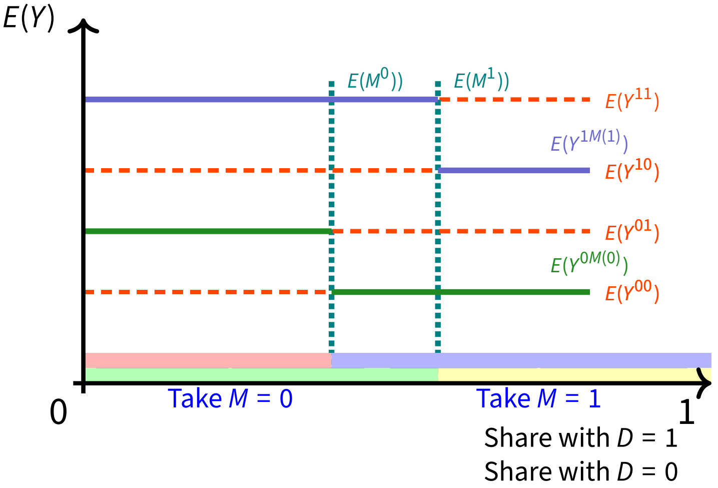

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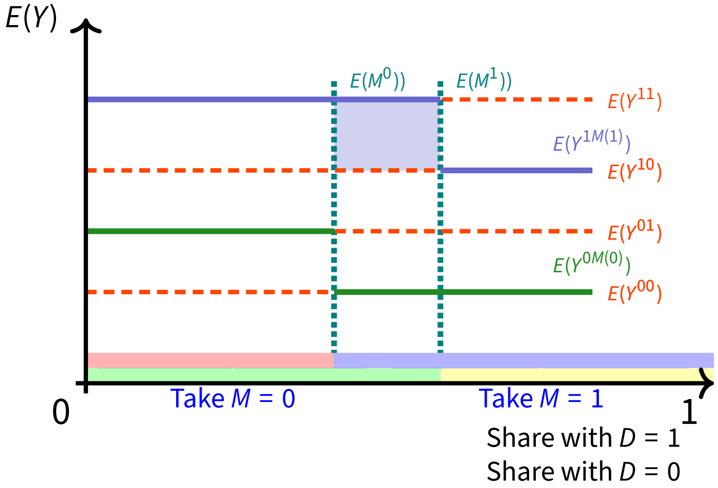

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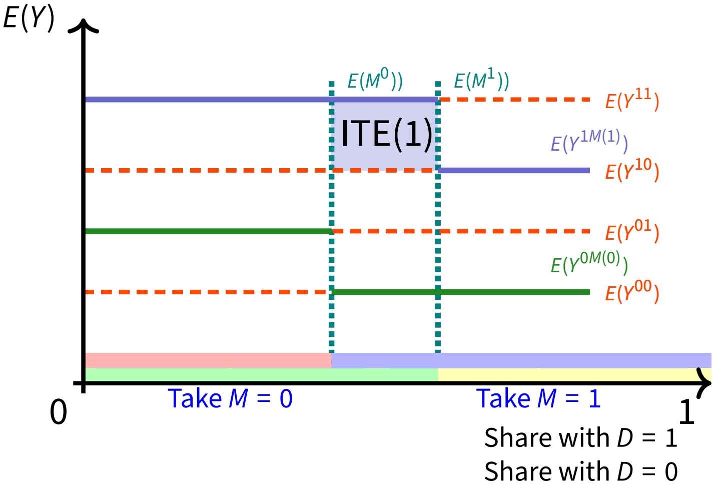

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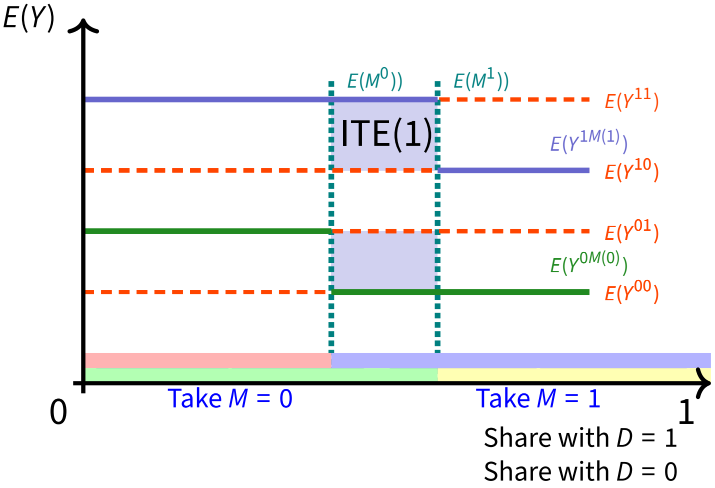

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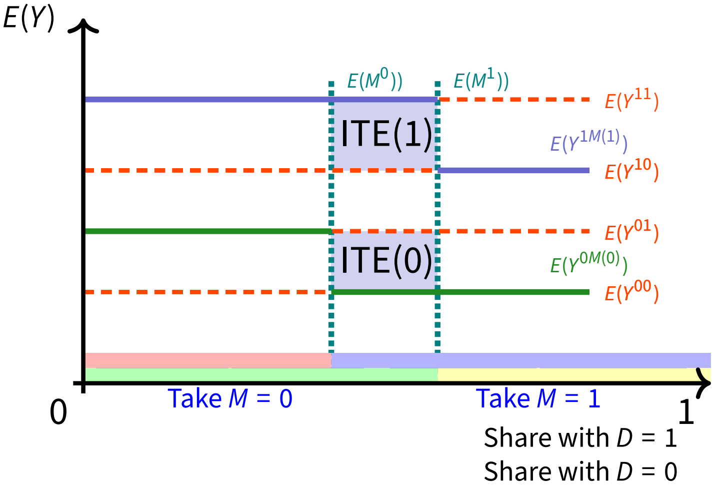

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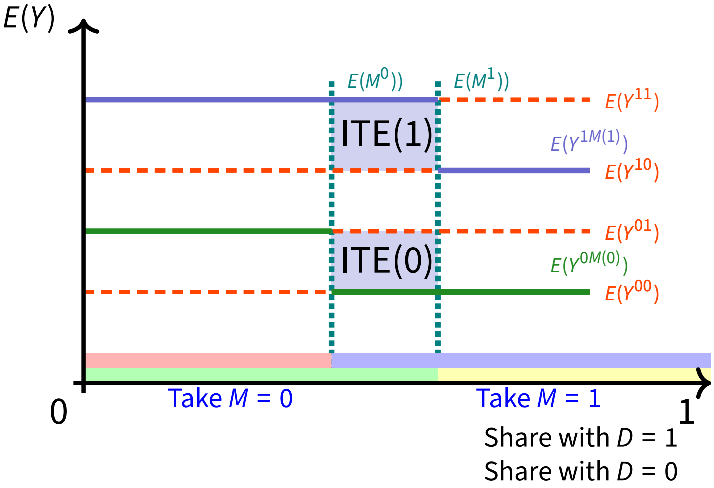

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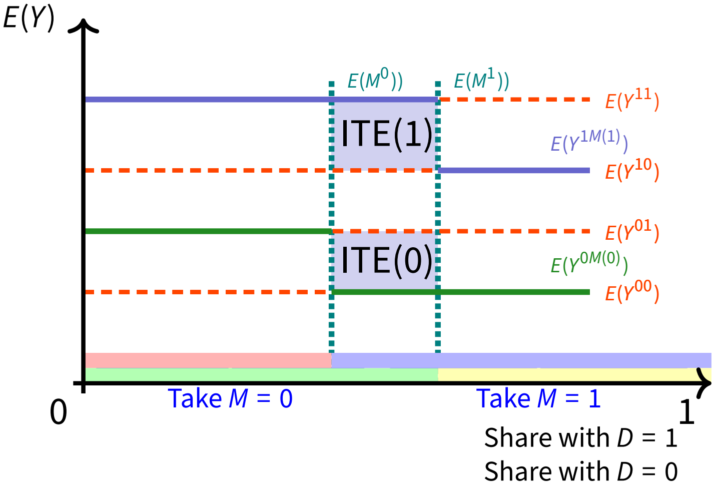

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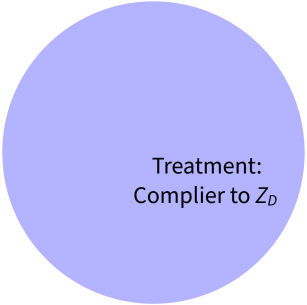

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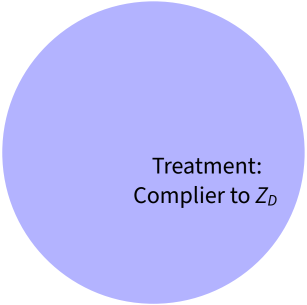

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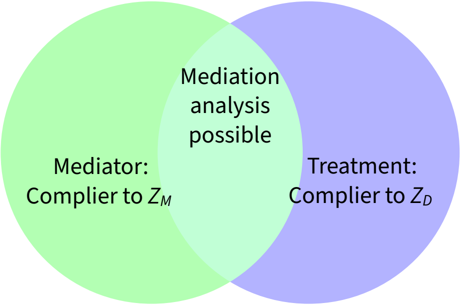

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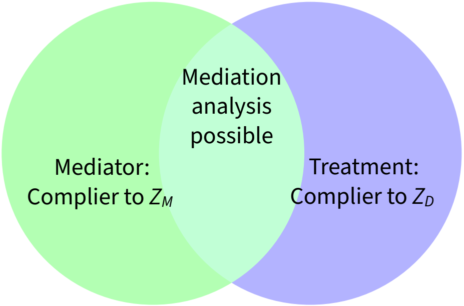

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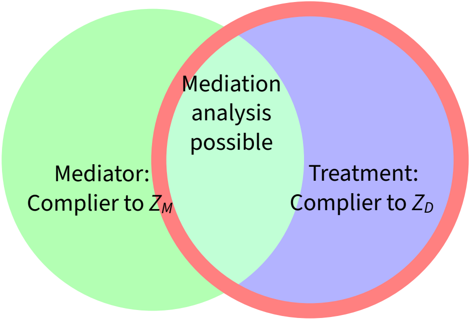

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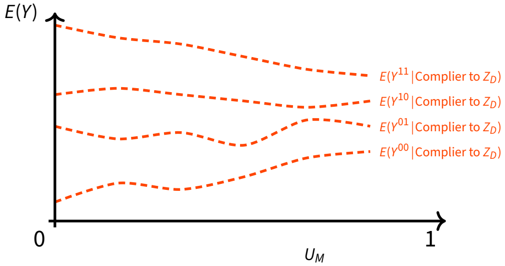

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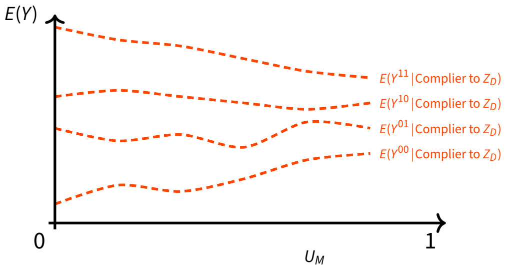

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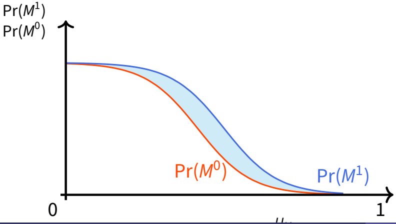

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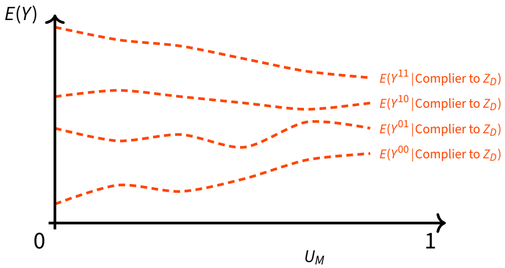

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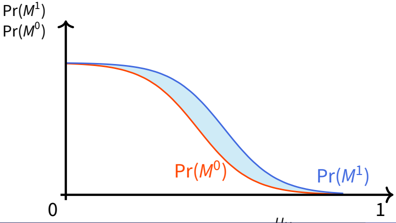

Mediation effects:

$$
\begin{aligned}
ITE(1) &= E\left(Y^{11} - Y^{10}\right)\left(\Pr(M^1 = 1) - \Pr(M^0 = 1)\right) \\
DTE(0) &= E\left(Y^{10} - Y^{00}\right) \\
&\quad + \left(\Pr(M^0 = 1)\right) E\left(Y^{11} - Y^{01} - (Y^{10} - Y^{00}\right)\right)
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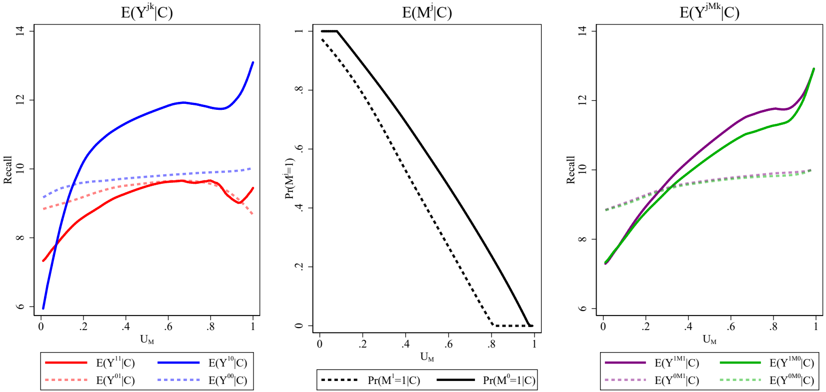
▸ Estimation Protocol ▸ Simulation results

Causal Mediation Analysis—Results



Causal Mediation Analysis—Results

	Total treatment effect	Effect decomposition				
		Indirect TEs		Direct TEs		
	$TTE = LATE$	$ITE(1)$	$ITE(0)$	$DTE(1)$	$DTE(0)$	N
Baseline results	0.864*	0.293*	0.043	0.822*	0.571	80,763
	(0.505)	(0.153)	(0.052)	(0.494)	(0.488)	

Number of observations: 80,763. Control varixables are birth year fixed effects, interview wave fixed effects, country fixed effects, country-specific linear age trends, test repetition fixed effects and male. Bootstrap standard errors (200 replications) in parentheses clustered on birth year-country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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Male	0.582	0.552**	0.099	0.483	0.0294	43,397
	(0.659)	(0.261)	(0.0754)	(0.631)	(0.612)	
Female	1.148	0.365	0.0274	1.121	0.783	37,366
	(0.827)	(0.309)	(0.0677)	(0.811)	(0.665)	

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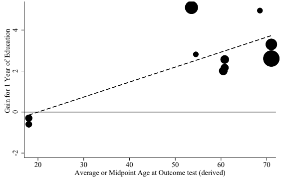
By this, we put the results found in the literature so far in a more consistent perspective:



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Steps: **1. Stratification by Z_D type** **2. Separate Evaluation** **3. Assess effects of M**

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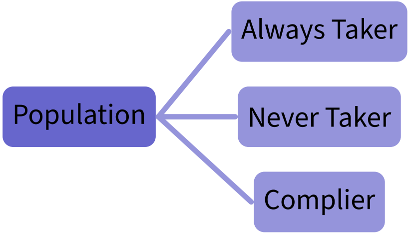

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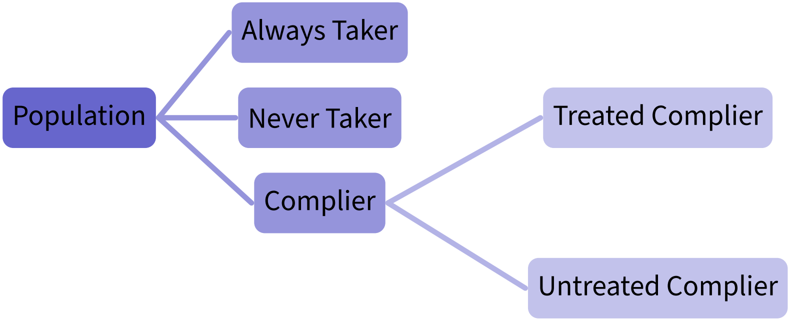

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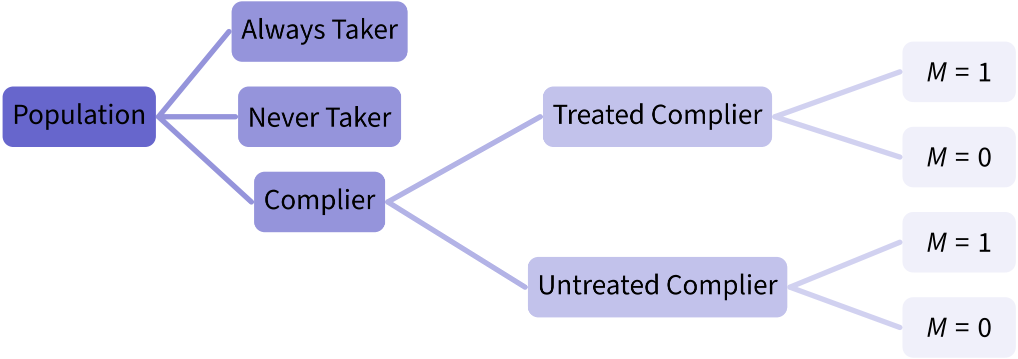

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- X affecting Y, M, D, and instruments
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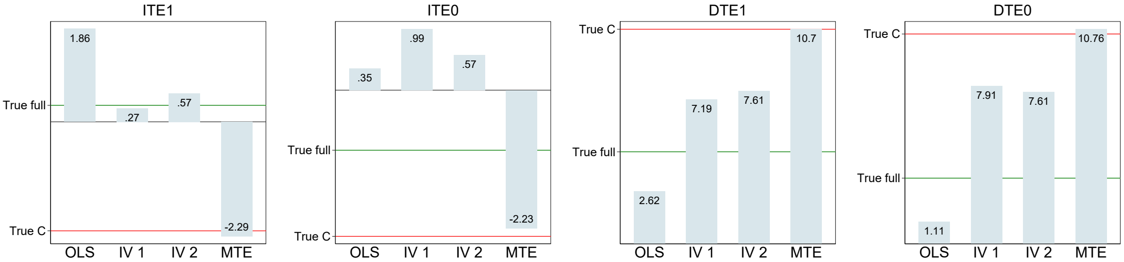

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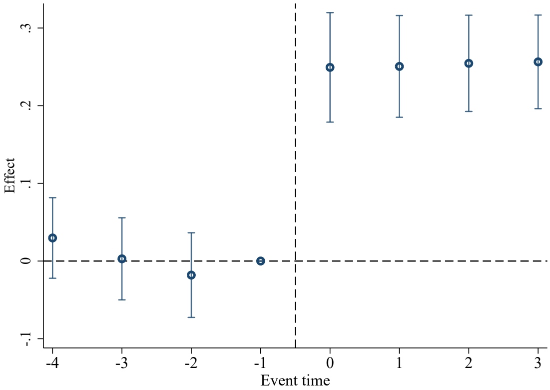
Simulation



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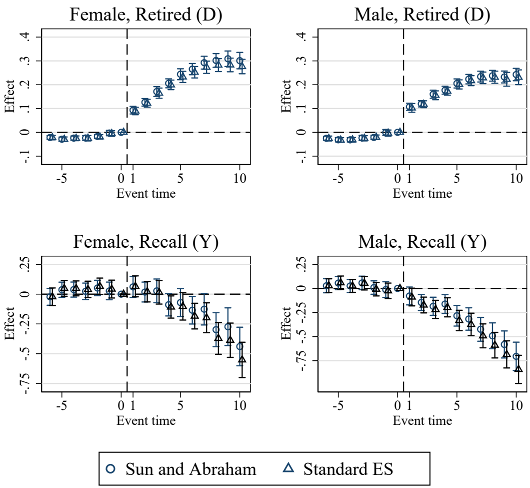
Simulation



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Simulation

Total, direct, and indirect treatment effects:

	Total treatment effect	Effect decomposition			
		Indirect TEs		Direct TEs	
	$TTE = LATE$	$ITE(1)$	$ITE(0)$	$DTE(1)$	$DTE(0)$
MTE	0.864^{*}	0.293^{*}	0.043	0.822^{*}	0.571
	(0.505)	(0.153)	(0.052)	(0.494)	(0.488)

Number of observations: 80,763. Control variables are birth year fixed effects, interview wave fixed effects, country fixed effects, country-specific linear age trends, test repetition fixed effects and male. Bandwidth = 0.25. Bootstrap standard errors (200 replications) in parentheses clustered on birth year-country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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2SLS	0.804^{**}	0.184	-0.209	1.013^{**}	0.620^{*}
	(0.379)	(0.140)	(0.164)	(0.485)	(0.354)
OLS	1.418^{***}	0.039^{***}	0.050^{***}	1.368^{***}	1.380^{***}
	(0.052)	(0.005)	(0.009)	(0.054)	(0.054)

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