Heuristic Learning from Test Scores and Human Capital Decisions

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*I would like to thank the CBS for providing access to the data I use in this study

Do Students Update Ability Beliefs Heuristically?

- Test scores affect human capital investment decisions by providing ability signals
- Prior literature focused on rational learning from test scores; No attention to heuristics
- Left-digit bias might imply a discontinuity in the perception of signals at round scores

→ Study the impact of crossing 600 in the Psychometric Entrance Test (PET)

  - *Empirical strategy*: RDD
  - *In the short term*: 30% increase in applications to CS and EE programs in universities
  - *In the long term*: 20% increase in CS degrees; 10% increase in employment in tech firms; 5% increase in annual income (about 7K NIS annually)

(Partial) Review of Related Literature

Test scores affects human capital decisions

- Avery et al. (2018) [*major*]
- Goodman (2016); Diamond and Persson (2017); Bond et al. (2018) [*enrollment*]
- Stinebrickner and Stinebrickner (2012); Arcidiacono et al. (2016); Avery et al. (2017) [*completion*]

Heterogeneity in the response to signals:

- Ahn et al. (2019); Owen (2021a); Coffman et al. (2021); McEwan et al. (2021) [*women respond more*]
- Bestenbostel (2021); Owen (2021b) [*no gender heterogeneity*]
- Graetz et al. (2020) [*low-SES individuals respond more*]

Heuristic interpretation of test scores:

- Goodman et al. (2020) document a decrease in SAT retaking rate above round score cutoffs

Outline

Administrative database (Israeli CBS)

- *Data*: PET scores, university applications, degrees (colleges and universities), labor market, demographics, Bagrut; Available until 2018
- *The Psychometric Entrance Test* (PET):
  - Normalized test scores; Approximately $\sim \mathcal{N}(550, 100)$
    Score distribution
  - Differences in testing regularities between Jews and Arabs (also among Jews, by gender/age)
    Testing, by population group
- *Sample*: All individuals who participated in their first PET between 1995–2008
  [wo/w Arabs]

Outcome Variables

- *Main Outcomes*: CS and EE applications
  - Very selective fields in terms of PET scores, and futural labor market outcomes
    Elite fields
  - Admission decisions are based on a weighted average of the PET score and the mean composite score in the Bagrut
  - Very low rate of acceptance to CS/EE programs with PET of 600
    Acceptance rate
  - Conditional admission chances are continuous at 600
    Conditional acceptance rate
  - Individuals with 600 (in the first test) usually retake before applying
    Share retaking
- *Long Term Outcomes*: Enrollment, Degree Attainment, Employment, Income

Outline

Identification Based on a Heuristic

- The left-digit bias is the tendency of humans to judge the difference between 600 and 599 to be larger than that between 601 and 600

  Evidence: consumers' decisions (Lacetera et al., 2012); experts' decisions (Olenski et al., 2020); *Response to high-stakes test scores* (Goodman et al., 2020)

- Implies a discontinuity in the perception of scores at 600

→ Allows RDD under the assumption that the potential outcomes are continuous at 600

  - Admission chances are continuous at 600 (was shown)
  - Density of observations is smooth at 600 (was shown)
  - Pre-determined outcomes are continuous at 600 (soon)

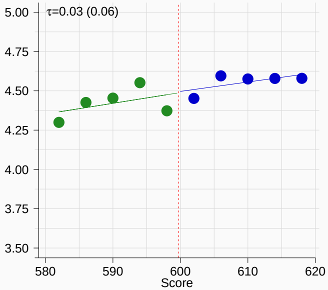
Main Estimation – Local Linear RD

- $Score_i$ is the *first* score of subject i
- Bandwidth of 20: observations within $Score_i \in [580, 619]$
- $Above600_i$ is an indicator for $Score_i \in [600, 619]$
- R_i is a continuous variable with the value $Score_i - 600$

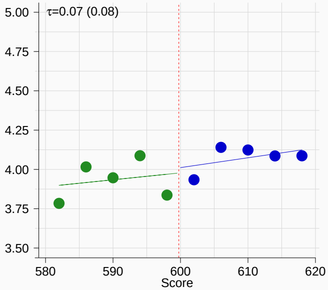
Then, estimate:

$$Y_i = \alpha + \tau \cdot Above600_i + \beta_l \cdot R_i + (\beta_r - \beta_l) \cdot Above600_i \cdot R_i + \varepsilon_i$$

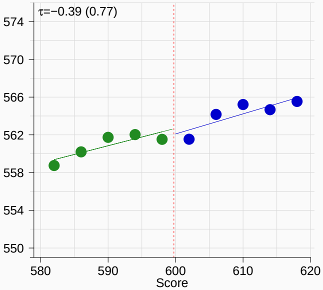
The "Impact" of Crossing 600 on Predicted Outcomes



(a) Predicted CS



(b) Predicted EE



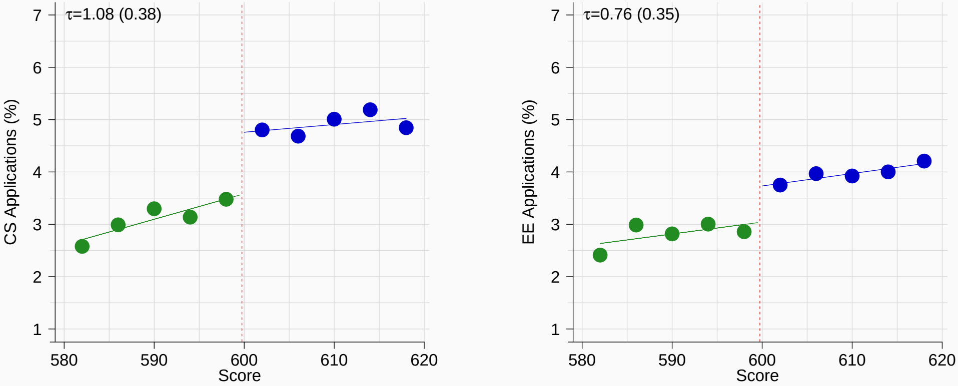
(c) Predicted Score

- No discontinuous change in covariates (Table) and in predicted outcomes (based on covariates) at 600

Outline

Crossing 600 and University Applications

Within Three Years After the Test



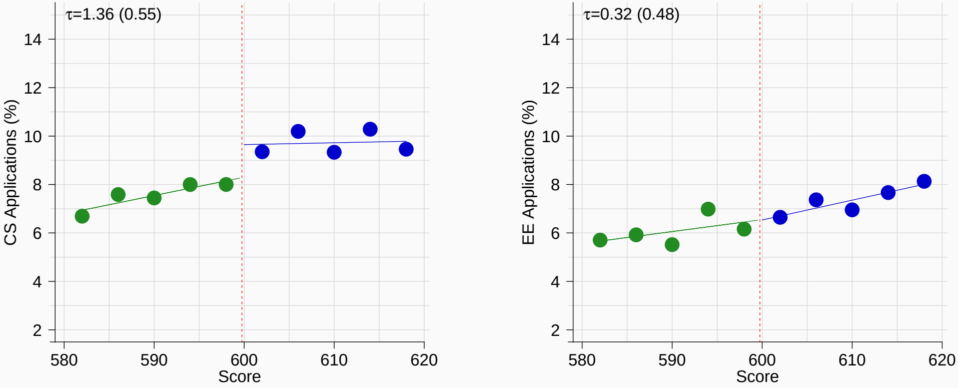
(a) Computer Sciences (CS) (b) Electrical Engineering (EE)

- CS and EE applications increase by 30% and 25%

Full distribution | Alternative Outcomes | Alternative Specifications | Alternative cutoffs (placebo) | Using all tests

Crossing 600 and University Applications

Ever

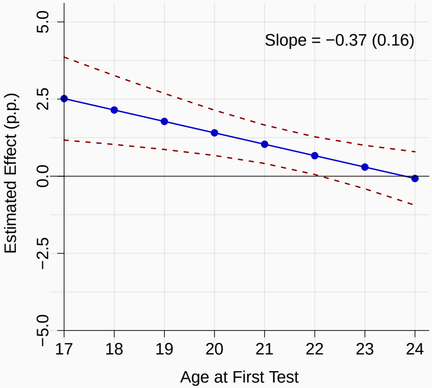


(a) Computer Sciences (CS) (b) Electrical Engineering (EE)

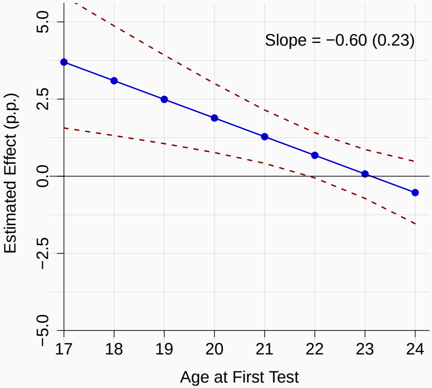
- The increase in CS applications persists (20%) and the increase in EE applications dissipates

After high school Effects on Arabs

Heterogeneity of the Impact of Crossing 600 on CS Applications, by Age



(a) Within three years



(b) Ever

- The effect is driven by the younger test-takers (consistent with learning on ability mechanism)

Estimation | Two groups (17-21, 22+)

Heterogeneity by Gender and SES, Younger Test-takers (21 and Below)

By Gender	Men ($N = 10,971$)		Women ($N = 18,832$)	
	Mean	Est. Effect	Mean	Est. Effect
Within three years	5.165	1.758* (0.994)	2.403	1.285** (0.502)
Ever	15.777	2.917* (1.489)	5.641	1.262* (0.723)
By SES: $parental\_years\_of\_education > 12$	Low ($N = 13,276$)		High ($N = 16,527$)	
(Both Parents)	Mean	Est. Effect	Mean	Est. Effect
Within three years	3.043	1.438** (0.716)	3.699	1.617** (0.659)
Ever	8.432	1.417 (1.045)	10.026	2.588*** (0.996)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

- Similar (relative) increase among men/women and low/high SES test-takers

Summary – Main Results

Crossing 600 in the first PET increases CS & EE applications:

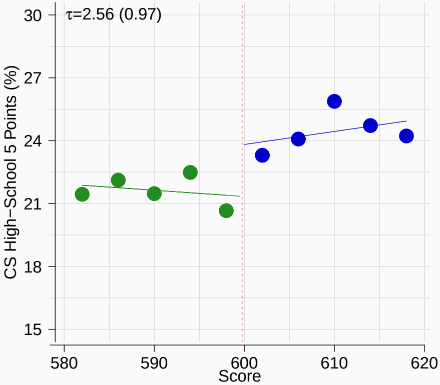
- *CS*: $\uparrow$ 1.1p.p. (30%) within three years; $\uparrow$ 1.4p.p. (20%) ever
- *EE*: $\uparrow$ 0.8p.p. (25%) within three years; no persistent increase
- Driven by the younger test-takers (ages 17-21)
- Similar effects for men and women, low and high SES

$\rightarrow$ **Open Questions**:

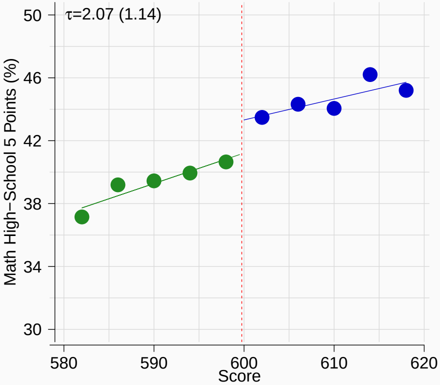
1. What are the effects on admission-related outcomes (PET and Bagrut)?
2. What are the long-term implications (degrees and labor market)?

   [Focus on the younger test-takers, 21 and below]

The Impact of Crossing 600 on Bagrut Outcomes



(a) 5 Points in Computer Sciences

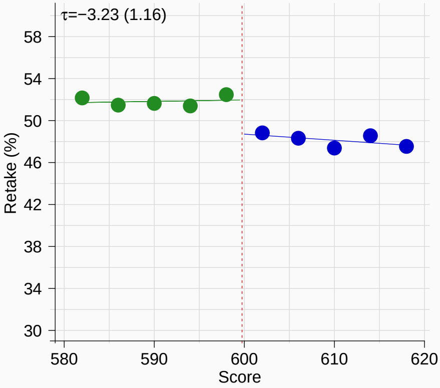


(b) 5 Points in Math

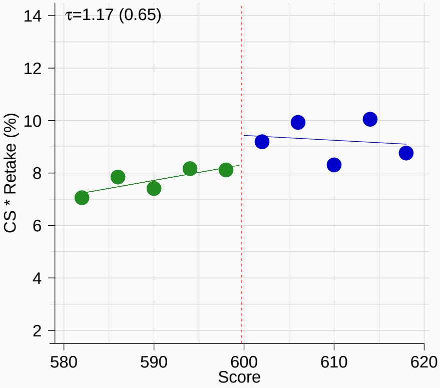
- Individuals who score just above 600 improve high-school outcomes in scientific programs

Table

The Impact of Crossing 600 on PET Retake



(a) Retake



(b) CS application * Retake

- Before applying to CS, individuals who score just above 600 retake the PET *and massively improve their PET scores*
- The average effect of crossing 600 on retaking is negative (Goodman et al., 2020)

Table

Estimating Long-Term Effects – Local Randomization Approach

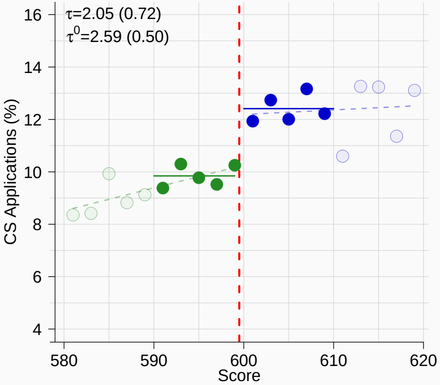
- Study the effects on *degrees*, *employment* and *income*
- To increase precision, I use an *additional* specification:

$$Y_i = \alpha^0 + \tau^0 \cdot Above600_i + \varepsilon_i^0 \quad within[590:609]$$

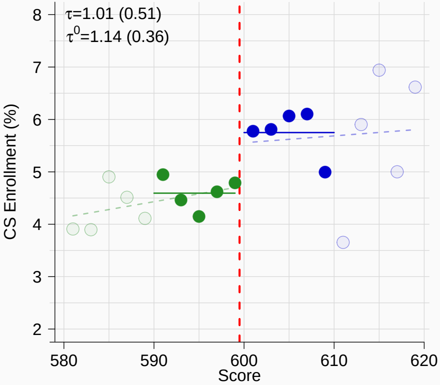
- To support the validity of this specification:
  - Point estimates are not sensitive to specification
  - Controlling for *quantitative and Hebrew* PET scores (only excluding English) and other characteristics does not change the results
  - Falsification tests yield small and mostly insignificant results

Table

The Impact of Crossing 600 on CS Studies



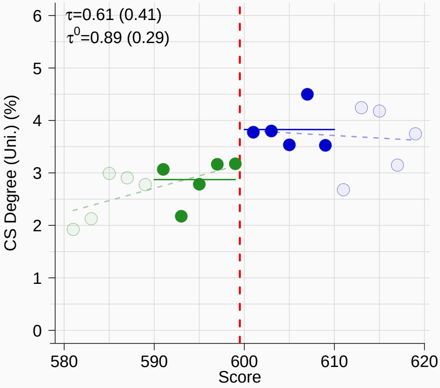
(a) CS Application



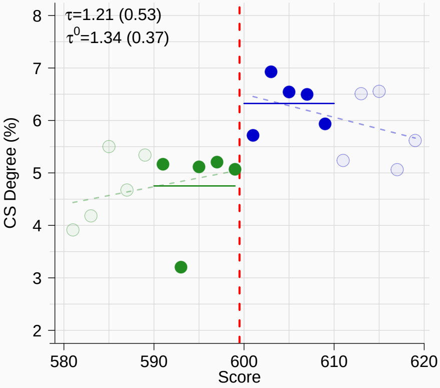
(b) CS Enrollment

- CS enrollment increase by 22-25%

The Impact of Crossing 600 on CS Studies



(c) CS Degree

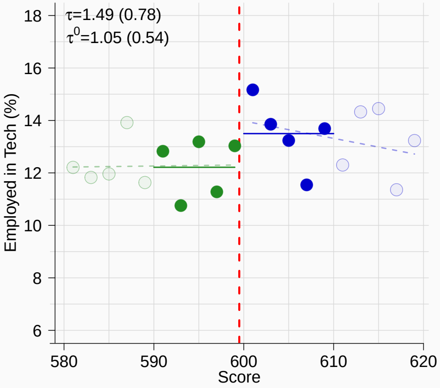


(d) CS Degree, including colleges

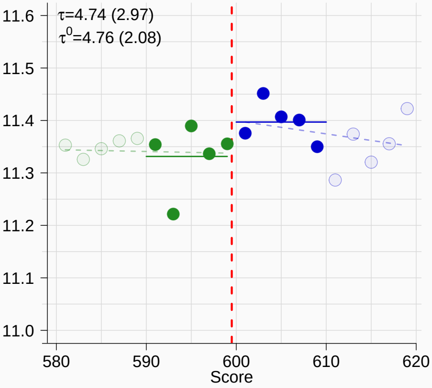
- CS degree attainment increase by 22-30%; Driven by a change in the preferred *field* (not institution)

Table

The Impact of Crossing 600 on Labor Market Outcomes



(a) Employed in Tech



(b) Log Income * 100

- Tech employment increase by 8-12%; Annual income increase by 5% (7K NIS)

Table

Summary – Long Term Effects

- $\uparrow$ 22-30% in CS degrees in universities
- Driven by a change in the preferred field, mostly from social sciences and semi-medical studies
- $\uparrow$ 8-12% on employment in tech
- $\uparrow$ 4.5-5% income; Implying huge marginal returns (200-300%)

Outline

Conclusion

Main Findings:

- Significant increase in CS & EE applications above a round score (600) in the first PET
- Driven by the younger test-takers; Men and women
- *In the long term*: Increase in the attainment of CS degrees; Increase in employment in tech industry; Income gains

Takeaways:

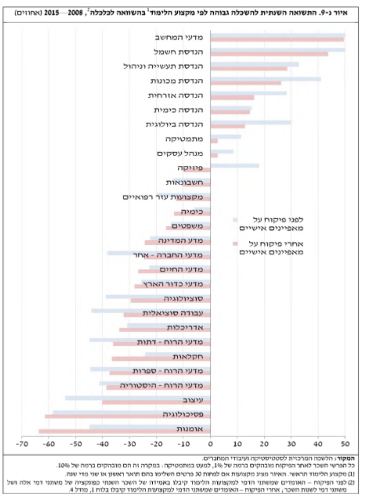
- Ability signals could influence young adults' human capital decisions
- Heuristics are central in interpreting signals (grading policy?)
- Huge labor-market returns for the students on the margin of *applying* to CS programs

Most Common Fields of Study in Universities in Israel

	Q. Score (50-15)	Total Score (200-800)	Tech (%)	Females (%)	Father Educ. (years)
Electrical Engineering	132.9	651.9	41.9	14.8	15.0
Computer Sciences	131.1	648.6	30.7	30.2	15.0
Economics	123.5	610.6	11.1	46.0	14.2
Law	123.0	636.8	3.2	60.2	14.8
Biology	120.3	613.0	14.2	73.3	14.7
Psychology	119.4	619.9	7.3	80.3	14.7
Management	113.8	564.8	15.5	60.0	13.7
Politics	109.8	572.0	8.4	62.6	14.1
Social Work	108.3	554.6	1.5	92.6	13.6
Sociology	106.0	545.8	7.4	86.9	13.5
Humanities	102.4	514.6	6.9	72.2	13.2
Nursery	101.5	495.7	0.5	79.4	12.8
Social Sciences	88.7	422.3	4.6	80.0	11.5

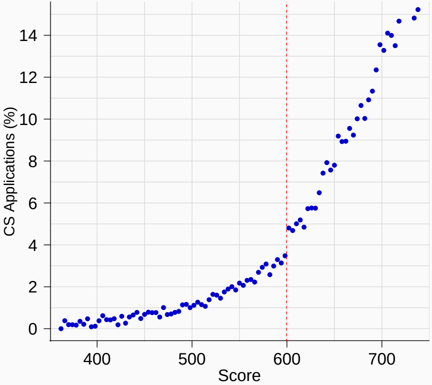
Returns by field (Achdut et al., 2018) Back

Returns to Field of Study (Achdut et al., 2018)

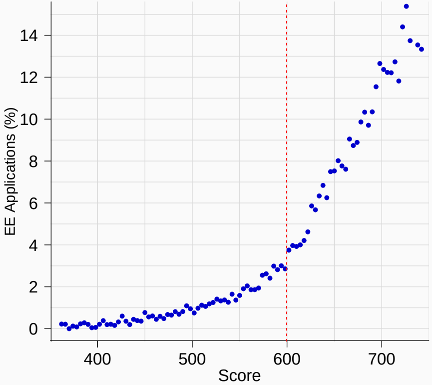


Back Back (main)

University Applications, by First PET Score



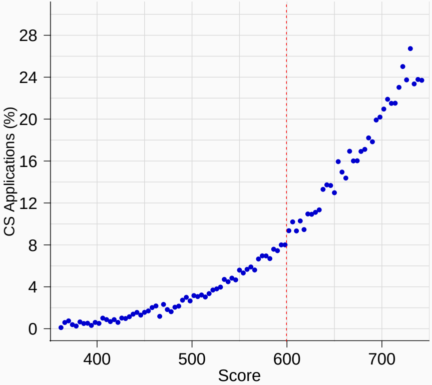
(a) CS applications, within three years



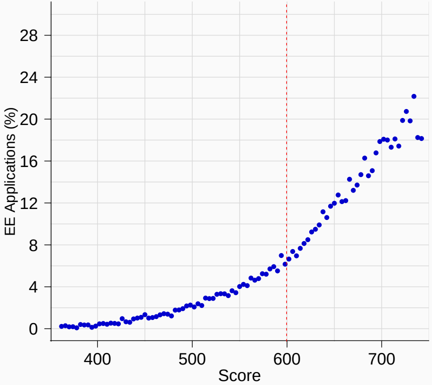
(b) EE applications, within three years

Back

University Applications, by First PET Score



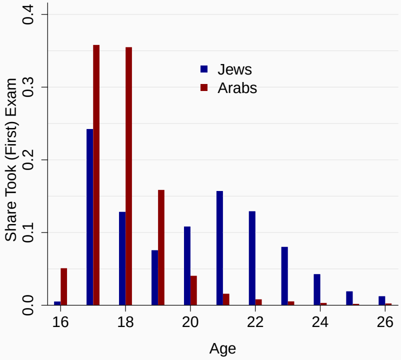
(a) CS applications



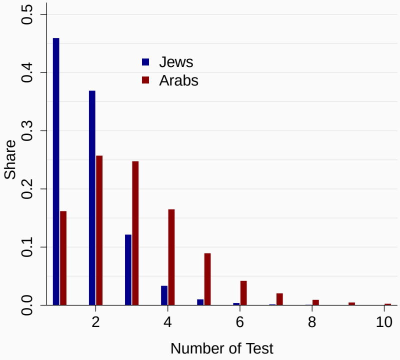
(b) EE applications

Back

Testing in the PET, by Population Group



(a) Age at First Test

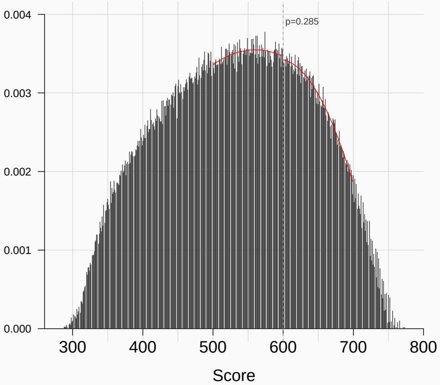


(b) Number of Tests

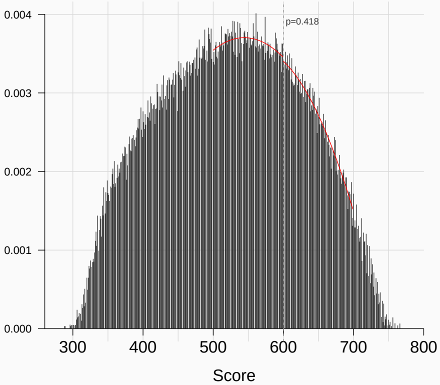
- Note: The average (first) PET score is about 400 for Arabs and about 550 for Jews

Back

PET Total Score Distribution



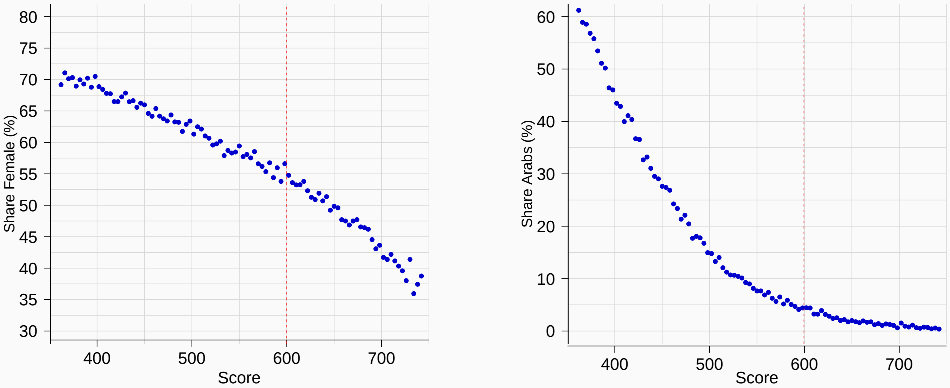
(a) All Tests



(b) First Tests

Back

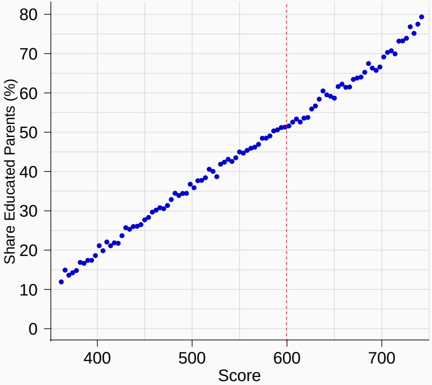
Background Covariates and PET Score



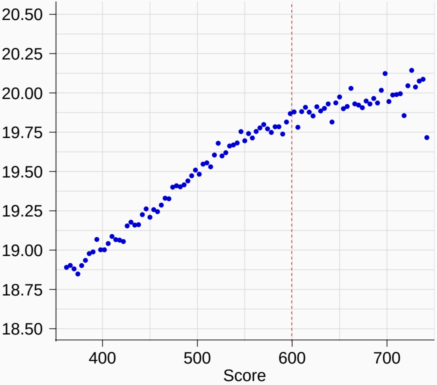
(a) Female share

(b) Arab share

Background Covariates and PET Score



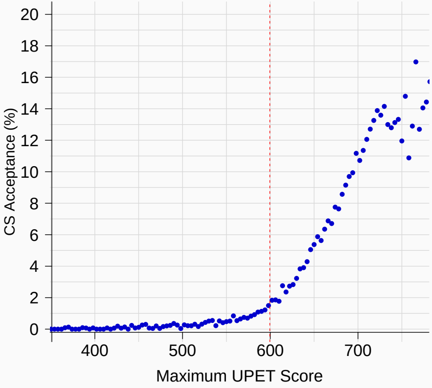
(c) Educated Parents



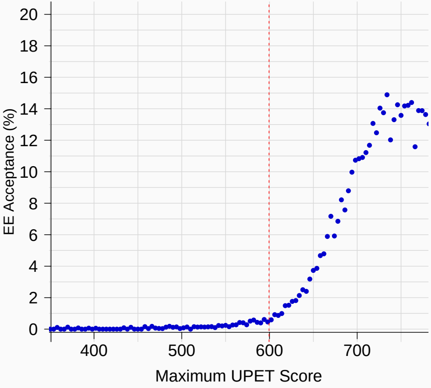
(d) Age

Back

Continuous Unconditional Acceptance Rate



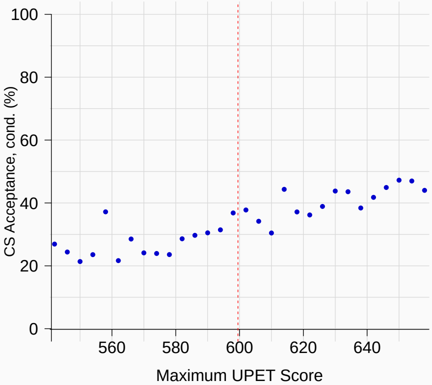
(a) Computer Sciences



(b) Electrical Engineering

Back

Continuous Conditional Acceptance Rate



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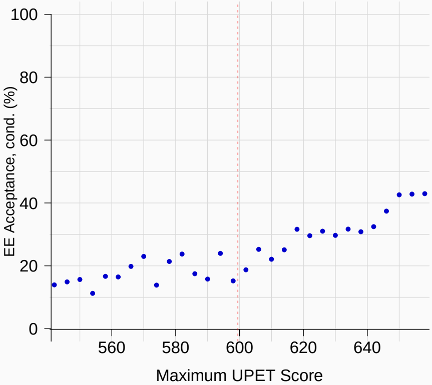
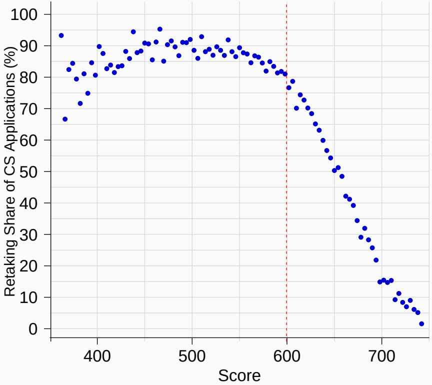


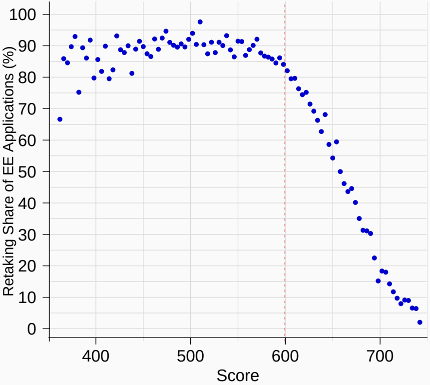
(b) Electrical Engineering

Back

Share Retaking The PET Among CS Applicants



(a) Computer Sciences



(b) Electrical Engineering

Back

"Impact" of Crossing 600 on Pre-determined Outcomes (I)

	Full Sample ($N = 44,075$)		Jews ($N = 42,147$)	
Outcome	Mean	Est. Effect	Mean	Est. Effect
Age	19.797	-0.020	19.919	-0.009
		(0.047)		(0.048)
Male Share (%)	44.336	1.288	44.026	1.385
		(0.944)		(0.965)
Arab Share (%)	4.868	0.535	0.000	-
		(0.391)		-
Non-Religious School (%)	82.487	0.558	81.595	0.486
		(0.727)		(0.757)
Born in Israel (%)	83.959	-0.543	83.251	-0.632
		(0.696)		(0.723)
Both Parents Born in Israel (%)	42.890	0.989	40.280	0.713
		(0.940)		(0.954)
Parental Income > 250K NIS (%)	53.947	-0.633	54.839	-0.578
		(0.944)		(0.964)
Educated Parents (%)	50.456	0.182	51.427	-0.058
		(0.948)		(0.970)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

“Impact” of Crossing 600 on Pre-determined Outcomes (II)

	Full Sample ($N = 44,075$)		Jews ($N = 42,147$)	
Outcome	Mean	Est. Effect	Mean	Est. Effect
Test's Year	2003.399	-0.062	2003.360	-0.019
		(0.065)		(0.066)
Test's Month	7.368	-0.044	7.365	-0.030
		(0.066)		(0.068)
PET Quantitative Score	117.01	-0.065	116.773	-0.098
		(0.174)		(0.177)
Applied to EE in Locality (%)	5.504	-0.033	5.563	-0.039
		(0.034)		(0.035)
Applied to CS in Locality (%)	7.086	-0.056	7.138	-0.061
		(0.041)		(0.043)
Educated Parents in Locality (%)	45.806	-0.575^{**}	47.232	-0.459^{*}
		(0.264)		(0.243)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back Back (main)

The Impact of Crossing 600 on University Applications

	Full Sample ($N = 44,075$)		Jews ($N = 42,147$)	
Outcome	Mean	Est. Effect	Mean	Est. Effect
A. Within Three Years				
CS (%)	3.801	1.366^{***}	3.104	1.083^{***}
		(0.402)		(0.383)
EE (%)	3.229	0.707^{**}	2.792	0.762^{**}
		(0.359)		(0.348)
B. Ever				
CS (%)	8.330	1.890^{***}	7.516	1.364^{**}
		(0.558)		(0.548)
EE	6.505	0.422	6.005	0.322
		(0.485)		(0.482)
C. After High-School				
CS (%)	7.810	1.534^{***}	7.100	1.079^{**}
		(0.536)		(0.527)
EE (%)	5.670	-0.114	5.249	-0.203
		(0.448)		(0.444)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$ Back

Mechanisms – Heterogeneity of the Effects

A. Relative Quantitative Score

	Low ($N = 7,426$)		Medium-High ($N = 22,385$)	
	Mean	Estimate	Mean	Estimate
Outcome:	(1)	(2)	(3)	(4)
CS	3.446	1.066	11.225	2.269**
		(0.959)		(0.895)
Retake	43.327	−5.168**	54.627	−2.719**
		(2.308)		(1.323)
CS * Retake	2.828	0.190	9.272	1.416*
		(0.819)		(0.810)

B. Predicted Retake Rate

	Low ($N = 7,453$)		Medium-High ($N = 22,358$)	
	Mean	Estimate	Mean	Estimate
Outcome:	(1)	(2)	(3)	(4)
CS	3.351	0.841	11.249	2.511***
		(0.922)		(0.91)
Retake	29.544	−4.137**	59.117	−2.756**
		(2.053)		(1.322)
CS * Retake	1.753	0.181	9.617	1.563*
		(0.667)		(0.834)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back Back (main)

Effects on CS & EE Applications – By Specification

	Linear	Linear+Controls	Triangular Kernel	Quadratic
A. CS				
20	1.083***	1.057***	1.062***	1.021*
	(0.383)	(0.382)	(0.411)	(0.580)
30	1.143***	1.128***	1.077***	0.994**
	(0.314)	(0.311)	(0.337)	(0.469)
Optimal (15)	1.010**			
	(0.474)			
B. EE				
20	0.762**	0.717**	0.868**	0.995*
	(0.348)	(0.341)	(0.366)	(0.512)
30	0.406	0.357	0.645**	1.006**
	(0.287)	(0.280)	(0.304)	(0.420)
Optimal (16)	0.909**			
	(0.416)			

Back

Effect on Applications (More Outcomes)

	Full Sample ($N = 44,075$)		Jews ($N = 42,147$)	
Outcome	Mean	Est. Effect	Mean	Est. Effect
Any (%)	40.277	0.430	38.606	0.356
		(0.939)		(0.956)
STEM (%)	19.682	1.776^{**}	18.007	1.738^{**}
		(0.786)		(0.784)
Non-STEM (%)	20.595	-1.345^{*}	20.599	-1.383^{*}
		(0.773)		(0.790)
Predicted Income (1,000 NIS)	206.281	4.703^{***}	203.737	4.217^{***}
		(1.688)		(1.741)
CS, Top Choice	1.920	0.703^{**}	1.584	0.527^{*}
		(0.298)		(0.285)
CS, Elite University	2.333	0.919^{***}	1.688	0.663^{**}
		(0.320)		(0.290)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back

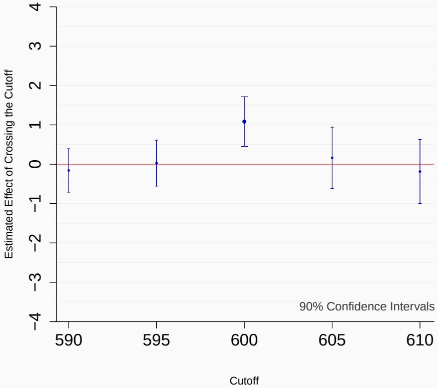
Effect of Crossing 600 on Applications (All Tests)

	Full Sample ($N = 69,336$)		Jews ($N = 60,911$)	
Outcome	Mean	Est. Effect	Mean	Est. Effect
CS	5.990	1.033***	3.946	0.915***
		(0.386)		(0.348)
EE	4.647	0.699**	3.221	0.710**
		(0.333)		(0.307)
Any	51.820	0.432	46.285	0.259
		(0.757)		(0.811)
Predicted Income	224.899	3.653***	218.485	3.940***
		(1.268)		(1.402)

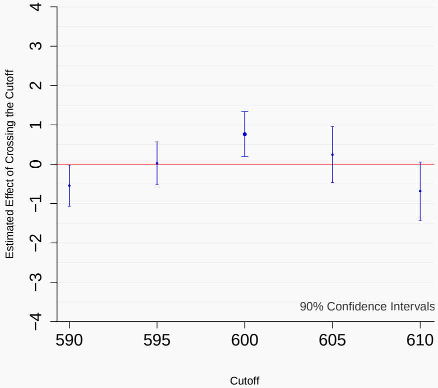
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back

Effects on CS & EE Applications – Alternative Cutoffs



(a) CS applications



(b) EE applications

Back

Effects on CS & EE Applications, Sample of Arabs

	CS		EE	
	Three years	Any	Three years	Any
A. Above 600				
	5.667	11.157***	-1.568	1.246
	(3.537)	(4.004)	(2.976)	(3.356)
$N = 1,808$				
Mean	17.465	24.291	11.791	16.312
B. Above 500				
	2.166*	1.264	-0.588	-1.142
	(1.221)	(1.469)	(1.086)	(1.280)
$N = 6,972$				
Mean	5.983	4.118	9.298	6.630

Numbers represent percentage points; * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back

Heterogeneity of the Impact by Age, Estimation

$$
\begin{aligned}
Y_i = &\theta + \theta^a \cdot Age_i^* + \delta \cdot Above600_i + \delta^a \cdot Age_i^* \cdot Above600_i + \\
&\gamma_l \cdot R_i + \gamma_l^a \cdot Age_i^* \cdot R_i + (\gamma_r - \gamma_l) \cdot Above600_i \cdot R_i + \\
&(\gamma_r^a - \gamma_l^a) \cdot Age_i^* \cdot Above600_i \cdot R_i + \varepsilon_i^1
\end{aligned}
$$

Where $Age^* = Age - 18$

Back

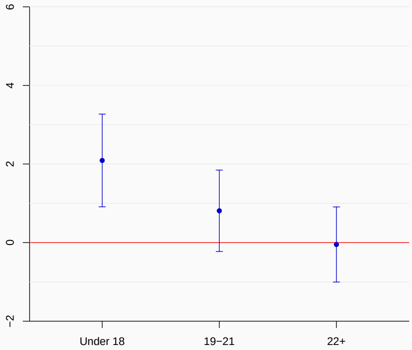
Heterogeneity of the Effect of Crossing 600, by Age, Three Groups Estimation

By Age	$Age < 22$ ($N = 29,676$)		$Age \geq 22$ ($N = 12,475$)	
	Mean	Est. Effect	Mean	Est. Effect
Within three years	3.441	1.500***	2.386	−0.048
		(0.483)		(0.581)
Ever	9.496	2.011***	3.119	−0.303
		(0.724)		(0.639)

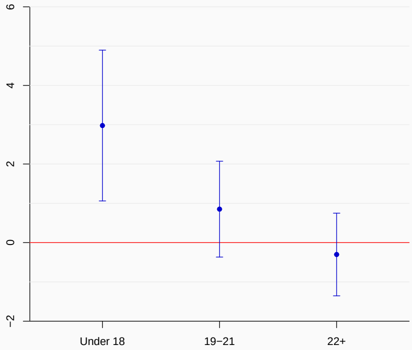
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Three groups (17-18, 19-21, 22+) Back

Heterogeneity of the Effects, by Age, Three Groups Estimation



(a) CS, within three years



(b) CS, ever

Back Back (main)

The Impact of Crossing 600 on Bagrut Outcomes

	Ages 21 and Below ($N = 29,803$)	
Outcome	Mean	Est. Effect
5 Points CS (%)	21.568	2.584^{***}
		(0.966)
5 Points Math (%)	39.252	2.069^{*}
		(1.142)
Total Points > 30 (%)	24.600	1.887^{*}
		(1.012)
Mean Composite Score	99.690	0.140
		(0.187)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back

The Impact of Crossing 600 on PET Retake

	Jews, 21 and Below ($N = 29,803$)	
Outcome	Mean	Est. Effect
Retake (%)	51.830	-3.233^{***} (1.155)
Retake * CS (%)	7.682	1.174^{*} (0.649)
Maximum PET Score $>$ 640 (%)	33.760	-1.176 (1.106)
Maximum PET Score $>$ 640 * CS (%)	5.995	0.977^{*} (0.585)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Heterogeneity Back

The Impact on Degree Attainment

	Main ($N = 29,803$)		Secondary ($N = 15,461$)	
Outcome	Mean	Est. Effect	Mean	Est. Effect
A. CS Programs				
Enrollment (%)	4.396	1.007**	4.605	1.138***
		(0.512)		(0.356)
Degree (%)	2.721	0.614	2.948	0.882***
		(0.415)		(0.291)
Degree, Inc. Colleges. (%)	4.783	1.211**	4.924	1.344***
		(0.528)		(0.370)
B. All Programs				
STEM Degree (%)	30.443	1.519	31.152	2.076***
		(1.077)		(0.751)
Non-STEM Degree (%)	55.252	−1.830	55.364	−1.640**
		(1.150)		(0.801)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Heterogeneity Robustness Optimal Bandwidths, by Order and Kernel Function Above 21 Back

Robustness, Secondary Estimation, Degree Attainment

Bandwidth	No Controls	With Controls
A. CS Enrollment		
10	1.138***	1.135***
	(0.356)	(0.360)
5	1.472***	1.368***
	(0.509)	(0.505)
B. CS Degree		
10	0.882***	0.801***
	(0.291)	(0.295)
5	0.797*	0.716*
	(0.414)	(0.413)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back Back (main)

Optimal Bandwidths, by Polynomial Fit Order, CS Studies

Order	0	1	2	3
A. CS Enrollment				
Uniform Kernel	1.151**	1.173*	1.215*	1.474**
	(0.517)	(0.615)	(0.626)	(0.717)
	6	18	37	47
Triangular Kernel	1.073**	1.096*	1.364**	1.399*
	(0.511)	(0.561)	(0.663)	(0.818)
	10	26	37	42
B. CS Degree				
Uniform Kernel	0.533	0.624	0.594	0.765
	(0.386)	(0.505)	(0.568)	(0.589)
	6	18	30	48
Triangular Kernel	0.591	0.568	0.626	0.706
	(0.424)	(0.457)	(0.516)	(0.590)
	9	28	43	54

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back Back (main)

Robustness, Secondary Estimation, Labor Market

Bandwidth	No Controls	With Controls
A. Employed in Tech (%)		
10	1.054*	1.359**
	(0.540)	(0.543)
5	1.886**	1.777**
	(0.779)	(0.765)
B. Log Annual Income * 100		
10	4.755**	4.358**
	(2.076)	(2.206)
5	4.340	4.459
	(2.923)	(2.825)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back Back (main)

The Impact on Labor Market Outcomes

	Main ($N = 29,803$)		Secondary ($N = 15,461$)	
Outcome	Mean	Est. Effect	Mean	Est. Effect
Employment	85.585	0.927	85.390	0.182
		(0.818)		(0.567)
Employment in Tech (%)	12.370	1.487*	12.400	1.054*
		(0.780)		(0.540)
Annual Income (1,000 NIS)	140.703	6.164	140.758	6.809**
		(4.868)		(3.376)
Log Annual Income * 100	1134.753	4.738	1134.353	4.755**
		(2.974)		(2.076)
Rank Annual Income * 100	45.751	1.640**	45.539	1.236**
		(0.745)		(0.518)
An. Salaried Inc. (1,000 NIS)	136.031	7.356	135.403	7.237**
		(4.762)		(3.301)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Heterogeneity Robustness Optimal Bandwidths, by Order and Kernel Function Above 21 Back

Optimal Bandwidths, by Order of the Polynomial Fit, Labor Market

Order	0	1	2	3
A. Employed in Tech (%)				
Uniform Kernel	1.231*	0.989	1.994*	1.588
	0.740	0.755	1.075	1.111
	9	28	29	47
Triangular Kernel	1.256*	1.233*	2.241**	2.699**
	0.703	0.742	1.098	1.301
	14	36	32	39
B. Log Annual Income * 100				
Uniform Kernel	5.725**	4.448	3.100	3.399
	(2.546)	(3.553)	(3.980)	(4.369)
	10	19	31	42
Triangular Kernel	4.859*	4.588	5.574	5.214
	(2.894)	(3.413)	(3.592)	(4.854)
	12	25	45	40

[* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back Back (main)

Effects on Long Term Outcomes (Jews, 22 and Above)

	Main ($N = 12,343$)		Secondary ($N = 6,414$)	
Outcome	Mean	Est. Effect	Mean	Est. Effect
A. Degrees				
CS Degree	0.568	-0.159	0.585	-0.080
		(0.266)		(0.184)
CD Degree, Any Inst.	2.840	-0.350	2.957	-0.401
		(0.600)		(0.409)
B. Labor Market				
Employment in Tech	7.178	0.357	7.548	0.880
		(0.955)		(0.677)
Log(Income)	11.923	0.001	11.903	-0.003
		(0.045)		(0.031)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back 1 Back 1 (main) Back 2 Back 2 (main)

Long Term Impact, Heterogeneity

A. By Gender	Men ($N = 10,971$)		Women ($N = 18,785$)	
Outcome	Mean (1)	Est. Effect (2)	Mean (3)	Est. Effect (4)
CS Degree, Inc. Colleges	8.316	2.125*** (0.771)	3.012	0.720** (0.366)
Log Annual Income * 100	1121.173	6.813* (3.883)	1141.026	4.263* (2.409)

B. By SES (Parental Education Above 12 Years)	Low ($N = 6,879$)		High ($N = 8,586$)	
Outcome	Mean (1)	Est. Effect (2)	Mean (3)	Est. Effect (4)
CS Degree, Inc. Colleges	4.819	1.053* (0.543)	5.009	1.573*** (0.504)
Log Annual Income * 100	1140.406	-0.013 (2.992)	1129.397	8.688*** (2.870)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Back 1 Back 1 (main) Back 2 Back 2 (main)

Falsification Tests, Secondary Estimation

Bandwidth	10 ($N = 15,465$)		5 ($N = 7,692$)	
	Mean	Estimate	Mean	Estimate
Age	18.679	0.006	18.698	−0.022
		(0.026)		(0.037)
Male Share	163.949	−1.754**	165.125	−1.912*
		(0.776)		(1.103)
Non-Religious School (%)	80.176	−0.409	79.926	−0.650
		(0.644)		(0.927)
Born in Israel (%)	80.674	0.116	80.851	−0.952
		(0.634)		(0.914)
Both Parents Born in Israel (%)	38.462	0.982	38.298	0.330
		(0.784)		(1.118)
Parental Income > 250K	56.959	1.420*	56.660	0.139
		(0.795)		(1.139)
Educated Parents	55.262	0.521	55.851	−0.774
		(0.799)		(1.142)
Test's Year	2002.492	0.025	2002.490	0.004
		(0.057)		(0.081)
Test's Month	8.010	−0.010	7.950	0.001
		(0.054)		(0.077)
Share Applied to CS in Locality (%)	7.245	0.001	7.278	−0.067
		(0.034)		(0.049)
Share Educated Parents in Locality (%)	46.993	0.132	47.186	−0.355
		(0.198)		(0.286)

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$ Back

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