Learning from Round Test Scores: University Field Choices and Career Outcomes

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Abstract

University field of study choices shape future career opportunities. However, we know little about the barriers that might deter students from pursuing highly rewarding fields. One potentially important psychological barrier is perceived academic ability. This study uses left-digit bias in test score interpretations to analyze how varying ability perceptions affect field choices and career outcomes. The findings reveal that scoring just above a round number on university entrance tests significantly increases applications to high-earning fields, even though admission probabilities remain low around these scores. Students who score just above the round number often retake the test to improve their scores before applying, indicating their awareness that their initial scores were insufficient for admission. In the long term, these efforts lead to higher earnings, demonstrating that aiming higher in field of study choices pays off.

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1 Introduction

The returns on academic degrees vary widely by field of study (Kirkeboen et al., 2016; Hastings et al., 2013; Heinesen et al., 2022; Bleemer and Mehta, 2022; Daly et al., 2022), prompting the question: why do some students avoid the most lucrative fields? Research shows that expected earnings play a limited role in these decisions (see a review by Patnaik et al., 2021, and references therein), suggesting students consider more than financial gains. These fields are challenging and often set high admission requirements and high academic standards. Consequently, some students might avoid highly rewarding fields due to underestimating their abilities, thus missing out on better career opportunities and higher earnings. However, it is not clear whether students truly undervalue their abilities or if they accurately assess their capacity to succeed in these challenging fields.

Examining this issue empirically is difficult. Survey experiments often fail to track students for the long term, which is essential to evaluate the benefits of aiming higher. In contrast, administrative data can follow students into the labor market, but usually lack measures of ability perception. To address this challenge, this study examines variations in ability perception caused by biased test score perceptions due to left-digit bias. It investigates how these variations affect students' decisions to apply to highly rewarding fields and their post-graduation labor market outcomes.

Using data from Israel on university entrance tests, applications, and career outcomes, the study focuses on a crucial decision: whether to apply to the most rewarding university fields in Israel, specifically computer science and electrical engineering ("CS" and "EE" or "high-tech fields"). These fields are known for their high earning potential, fueled by Israel's booming tech industry. Admission typically requires scores well above 600, posing a challenge for those with scores close to 600–either just below or just above. While their scores may be insufficient, they are close enough to suggest the potential for improvement through retesting.

The analysis uses a regression discontinuity design (RDD) around the 600 score cutoff, examining differences in university decisions and career outcomes for students scoring just above and below this score on their first university entrance test attempt.[1] The underlying assumption is that the only factor changing discontinuously at the 600 score is its perception. The institutional context supports this assumption: test-takers cannot manipulate their scores relative to

[1]Scores range from 200 to 800, with only 20% scoring 600 or higher on their first attempt. While the impact of crossing other round scores is discussed in the appendix, this study focuses on the effects of crossing 600 due to its proximity to high-tech field admission requirements, making it a critical decision point.

the 600 cutoff, and admission probabilities to high-tech fields are continuously low around this threshold.

The results show a significant, discontinuous increase in the likelihood of applying to high-tech university fields among those scoring just above 600 on their first test. This increase is 1.3 percentage points from a 4.5% baseline, marking a 30% relative increase (significant at the 99% level). However, there is a decrease in the likelihood of applying to other, less rewarding university fields, resulting in no net change in the overall probability of applying to any university field. This behavior suggests that scoring just above the round number boosts students' confidence in their abilities, encouraging them to pursue the most rewarding and challenging university fields.

An alternative interpretation could be that students mistakenly believe scoring just above 600 improves their admission chances, although in practice, it does not affect their likelihood of admission, which remains low just above 600. However, evidence suggests this misunderstanding is unlikely to explain the increase in applications. Most students who apply to high-tech fields with first UPET scores around 600 take proactive measures to enhance their admission prospects before applying, such as retaking the test (improving their scores to 650 on average) or acquiring additional matriculation credits. This indicates their awareness that their first scores were insufficient and their additional efforts to secure admission.

However, I observe an additional result: crossing the 600 cutoff leads to an overall average decrease in test retaking, aligning with previous findings (Pope and Simonsohn, 2011; Goodman et al., 2020). This suggests significant heterogeneity in responses to round scores. Some students, who might have already considered high-tech fields but doubted their abilities, are motivated by achieving a 600 score to enhance their admission outcomes and submit applications. In contrast, students with initially lower ambitions, who had not seriously considered high-tech studies, may feel satisfied with reaching a 600 score and are less inclined to retake the test.

Furthermore, biased perceptions can extend beyond individuals to their friends, family, and other social influences.[2] To explore the extent of these social influences, I investigate whether younger siblings alter their testing decisions based on their older siblings' scores. The findings reveal that younger siblings are more likely to take the test if their older siblings score just above 600. This suggests that biased test score perceptions not only influence individual decisions but also create spillover effects within families.

[2]Growing literature shows how older siblings' educational experiences influence the decisions of their younger siblings (Joensen and Nielsen, 2018; Gurantz et al., 2020; Karbownik and Özek, 2021; Altmejd et al., 2021).

Given the diverse responses to round test scores, I further explore the heterogeneity of effects to understand how different groups are affected by crossing the 600 score. By stratifying the sample according to age at the first test,[3] the results show that younger test-takers, who often set higher university goals early on, are the primary drivers of increased applications to high-tech degree programs. This group benefits from more time to enhance their qualifications before university enrollment, making it easier for them to improve their admission chances by retaking the test or earning additional matriculation credits.

Further stratification of the sample of younger test-takers based on their baseline predicted likelihood of choosing high-tech fields reveals that those with the highest predicted likelihood are the main contributors to the increase in applications to these fields. In contrast, older test-takers and those with lower predicted likelihoods tend to reduce their efforts in retaking the test. This supports the interpretation that responses to round scores vary by students' baseline aspirations: for those who consider challenging fields but doubt their abilities, achieving a round score boosts confidence and pushes them to aim higher. In contrast, for those who do not consider these fields, achieving a round score makes them satisfied and decreases their motivation to retake the test.

Finally, I also investigate whether increased applications to challenging and rewarding fields yield benefits for students or if they are aiming too high. The long-term analysis reveals substantial benefits for younger test-takers who cross the 600 threshold. At age 30, their employment in the tech industry increases significantly, with their average annual earnings increasing by NIS 7,400 (more than USD 2,000, or 6.5%). In contrast, no long-term benefits are observed among older test-takers, as their likelihood of application remains unchanged. Further heterogeneity analysis also shows that students with the highest baseline predicted likelihood of applying drive these labor-market benefits.

These results suggest that choosing high-tech fields was beneficial for these students. To support this interpretation further, I demonstrate that labor-market gains evolve over time, aligning with a human capital investment mechanism. Additionally, I analyze the earnings of those who apply to high-tech fields just around the 600 score cutoff. The findings reveal that the average earnings for these students, on both sides of the 600 cutoff, are very high–comparable to the earnings of graduates from high-tech fields and significantly above the average for university graduates from other fields.

The findings of this paper highlight the uncertainties young adults face when making life-changing decisions. They demonstrate that test score perceptions are

[3]The variability in age at the first test is due to mandatory army service, causing most students to begin their higher education around ages 22-23.

influenced by left-digit bias. While previous research has established that test retake rates may decrease above round score cutoffs (Pope and Simonsohn, 2011; Goodman et al., 2020), this analysis demonstrates that crossing these thresholds can also motivate students to apply to more rewarding university programs due to a boost in their perceived abilities. A parallel study by Li and Qiu (2023) supports this observation, noting increased university aspirations among students crossing round-score thresholds in China. The unique contribution of this paper is in documenting that enhanced perceived abilities, driven by left-digit bias, can be pivotal for some students, encouraging them to pursue more rewarding university and career paths. This finding suggests that self-doubt, rather than a lack of ability, may be a significant barrier for students.

Furthermore, this paper advances our understanding of how ability perceptions shape human capital decisions. The significance of ability beliefs is well documented in both theoretical (e.g., Altonji et al., 2016) and experimental studies (e.g., Wiswall and Zafar, 2015).[4] While previous research has shown the influence of test score signals on educational decision-making (Stinebrickner and Stinebrickner, 2012; Papay et al., 2016; Goodman, 2016; Smith et al., 2017; Avery et al., 2018; Bond et al., 2018; Li and Xia, 2022; Graetz et al., 2023), this study highlights the role of heuristics in interpreting these signals. Moreover, it sheds light on the negative labor-market consequences of underestimating one's abilities.

Finally, this paper contributes to the literature on how returns to academic degrees vary by field of study (Hastings et al., 2013; Kirkeboen et al., 2016; Heinesen et al., 2022; Bleemer and Mehta, 2022; Daly et al., 2022). While previous studies have focused on the marginal returns for students at the margin of admission, this research highlights the potentially high returns for a different group: students uncertain about whether to apply to high-reward fields. This insight suggests that beyond expanding the number of slots in these fields, policymakers and educators could increase applications by helping students recognize their suitability for these programs, potentially leading to significant earnings gains for those students.

The rest of this paper is organized as follows: Section 2 provides background on the university system in Israel. Section 3 describes the data, and Section 4 outlines the empirical strategy. Section 5 presents and discusses the empirical evidence. Finally, Section 6 concludes.

[4]This relates to the growing evidence that within-class ability rankings influence students' decisions and outcomes (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020; Denning et al., 2023), possibly by affecting how students or their social environments perceive their abilities.

2 Background—The Israeli University System

During the sample period, Israel had seven universities and around fifty colleges offering undergraduate degrees.[5] Colleges are generally perceived as lower-tier institutions, as reflected in the quality of academic teaching, student ability, and graduates' earnings (Achdut et al., 2019, e.g.,). This study focuses on university field of study decisions for two main reasons: university programs are typically more challenging and lucrative than those offered at colleges, and I only have data on university application decisions, which is essential for this research.

2.1 University Fields of Study

University fields in Israel, as in many other countries, show significant variation in admission requirements and labor-market outcomes for graduates. Notably, Israel's thriving tech sector creates substantial labor-market demand for graduates from tech-oriented fields, such as CS and EE. Figure 1 illustrates this by showing the average earnings and tech employment rates across all fields of study in Israel. It highlights that graduates from high-tech fields not only earn more than double the earnings of other fields' graduates but also enjoy very high employment rates in the tech industry. This finding aligns with several Israeli policy papers, including Achdut et al. (2019), which document significant returns to high-tech fields compared to others.

Recognizing the need to attract more young adults to high-tech university fields, Israel's policy circles are actively exploring measures to encourage enrollment in these fields.[6] Understanding the decision-making process of young adults in Israel regarding applications to high-tech fields is therefore crucial, with significant policy implications. This issue may also resonate in many other developed countries facing ongoing demand for high-skilled technology-oriented workers.

2.2 The University Admission System

In Israel, the admission process for universities and colleges is decentralized, with each institution handling its own admissions. During the application process, students in Israel are allowed to choose three fields of study in order of preference. The admission criteria for academic programs are based on two main factors: the University Psychometric Entrance Test (UPET) and academic performance in the

[5]Two of these colleges have recently gained university status, increasing the current total to nine universities offering undergraduate degrees. Furthermore, a tenth university focuses exclusively on graduate studies.

[6]Recently, the Israeli government allocated NIS 100 million for this purpose (retrieved from https://che.org.il/hi-tech on November 21^{st}, 2022).

Israeli matriculation program. Each university program (field by institution) sets an annual admission threshold: a weighted average of the highest UPET score and the matriculation GPA score.

The University Psychometric Entrance Test (UPET). The UPET is a standardized test. Figure 2a presents the distribution of scores in the sample, ranging from 200 to 800.[7] The figure presents a smooth density of observations at the score of 600, confirming that cutoff manipulations are implausible. In particular, the score of 600 is relatively high in the distribution, with only 22% of the individuals in the sample achieving or exceeding it.

The age at which individuals first take the UPET varies. Most Jewish students in Israel start their academic studies at ages 21–24 because they begin compulsory military service immediately after high school graduation (three years for men, two years for women). Furthermore, approximately half of the Jewish candidates take their first test during high school or within two years after graduation (age 20 and below), and the other half do so later. Arab candidates tend to take the UPET earlier than Jews (as can be seen in Appendix Figure A.1a) because they have no service requirements.

The UPET is relatively inexpensive, and students can take it multiple times, with universities considering only the highest score. As a result, retesting before university application is widespread. Indeed, more than half of Jewish test-takers and more than 80% of Arab students retake the UPET (Appendix Figure A.1b). The discrepancy between the groups may be attributed to variance in their average scores on the first UPET (approximately 550 for Jews and 400 for Arabs). Note that since Arab students score relatively low on their first tests, only a few score around 600 and are part of the RD analysis. This decreases the statistical power to analyze the effects within this group.

Israel's matriculation program. Matriculation tests are taken in grades 10–12, with students having the option of being tested at different proficiency levels that award one to five credit units per subject. Students may also retake these tests after high school to improve their university admission prospects. For more details on Israel's high school and matriculation system, see e.g. Lavy and Goldstein (2022).

[7] Given the nearly normal distribution of scores, there is a scarcity of individuals at the extremes of the distribution, potentially leading to their exclusion from the dataset due to a cell-suppression policy. For the analysis that follows, I concentrate on scores that fall within the range of 370 to 730. This ensures adequate data coverage across each point without impacting the analysis, which centers on observations proximate to the 600 cutoff.

2.3 University High-Tech Fields' Admission Requirements

Admission requirements for university high-tech fields are higher compared to most other fields. Appendix Figure A.4 displays the median and tenth percentile of admission-relevant UPET scores for students in the most common fields. Both CS and EE have a median score near 700, while their tenth percentile is around 625. This aligns with institutional information indicating that the official admission requirements for these programs are high, generally necessitating UPET scores above 600 unless an applicant possesses an exceptionally high matriculation GPA.[8] Therefore, this study aims to focus on the 600 score round score cutoff, as students scoring around this mark are below the admission threshold yet close enough to improve their scores and possibly gain admission.

This supports the identification assumption that the only discontinuous change at the 600 score cutoff is in the perception of the score. Left-digit bias should not affect admission chances to university fields in Israel, as decisions are based on objective measures rather than subjective evaluations. Generally, admissions requirements depend on a weighted average of the UPET and matriculation GPA. Additionally, in this study, scores around 600 fall below the admission requirements, which requires retakes for potential admission. To further validate this, Appendix Figures A.5a and A.5b illustrate the low likelihood of being admitted to high-tech fields with a maximum score of 600. Appendix Figures A.5c and A.5d confirm that the likelihood of attending such programs, conditional on applying, remains continuous at the 600 threshold.

3 Data

3.1 Database and Sample

The analysis in this paper uses an administrative database from the Israel Central Bureau of Statistics (CBS), which combines data from various sources. The sample comprises individuals who first took the UPET between 1999 and 2008, allowing me to examine effects up to 12 years after the test (labor market data are available up to 2020). For further details on the data, their sources, the baseline sample, and the sample restriction procedure, see the Appendix A.1.

3.2 Main Outcome Variables

University decisions. To evaluate the effects on the likelihood of applying to university high-tech fields, I created an indicator variable set to 1 if an individual

[8]For more details on the official admission requirements, see Appendix A.4.

applies to any high-tech field (CS or EE). This analysis focuses on applications within five years post-test, though I also show that the results are consistent across other periods. I also explore alternative definitions for high-tech fields, including any field where at least 40% of graduates are employed in tech at age 30. In addition, I analyze indicators for application to other fields (with less than 40% tech employment) and for fields grouped according to the Israeli CBS definitions.

To capture the overall level of ambition in applications in terms of labor-market potential, I calculate the average earnings of graduates from each program twelve years after their first test and assign this value to the corresponding application. When an individual applies to multiple programs, the highest value is selected.

I also have data on university enrollment and degree attainment, enabling a further examination of these outcomes. While the dataset of applications is limited to universities, information on degree enrollment and attainment spans both universities and colleges. Consequently, the analysis in the appendix extends to include college degrees. This expansion helps assess whether the observed effects stem from students transferring from college high-tech programs to university high-tech programs. Findings indicate this is not the case; rather, there is an overall increase in the likelihood of attending a high-tech field degree program at any institution.

Labor-market outcomes. To explore long-term effects, I analyze the early career outcomes of students, focusing on the 12th year after their first UPET, which is the last time point at which all individuals in my sample can be followed. I define indicators for salaried employment, self-employment, and employment within the tech industry. Additionally, I consider total earnings, the natural logarithm of earnings, and earnings rank conditional on age. I also examine these outcomes at age 30, a point by which nearly all (approximately 99%) individuals in my sample are observed.

3.3 UPET Scores and Applications to High-Tech Fields

Visual representations of RD results complement more rigorous econometric inference (as discussed recently by Korting et al., 2023). Therefore, before presenting the estimation method, I offer a visual representation of the main findings. Figure 2b illustrates the relationship between first UPET scores and the probability of applying to a university high-tech field. The bin selection for this figure is data-driven, following the guidelines provided by Calonico et al. (2015). Additionally, I omitted fit lines on both sides of the cutoff in the figure, as recommended by Korting et al. (2023).

The figure demonstrates a noticeable positive correlation between the variables, possibly influenced by various observed and unobserved factors associated with the score, such as ability, motivation, socioeconomic status and gender. Notably, the figure also highlights a *discontinuous* increase in the probability of applying at the score cutoff of 600. This result, corroborating the research hypothesis, suggests that young adults perceive 600 as an important signal of their abilities; attaining it encourages them to aim higher in their university application decisions. To investigate this more rigorously, I employed a local linear RD, as elaborated in the next section.

The figure also provides further justification for focusing on the round score of 600 when analyzing university high-tech applications. It shows that individuals who score around this cutoff are more likely to be in the process of considering, though not entirely certain about, applying to the program. Scores around lower round cutoffs may be too distant from the admission threshold, while scores around the highest round cutoff result in direct admission, making the decision more straightforward. Additionally, note that around the highest round score cutoff, 700, there are significantly fewer observations (as shown in Appendix Figure 2a), which limits the statistical power of analysis at this cutoff.

4 Empirical Strategy

The main empirical goal of this paper is to explore how biased perceptions of test scores, influenced by left-digit bias, affect university field choices. Specifically, this study analyzes the discontinuous changes in these choices at the round score cutoff of 600. This score represents an important decision point where students must choose between investing additional efforts to gain admission to high-tech fields or settling for less lucrative fields. Therefore, I use an RDD around the score of 600 in each student's first UPET attempt, estimating the impact of crossing 600 on the likelihood of applying to high-tech fields and other related outcomes.

4.1 Identification Assumption and Challenges

The underlying assumption of this analysis is that the potential outcomes are continuous at a score of 600, which means in our context that the only discontinuous change at this threshold is the perception of the score. This assumption is plausible due to the unlikelihood of cutoff manipulations and the constancy of admission chances just around this threshold, and it is also supported by empirical evidence. First, the density of observations around the 600 cutoff is smooth (see Section 2.2) and predetermined outcomes are continuous at the 600 score (see Section 4.3), indicating no manipulations. Second, the probability of high-tech field admission remains low and stable, not showing any discontinuous jumps at the score of 600, which reinforces that the cutoff itself does not directly affect the admission chances (see Section 2.3).

Nevertheless, there are two additional challenges worth considering when interpreting these results. First, although admission chances for university high-tech fields are consistently low just below and just above 600, there is a possibility that students mistakenly believe that a score of 600 enhances their admission prospects, thereby increasing their applications. This misconception relates to how students perceive the implications of their scores for admissions rather than their academic abilities. However, empirical evidence does not support this misunderstanding as a likely explanation for the observed increase in applications.

The results indicate that most individuals understand that a UPET score of 600 is below the admission threshold for these competitive programs. Figure A.6 illustrates that the majority of those who scored around 600 and applied to university high-tech fields did so only after retaking the test and significantly improving their scores, recognizing that their initial score was insufficient. Note that, in contrast, most applicants scoring around 700 did not retest before applying to high-tech fields. These patterns, further discussed in Section 5, indicate a general awareness that a 600 score is not competitive for university high-tech field admission.

Second, social influences, such as family and friends who also exhibit left-digit bias, may affect individuals' decisions. While it is challenging to determine whether the increase in applications is driven by individuals' own perceptions of their scores or those of their social circle, I can directly examine the role of social influence by analyzing how younger siblings of individuals in our sample respond to their older siblings' scores. To explore this channel further, I include the testing decisions of younger siblings as an outcome, providing evidence that supports social influence as a potential mechanism.

4.2 Estimation

Let s_i be the first UPET score of the individual i. To employ a local linear RD approach, I restrict the sample to $s_i \in [580, 620]$ and estimate the equation:

$$Y_i = \alpha + \tau \times \mathbf{1}_{\{s_i \geq 600\}} + \beta \times (s_i - 600) + \gamma \times (s_i - 600) \times \mathbf{1}_{\{s_i \geq 600\}} + \varepsilon_i \qquad (1)$$

The coefficient of interest is τ, which captures the impact of crossing 600 in the first UPET on the outcome. All standard errors calculated throughout the analysis are heteroskedasticity-robust and clustered at the score level (as suggested by Cattaneo et al., Forthcoming, for discrete running variables).

I also use other specifications to validate the robustness of the results. Specifically, I employ the algorithm developed by Calonico et al. (2014) to estimate non-parametric RD models with different polynomial orders and kernel functions (uniform and triangular). The estimates appear to be stable across specifications, and the chosen bandwidths resemble those used in the main estimation.

4.3 Falsification Tests

If the identification assumption holds, pre-determined outcomes should be continuous at the cutoff. Therefore, I test the continuity of predetermined outcomes by estimating Equation 1. Table 1 shows the results. In Panel A, I use the characteristics of the individuals as outcome variables. This includes age at the time of the test and dummies for Arabs, females, students in non-religious schools, and individuals born in Israel.[9] In Panel B, I analyze the year and month of the test and the scores in each of its three domains. In Panel C, I use family characteristics as outcome variables. This includes parental years of education and total annual income (at age 14-16) and the number of siblings. Only one of these 15 estimates is significant at the 90% level, and all estimated discontinuities are small.

For further validation, I predict the main outcome, which is an indicator for high-tech applications, using all predetermined outcomes. I then demonstrate that these predicted values are continuous at the 600 score cutoff, as illustrated in Figure A.2. Additionally, I conduct a falsification test using placebo cutoffs to estimate discontinuous changes in the main outcome at non-round score cutoffs. The results presented in Figure A.3, support the interpretation that the only significant discontinuity occurs precisely at 600.

5 Impacts of the Biased Test Score Perceptions

5.1 University Application Decisions

Figure 3 presents the main estimation results of the impact of crossing 600 in the first UPET. Figure 3a, focuses on the likelihood of applying to university high-tech fields. Unlike Figure 2b, this figure is focused on observations within the estimation window and uses a reduced bin size of two points each. Furthermore,

[9] The tables also present the baseline mean of each outcome, the average below the cutoff within the bandwidth ($s_i \in [580, 599]$). Additionally, note that all binary variables throughout the paper are multiplied by 100 in order to make the coefficients more informative.

it presents the estimation results of Equation 1 with prediction lines on each side of the cutoff, and the estimated discontinuous change in the outcome at the 600 cutoff (τ). The estimation reveals a sharp increase of 1.3 percentage points from a baseline likelihood of 4.4%, representing a relative increase 30%. This estimate is highly statistically significant, well beyond the 99% confidence level.

Furthermore, Panel A of Table 2 presents estimates of the effects on other outcomes related to applications to high-tech fields. It shows an increase in applications to both CS and EE, with a larger increase for CS. Additionally, the table indicates that using alternative definitions of high-tech fields–by including all fields with at least 40% or 60% tech employment–yields very similar results, demonstrating a significant increase in the likelihood of applying to these fields. Table A.1 lists the fields included in this analysis.

Panels B and C of Table 2 present additional estimates concerning the likelihood of applying to other university fields. Notably, the observed increase in applications to high-tech programs does not correspond with a decrease in applications to other STEM fields. Instead, there are modest declines in many non-STEM fields, such as Education and Business. The net change in university applications to any field is null (the estimated effect is 0.08 negative with 0.98 standard error).

These results suggest that university application decisions become discontinuously more ambitious in terms of the earnings associated with the fields students choose. To gain further insight into this pattern, I also analyze potential earnings based on all applications made by each individual (university-field earnings). Figure 3b shows that individuals who score just above the 600 cutoff make significantly more ambitious choices about future earnings associated with the programs to which they apply than do those just below the 600 cutoff. The estimate for the discontinuous increase stands at NIS 7,300 (approximately USD 2,000) and is statistically significant at the 99% level.

5.2 Admission-Related Outcomes

Applications to high-tech fields show a discontinuous increase for individuals scoring just above 600, despite continuously low admission chances. This prompts the question: do these individuals attempt to secure admission by retaking the test and other means, or do they simply believe that a score of 600 is sufficient for admission?

To explore decisions related to retesting, I define an indicator variable with a value of 1 if an individual retakes the test within five years of their first attempt. I also consider the highest score achieved during this period as the admission-relevant score. Since crossing round scores may directly affect retaking decisions (see, e.g., Goodman et al., 2020), it is important to specifically analyze the behavior of high-tech field applicants. To achieve this, I examine the interaction of these outcomes with the indicator of applying to high-tech fields.

I estimate Equation 1 for each of these outcomes, presenting the results in Table 3. In Panel A, I observe a negative average effect of crossing the 600 cutoff on the likelihood of retesting (-2.8 p.p. from a 38.3% baseline). The decrease in admission-relevant scores is statistically insignificant. However, Panel B reveals that most high-tech applicants retake the test before applying. The combined effect on retaking the UPET and applying to high-tech fields is positive, showing a 1.0 percentage point increase from a 3.5% baseline. This suggests that 72% (=0.0096/0.0134) of the increase in high-tech applications is attributable to individuals who retook the test before applying, as further illustrated in panel (a) of Figure A.6. Additionally, when examining the admission-relevant scores of high-tech applicants, I find that they generally apply with much higher scores. The average increase of 8.74 points implies an average score of approximately 650 (=8.74/0.0134) among applicants driving the increase (as further illustrated in panel (b) of Figure A.6).

These results suggest that the left-digit bias leads to heterogeneous effects across two groups of test takers. The first group, initially uncertain about their qualifications for success in high-tech fields, may find that achieving a score of 600 boosts their confidence. This confidence could motivate them to improve their admission-related outcomes and ultimately apply. Conversely, the second group, which might have started with less ambitious goals and not initially considered high-tech fields, may feel satisfied upon reaching a 600 score, thus becoming less inclined to retake the test. The heterogeneity analysis, discussed in Section 5.4, further supports this varying response.

Another way to improve admission chances is by enhancing matriculation outcomes. Therefore, I also analyze these outcomes, such as an indicator that takes the value of 1 if the individual earns five matriculation credits in CS and an indicator for a total number of matriculation credits above 30.[10] The results, shown in Panel C of Table 3, indicate a 1.9 p.p. increase in the probability of earning five credits in CS (significant at the 99% level). The change in total credits is statistically insignificant, perhaps due to noise and the heterogeneity nature of the effects (as shown in Section 5.4, this estimate is positive and significant for the relevant subsample of test-takers).

[10]I also have access to matriculation test scores, but I leave them out of this analysis due to noise in measurements for most students.

5.3 Social Influence

The influence of ability beliefs might extend beyond individual decisions to include social influences, such as family and friends, who may also exhibit left-digit bias. These social influences could encourage individuals to set higher goals if they cross the 600 cutoff. While it is difficult to separate the effects of social influence from self-learning mechanisms in the decision to apply to high-tech fields, I demonstrate that biased perceptions might induce social influence by analyzing younger siblings' testing decisions. Previous research has shown that educational decisions can be influenced by the experiences of older siblings (Joensen and Nielsen, 2018; Gurantz et al., 2020; Karbownik and Özek, 2021; Altmejd et al., 2021). Therefore, the biased perception of the 600 score as a significant ability signal could also create spillover effects within families, indirectly suggesting that social influence may be one of the mechanisms driving the increased high-tech applications.

To investigate this, I define outcome variables to indicate whether any younger sibling took the UPET within three or five years after the older sibling's test. The results reveal that test scores of 600 by older siblings significantly raise the likelihood that younger siblings will take the test within three years, indicating a 2.3 p.p. increase in testing probability among younger siblings within three years (significant at the 99% level, as shown in Panel D of Table 3). The estimate remains similar, but less precise, in the five-year period. This result supports the interpretation of a 600 score as an important ability signal, which may also create spillovers within families.

5.4 Heterogeneity of the Effects

The results discussed in the previous subsection indicate heterogeneous effects of the left-digit bias on test-takers' decisions. In this subsection, I explore several dimensions of this heterogeneity.

Ethnicity and age. I begin by splitting the sample according to the ethnicity and age of the test participants, categorizing them into Jews and Arabs. I further divide the sample of Jewish test-takers into two age groups: those twenty years old and younger when taking their first test and those older than twenty. This stratification reflects Israel's unique institutional context, where Jewish students often start their academic degrees relatively late, around the ages of 22 to 23, due to mandatory military service. Consequently, about half of these students take their first test after completing their army service and just before applying to higher education institutions. Yet, about half of the students take their first test already during high school or shortly after graduation.

The first row of Table 4 displays the falsification tests for each group, confirming the desired null results. Subsequent rows show that among Jewish test-takers, the increase in applications is driven exclusively by younger individuals, with no change observed among older ones (as is further demonstrated in Figure 4).[11] The probability of applying also increases significantly among Arab test subjects, although this analysis is limited by low statistical power due to their smaller sample size. This pattern extends to the earnings potential linked to these applications. Additionally, the negative impacts on retaking are mainly seen among older test-takers, with younger ones showing smaller (in relative terms) and insignificant declines. Additionally, only younger test-takers enhance their matriculation outcomes, aligning with their efforts to secure admission to the more demanding high-tech fields.

Several factors may contribute to the more pronounced effects observed among younger individuals. First, younger test-takers may be more sensitive to test score signals or to biases. Second, unlike older individuals who may already be employed or have other commitments, younger test-takers have the advantage of being able to dedicate more time to improving their test scores or matriculation outcomes. This conjecture is supported by their higher baseline test retake rates–48% compared to 25% among older test-takers–indicating that younger individuals are more proactive in improving their university prospects. Third, younger individuals may have higher academic aspirations from the start, making them more motivated to pursue competitive fields, such as high-tech fields at the university level. This is evident from their higher baseline rates and their better matriculation outcomes, such as the average total number of credits (29 for the younger group versus 25 for the older).

Endogenuous stratification. Next, I examine how the effects vary by test-takers' baseline likelihood to apply to university high-tech fields. To do this, I divided the sample of younger Jewish test-takers into three groups based on the tertiles in the distribution of their predicted likelihood to apply.[12] I then estimated the effects separately for each group.

The results, displayed in Figure 5, show that the higher a participant's predicted likelihood of applying, the more positive the effects. This finding further supports the discussion from the previous subsection, indicating that the increase in applications to high-reward fields is primarily driven by students who already exhibit a higher baseline probability of applying to these fields. Furthermore, the results

[11]In these figures and subsequent RD figures, the analysis focuses on Jewish test-takers divided by age at the time they are tested. Although the figures for Arab test-takers are not included due to the small sample size, the RD estimates for Arab test-takers are reported in the tables.
[12]These predicted values, used in the falsification tests, are estimated through a standard 2-fold cross-validation procedure to prevent overfitting.

show that these students are likely to improve their admission-related outcomes before applying (shown in Figure A.7).

Other heterogeneity dimensions. Finally, I also investigate heterogeneity by other characteristics such as test-takers' gender and socio-economic status (SES), proxied by whether parents' earnings and years of schooling are above the median of NIS 250,000 and 15 years. I use Z_i as an indicator for individual i's gender or SES and estimate the following equation:

$$\begin{aligned} Y_i =& \beta_0 + \beta_1 \times Z_i + \beta_2 \times (s_i - 600) + \beta_3 \times Z_i \times (s_i - 600) + \\ & \beta_4 \times \mathbf{1}_{\{s_i \geq 600\}} \times (s_i - 600) + \beta_5 \times \mathbf{1}_{\{s_i \geq 600\}} \times (s_i - 600) \times Z_i + \\ & \tau_0 \times \mathbf{1}_{\{s_i \geq 600\}} + \tau_1 \times Z_i \times \mathbf{1}_{\{s_i \geq 600\}} + \varepsilon_i^0 \end{aligned} \tag{2}$$

The coefficient τ_1 indicates how the effect varies by Z_i, and $\tau_z = \tau_0 + \tau_1 \times z$ represents the effect for those with $Z_i = z$. Results are displayed in Tables A.2 and A.3, focusing on the sample of younger Jewish test-takers. While results indicate stronger effects for males and students from higher socio-economic backgrounds, differences in coefficients are not statistically significant in most cases due to limited power. However, the results may suggest that the effects discussed maintain pre-existing disparities, such as gender gaps, as they affect students according to their baseline likelihood of applying.

5.5 Long-Term Consequences

The results from the previous subsections indicate that biased score perceptions lead test-takers to set higher educational goals if they exceed a round score threshold in their first university entrance test. This section extends the analysis to explore the long-term implications of these decisions, focusing on career outcomes. Examining these outcomes provides insight into whether applicants to university high-tech programs who respond to the 600 score signal are overly optimistic, or whether non-applicants are underconfident and might achieve better outcomes if they pursued these fields.

Figure 6 displays the main estimation results, detailing the impact of crossing the 600 score on tech employment and annual earnings at age 30. Panels (a) and (b) illustrate significant increases in both outcomes for younger test-takers, those who drive the increase in application to high-tech fields, with a 3 p.p. rise in tech employment and a NIS 7,400 increase in earnings (approximately USD 2,000 or 6.5%) at the 600 threshold. In contrast, Panels (c) and (d) show no significant changes in the earnings of older test-takers. Table 5 presents the estimated effects and their standard errors for both outcomes at age 30 and 12 years post-test (the latest I observe all individuals in our sample), confirming consistency across both time frames.[13]

The earnings increase for individuals just above the 600 cutoff may suggest that their decision to apply to high-reward fields is beneficial. However, the earnings gains might also reflect other factors at the 600 score cutoff, such as other educational and career decisions or perceptions by employers. This raises the question: Can the career gains be directly attributed to their applications to high-tech fields? The evidence suggests that application decisions explain, at least partially, the observed earnings increase.

First, many of these students not only apply but also secure admission and enroll in university high-tech degree programs, as indicated in Panel (c) of Table A.4. Moreover, there is an overall increase in the likelihood of attending any high-tech field degree program across all higher education institutions. This suggests that the rise in applications to university high-tech fields is not offset by a drop in college high-tech applications. Furthermore, the results may suggest that some applicants who could not gain admission to university programs choose instead to attend high-tech college programs (which require lower entry requirements).[14]

Second, the concentration of positive earnings and tech employment effects among younger test-takers, who notably increased their applications, further supports that these gains result from their decisions to apply to high-tech fields. This is further confirmed in Figure 7, where the benefits are primarily seen in those with a higher baseline likelihood of applying. This pattern aligns with the previous findings that this group drives the observed change in application behavior.

Third, I analyze the dynamic nature of these effects by estimating them for each post-test year, from the first to the twelfth. The results, shown in Figure 8, reveal no immediate effects but only long-term gains. This pattern supports a human-capital investment mechanism, where students initially invest time in securing admission and studying toward their degrees, with career gains materializing only years later. This finding also refutes the notion that round-test-score signals immediately affect earnings, such as through a boost in confidence or employers' left-digit bias.

[13]Additionally, Panels (a) and (b) of Table A.4 display insignificant and positive estimates for the impacts on employment and self-employment likelihood. In addition, using other earnings measures, such as the natural log of earnings or the within cohort earnings rank, results suggest a meaningful increase, but they are less precise.

[14]The table also shows a slight decrease in the likelihood of attending any university degree, with no net change in attending any degree across all institutions. This indicates a shift from non-high-tech university programs to non-high-tech college programs. However, these shifts primarily occur among those in the lower tertiles of baseline predicted likelihood of applying, not appearing in the highest tertile, suggesting that they are linked to the observed decline in retesting and are driven by other test-takers.

Finally, I assess the earnings of those who apply to high-tech fields around the 600 cutoff to determine if their earnings align with those typically seen in high-tech graduates. Panel (a) of Figure A.8 indicates that the average earnings for these students are comparable to those of applicants with higher (first) scores in high-tech fields. Panel (b) presents the RD estimation results using earnings interactions with high-tech field applications as the outcome. The findings indicate a significant increase in this outcome. Given that the increase in applications is 2.22 percentage points, an earnings times applications rise of 4.46 thousand NIS implies that the average earnings among those who increased applications are approximately 200 thousand NIS (=4.46/0.0222).This is on par with the average earnings of university high-tech field graduates and significantly higher than those in other fields.

Therefore, the results indicate that the increased applications to high-reward fields were beneficial for these students, suggesting that the marginal returns for these programs are significant not only at the margin of admission but also at the margin of application. This finding implies that in addition to increasing the number of slots in high-tech fields, policies aimed at boosting the number of high-skilled workers in Israel may also encourage students to set higher aspirations and apply to these fields, as it can yield long-term benefits for them.

5.6 Robustness and Generalizability

Tables A.5, A.6, and A.7 present a robustness analysis of the main results using non-parametric RD models, separately for young and old Jewish test-takers, and for Arab test-takers. The results consistently affirm the main findings across various specifications, employing MSE-optimal bandwidths with different polynomial orders (1–2) and kernel function choices (uniform and triangular), as recommended by Calonico et al. (2014). The bandwidths selected are also similar to those used in the main analysis.

Moreover, while the main analysis focuses on the round score of 600–where the decision to pursue a high-tech field is most relevant–Appendix B also briefly discusses the effects of crossing other round score cutoffs. There is no increase in university high-tech applications at lower round scores, aligning with these scores being far from meeting admission requirements and thus supporting the focus on 600. However, the estimates suggest that crossing other round scores may yield other meaningful and heterogeneous effects.

These findings reinforce the notion that left-digit bias significantly shapes test score perceptions and influences subsequent student decisions. However, due to the heterogeneity of these effects, the specific impact of crossing round test scores can vary depending on the population or context. This observation aligns with previous research documenting an increase in university application ambition (Li and Qiu, 2023) and a decrease in retesting decisions (Pope and Simonsohn, 2011; Goodman et al., 2020) across various higher education settings, including Chinese and American contexts.

6 Conclusion

In the context of growing interest in the determinants and lasting effects of university application decisions, this study highlights the influence of biased test score perceptions by documenting their impact on how young adults choose their university fields of study and develop their early careers. The analysis uncovers a remarkable jump in the likelihood of applying to the most rewarding fields when students cross a round-score cutoff on their first university entrance test. This finding is particularly intriguing because of consistently low chances of admission among those who score just around the cutoff. These individuals take proactive steps such as retaking the test and enhancing their matriculation outcomes in order to increase their admission chances before they apply to these lucrative university fields.

Furthermore, the study finds heterogeneity in the response to round test scores. While crossing the round-score threshold boosts confidence for some individuals, pushing them toward more ambitious university decisions, others who may have been initially less inclined to make such ambitious decisions find less motivation to retake the test once they surpass the round score. This reduced motivation for retaking could stem from the satisfaction of crossing the round score.

Additionally, the analysis reveals that the effects extend to the decisions of younger siblings. Younger siblings of those who cross the round-score threshold are more inclined to take the test themselves, suggesting that they also interpret their older siblings' round-test score as a significant ability signal.

Examining the long-term consequences of crossing the round-score cutoff yields intriguing insights. The evidence indicates that the increased applications to high-reward fields, triggered by biased score perceptions, translates into significant earnings benefits years after the test. By implication, individuals who score just below the round score cutoff may lack ambition in their academic choices, potentially missing out on more rewarding trajectories than those chosen. This result highlights the potential adverse consequences of underestimating one's abilities when making pivotal educational decisions.

In sum, this study enriches our understanding of how psychological factors shape educational decisions and career paths. The findings hold potential policy implications for education systems that rely heavily on test scores for university admission. They demonstrate the potential consequences of such reliance, emphasizing the importance of transparent communication with young adults in regard to self-assessment and interpretation of test scores.

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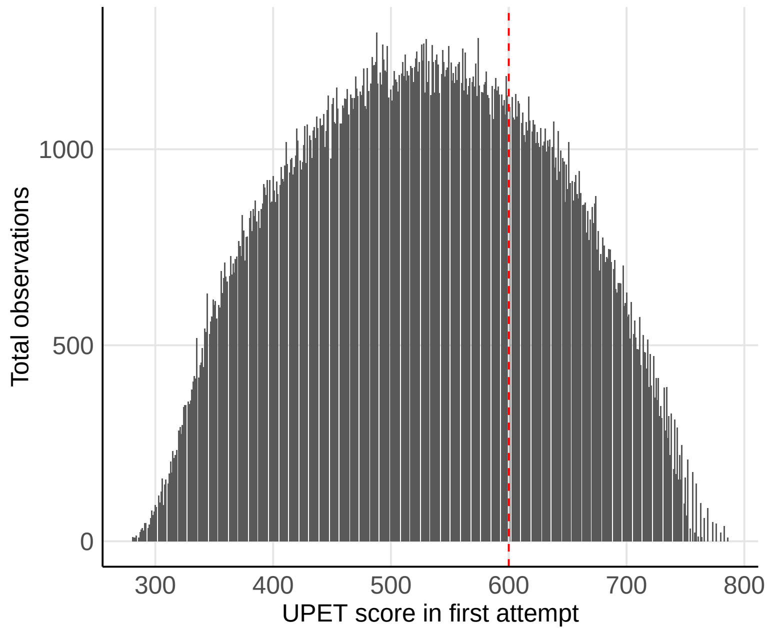
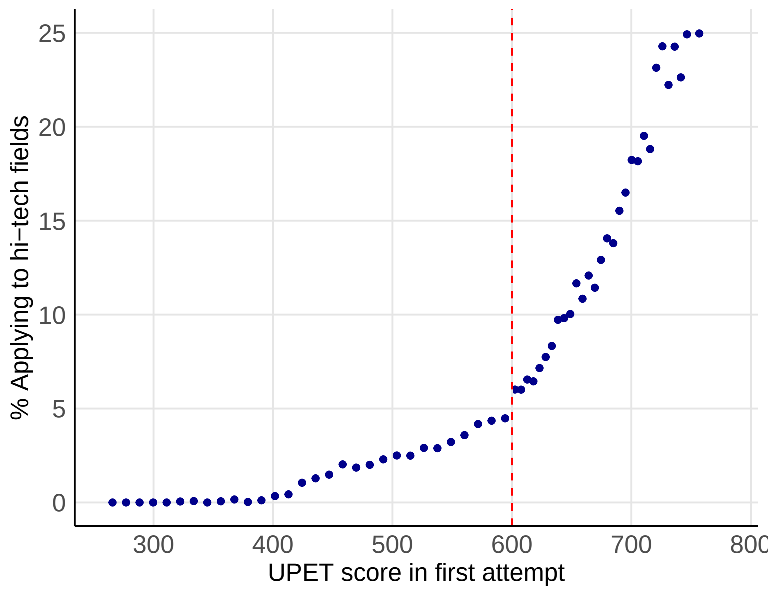
Figure 1: University Graduates' Labor-Market Outcomes, by Field of Study

Notes: This figure displays the labor-market outcomes of university graduates in Israel at age 30, grouped by field of study. The y-axis represents average annual earnings, while the x-axis indicates the tech employment rate. Each circle corresponds to a specific field program, with circle sizes proportional to the number of graduates in each field within our dataset. The most prevalent fields (with at least 5,000 observations) are labeled by name. Fields marked in red are those designated as "high-tech fields" in our main analysis. Abbreviations used: Com Sci for computer science and Ele Eng for electrical engineering. The sample encompasses all university graduates in our sample, totaling 153,124 students.

Figure 2: UPET Scores and Subsequent University High-Tech Applications



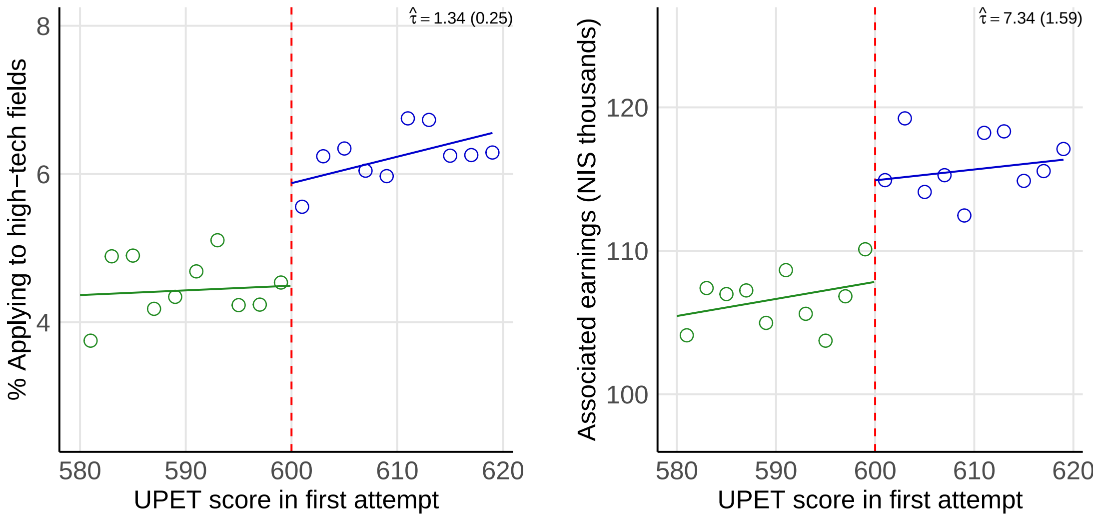
(a) UPET scores distribution



(b) % High-tech

Notes: The figure in panel (a) plots the share of observations (y-axis) according to the first UPET score (x-axis). The sample includes all individuals who took their first UPET between 1999–2008 (347,511 observations). The red vertical line represents the 600 score cutoff. The figure in panel (b) illustrates the relationship between first UPET scores and the subsequent likelihood of applying to university high-tech fields (computer science and electrical engineering). The x-axis displays the total score on the first UPET; the y-axis represents the probability of applying within five years after the test. The baseline sample includes all individuals in Israel who took their first UPET between 1999 and 2008, yielding 347,511 observations. I further restrict the sample to those scoring between 350 and 750 (due to the cell-suppression policy), yielding a final sample of 339,019 observations. The figure groups the observations into bins selected by an evenly-spaced mimicking variance method. The red dashed vertical line indicates the 600 cutoff score.

Figure 3: The Impact of Crossing 600 on University Applications

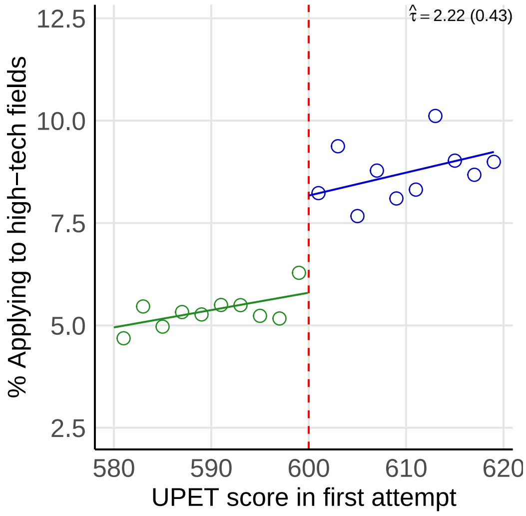


(a) % High-tech (b) Associated earnings (NIS 1,000)

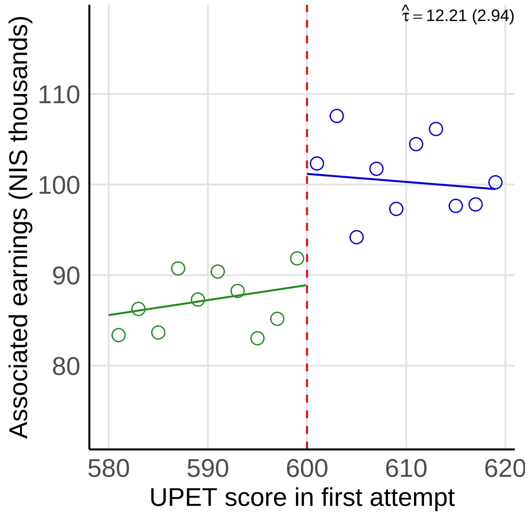
Notes: The figures illustrate the impact of crossing 600 on the first UPET on university application decisions. The x-axes display the total score on the first UPET, presented in two-point bins. The y-axes represent the probability of applying to university high-tech fields (panel a), and the earnings associated with the application in NIS thousands (panel b). The analysis includes all individuals in Israel who took their first UPET between 1999 and 2008, yielding 39,140 effective observations. The analysis in panel b is further restricted to those who applied to any university field within five years, yielding 28,272 effective observations. The red dashed vertical line indicates the 600 cutoff score. The blue and green solid lines are predicted values based on the estimation of Equation 1. The figures also present the estimates (and robust standard errors clustered at the score level) of the coefficient of interest, τ, which reflects the impact of crossing 600 on the outcome.

Figure 4: Effects of Crossing 600 on University Applications, by Age at First Test

Younger (20 and below)

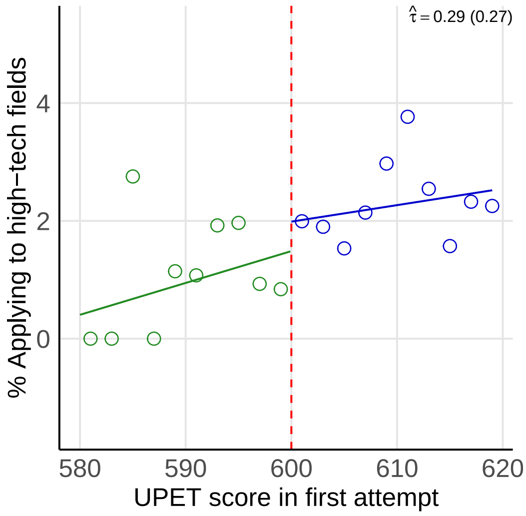


(a) % High-tech

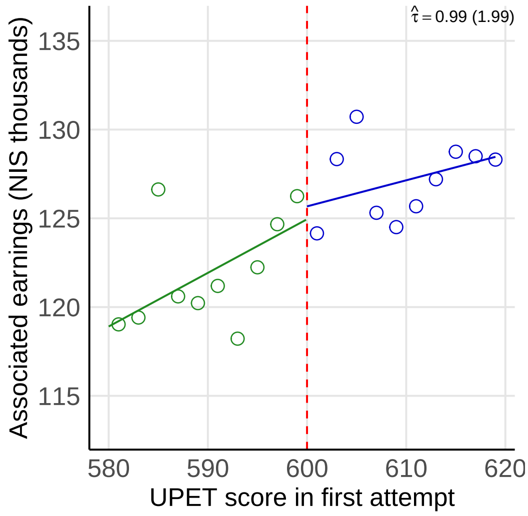


(b) Associated earnings (NIS 1,000)

Older (21 and above)



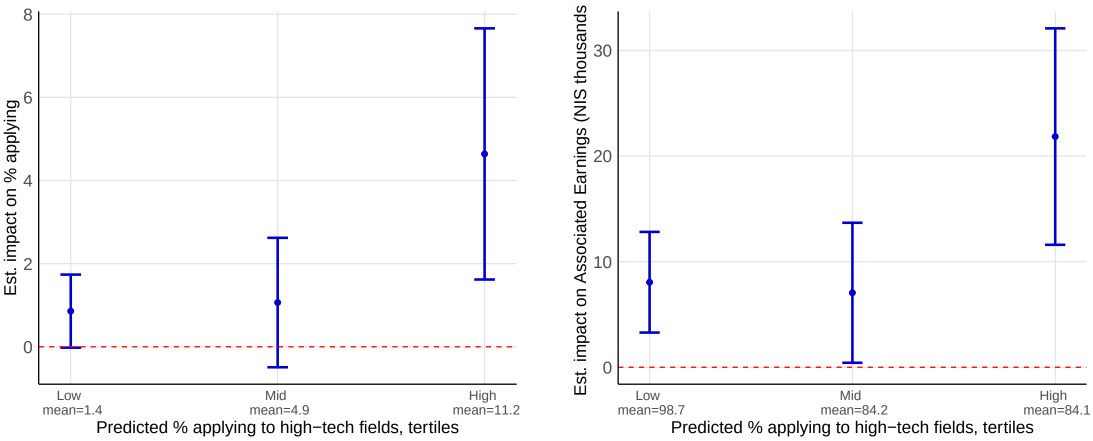
(c) % High-tech



(d) Associated earnings (NIS 1,000)

Notes: The figures illustrate the impact of crossing 600 in the first UPET on university applications, with separate analyses for younger and older test-takers.The x-axes display the total score on the first UPET, presented in two-point bins; the y-axes represents the probability of applying to high-tech fields (panels a and c), and the potential earnings associated with the applications in NIS thousands (panels b and d). The analysis includes all Jewish individuals in Israel who took their first UPET between 1999 and 2008, yielding 39,608 effective observations. Subsequently, the estimation sample is divided into two panels: panels (a) and (b) comprising those who took their first test by age 20 (18,629 observations) and panels (c) and (d) for those who took their first tests later (20,979 observations). The red dashed vertical line indicates the 600 cutoff score. The blue and green solid lines are predicted values based on the estimation of Equation 1. The figures also present the estimates (and their robust standard errors clustered at the score level) for the coefficient of interest, τ, which reflects the impact of crossing 600 on the outcome.

Figure 5: Heterogeneous Effects of Crossing 600 on University Applications, Endogenous Stratification

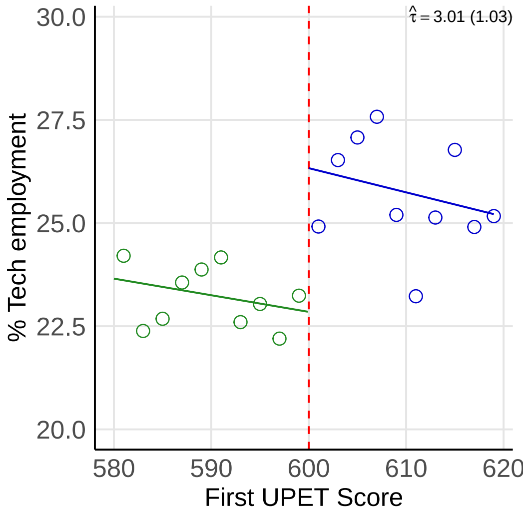


(a) % High-tech applications (b) Associated earnings (NIS 1,000)

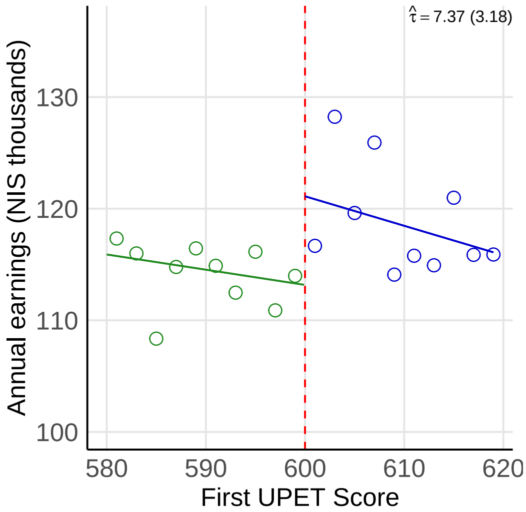
Notes: The figure presents the estimated effects of crossing 600 in the first UPET and their 90% confidence intervals, stratified by the individual's baseline predicted likelihood of applying. The estimates are based on the estimation of Equation 2, adjusted such that Z_i includes dummies for each tertile in the distribution of predicted values. The x-axis represents these tertiles. The y-axes display the estimated effect on the likelihood of applying to university high-tech fields (computer science and electrical engineering) within five years after the test. The analysis includes all individuals in Israel who took their first UPET by age 20 (18,629 observations). UPET stands for University Psychometric Entrance Test.

Figure 6: Effects of Crossing 600 on Employment Outcomes, by Age at First Test

Younger (20 and below)

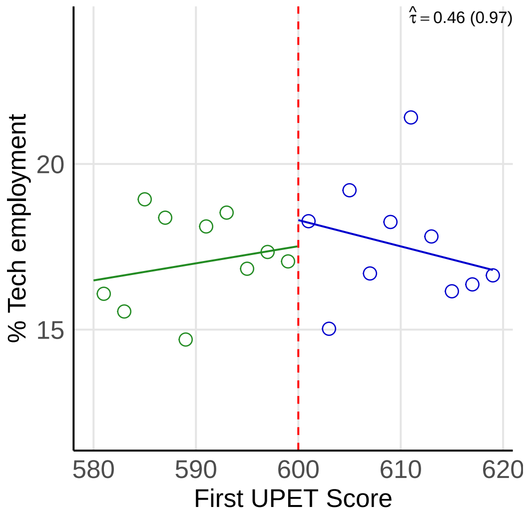


(a) % Tech employment

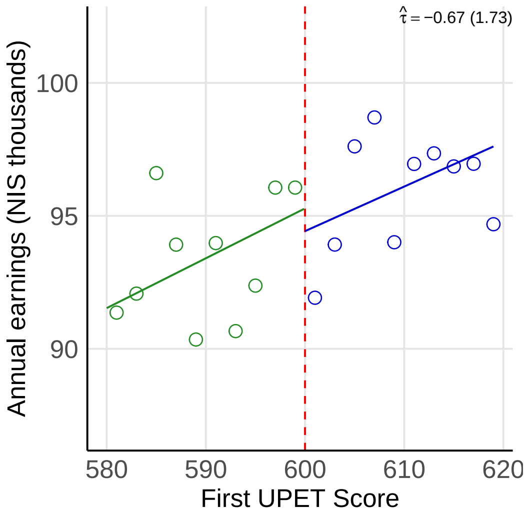


(b) Annual earnings (NIS 1,000)

Older (21 and above)



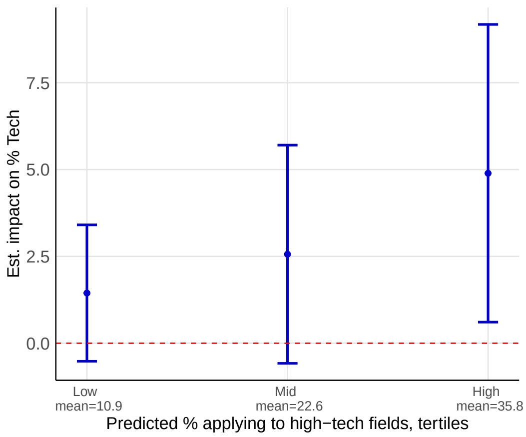
(c) % Tech employment



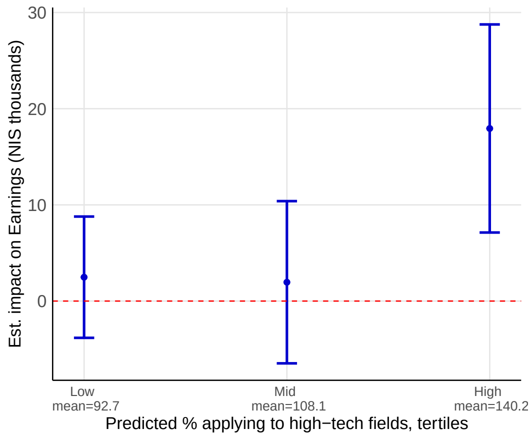
(d) Annual earnings (NIS 1,000)

Notes: The figures illustrate the impact of crossing 600 in the first UPET on employment outcomes at age 30, with separate analyses for younger and older test-takers. The x-axes display the total score on the first UPET, presented in two-point bins; the y-axes represents the probability of tech employment (panels a and c), and annual earnings in NIS thousands (panels b and d). The analysis includes all Jewish individuals in Israel who took their first UPET between 1999 and 2008 and were at age 30 or older in 2020, yielding 38,938 effective observations. Subsequently, the estimation sample is divided into two panels: panels (a) and (b) comprising those who took their first test by age 20 (17,957 observations) and panels (c) and (d) for those who took their first tests later (20,979 observations). The red dashed vertical line indicates the 600 cutoff score. The blue and green solid lines are predicted values based on the estimation of Equation 1. The figures also present the estimates (and their robust standard errors clustered at the score level) for the coefficient of interest, τ, which reflects the impact of crossing 600 on the outcome.

Figure 7: Heterogeneous Effects of Crossing 600 on Employment Outcomes, Endogenous Stratification



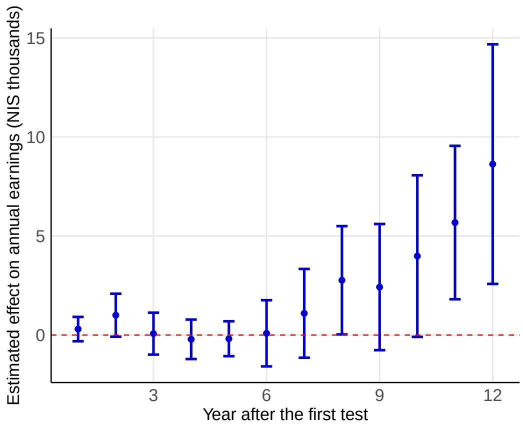
(a) % Tech employment



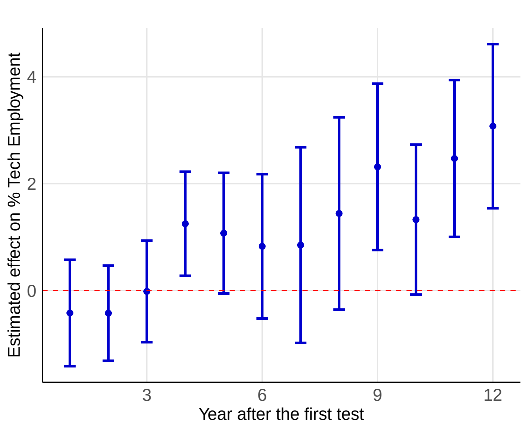
(b) Earnings

Notes: The figures present the estimated effects of crossing 600 in the first UPET and their 90% confidence intervals, stratified by the individual's baseline predicted likelihood of applying. The estimates are based on the estimation of Equation 2, adjusted such that Z_i includes dummies for each tertile in the distribution of predicted values. The x-axis represents these tertiles. The y-axes display the estimated effect on the likelihood of being employed in the tech sector (a) and on total annual earnings twelve years after the test. The analysis includes all individuals in Israel who took their first UPET by age 20 and were at age 30 or older in 2020, yielding 17,957 observations. UPET stands for University Psychometric Entrance Test.

Figure 8: Year-by-Year Effects of Crossing 600 on Labor-Market Effect, Sample of Younger Jewish Test-Takers



(a) Earnings



(b) % Tech

Notes: The figures present year-by-year effects of crossing 600 in the first UPET on labor-market outcomes. The x-axis displays the year relative to the first test; the y-axes represent the estimated year-by-year estimated effects (τ from Equation 1) on annual earnings (a) in NIS thousands and on tech employment (b) in p.p.. The figures also show 90% confidence intervals, based on robust standard errors clustered at the score level. The analysis includes all Jewish individuals in Israel who took their first UPET by age 20 between 1999 and 2008, yielding 18,629 observations.

Table 1: The "Impact" of Crossing 600 on Predetermined Outcomes

	(1)	(2)	(3)	(4)	(5)
A. Individual					
	Age	% Arab	% Female	% Israeli	% Regular
	0.01	-0.00	-1.10	-0.03	0.18
	(0.06)	(0.00)	(1.20)	(0.57)	(0.76)
Mean	20.20	0.05	56.20	84.39	82.25
N	41,422	41,422	41,422	41,422	41,422
B. Test					
			Score by domain		
	Year	Month	Quantitative	English	Qualitative
	-0.05	-0.02	-0.11	0.42	-0.04
	(0.03)	(0.07)	(0.19)	(0.26)	(0.19)
Mean	2004.44	7.03	116.81	117.17	113.84
N	41,422	41,422	41,422	41,422	41,422
C. Family					
	Mother		Father		Siblings
	Educ	Income	Educ	Income	
	0.03	-3.22**	-0.06	-4.14	-0.01
	(0.05)	(1.61)	(0.08)	(5.78)	(0.03)
Mean	14.05	88.09	13.60	191.49	2.41
N	41,422	41,422	41,422	41,422	41,356

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Notes: The table presents estimated discontinuous changes in predetermined outcomes at the 600 cutoff score on the first UPET. Columns (1)-(5) show the estimates for τ in Equation 1, along with robust standard errors in parentheses. The baseline sample comprises all individuals in Israel who took their first UPET in 1999–2008. The effective sample is further narrowed to individuals with first test scores falling within the window of 580–620. Earnings are measured in NIS thousands. Regular school stands for regular (non-religious) school.

Table 2: The Impact of Crossing 600 on University Applications

	(1)	(2)	(3)	(4)	(5)
A. High-Tech Fields					
	High-tech	CS	EE	Tech>60%	Tech>40%
	1.34***	0.93***	0.44*	1.05***	1.63***
	(0.25)	(0.26)	(0.23)	(0.26)	(0.49)
Mean	4.43	2.67	3.05	5.89	9.97
N	41,422	41,422	41,422	41,422	41,422
B. Other Fields					
	Any	STEM	Medicine	Law	Business
	-0.85	0.17	-0.08	0.02	-0.41
	(1.08)	(0.49)	(0.32)	(0.26)	(0.43)
Mean	22.22	10.77	2.74	3.25	3.73
N	41,422	41,422	41,422	41,422	41,422
C. Other Fields					
	Para-Med	Health	Social	Education	Humanities
	-0.22	-0.13	-0.11	-0.54**	-0.20
	(0.34)	(0.36)	(0.62)	(0.24)	(0.48)
Mean	6.19	3.32	13.08	2.03	7.21
N	41,422	41,422	41,422	41,422	41,422

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Notes: The table shows the estimatedimpact of crossing the 600 cutoff score on the first UPET on university applications. Columns (1)-(5) show the estimates for τ in Equation 1, along with robust standard errors in parentheses. The baseline sample comprises all individuals in Israel who took their first UPET in 1999–2008. The effective sample is further narrowed to individuals with first test scores falling within the window of 580–620. CS stands for Computer Science, and EE stands for Electrical Engineering.

Table 3: The Impact of Crossing 600 on Admission-Relevant Outcomes

	(1)	(2)
A. UPET retaking		
	% Retaking	Admission-relevant score
	-2.81***	-0.59
	(0.99)	(0.50)
Mean	38.30	612.06
N	41,422	41,422
B. × Applying to Hi-Tech Field		
	% Retaking	Admission-relevant score
	0.96***	8.74***
	(0.26)	(1.65)
Mean	3.55	28.43
N	41,422	41,422
C. Matriculation		
	% Total > 29	% with 5 Credits in CS
	0.66	1.93***
	(0.80)	(0.70)
Mean	28.29	18.00
N	40,946	40,946
D. Siblings' testing		
	Within 3 years	Within 5 years
	2.32***	1.41
	(0.73)	(1.40)
Mean	15.35	30.29
N	25,481	25,481
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

Notes: The table shows the estimatedimpact of crossing the 600 cutoff score on the first UPET on admission-related outcomes and young siblings testing. Columns (1)-(5) show the estimates for τ in Equation 1, along with robust standard errors in parentheses. The baseline sample comprises all individuals in Israel who took their first UPET in 1999–2008. The effective sample is further narrowed to individuals with first test scores falling within the window of 580–620. and CS stands for Computer Science.

Table 4: Effects of Crossing 600, Heterogeneity by Ethnicity and Age

	Jews		Arabs
	Age < 21	Age > 20	
	(1)	(2)	(3)
Falsification (predicted % Applying)	0.19	0.02	-0.14
	(0.14)	(0.02)	(1.03)
Mean	4.72	1.20	20.27
N	18,629	20,979	1,814
% Applying to high-tech fields	2.22***	0.29	5.74
	(0.43)	(0.27)	(4.02)
Mean	5.35	1.64	23.74
N	18,629	20,979	1,814
Associated earnings (NIS thousands)	12.21***	0.99	4.27
	(2.94)	(1.99)	(6.12)
Mean	87.18	121.87	165.28
N	14,607	11,993	1,672
% UPET Retaking	-2.52	-2.84**	-0.26
	(1.68)	(1.21)	(3.71)
Mean	47.82	24.94	84.24
N	18,629	20,979	1,814
Admission-relevant score	0.07	-1.05	1.47
	(1.11)	(0.70)	(4.58)
Mean	619.90	601.25	647.76
N	18,629	20,979	1,814
Matriculation credits > 30	2.50*	-0.65	2.93
	(1.40)	(0.83)	(4.00)
Mean	38.20	14.08	78.63
N	18,545	20,636	1,765

Notes: The table shows the estimatedimpact of crossing the 600 cutoff score on the first UPET on high-tech applications and admission-related outcomes, among different groups of test-takers by ethnicity and age. Columns (1), (2), and (3) show the estimates for *au* in Equation efeq:rdd (and their robust standard errors). The baseline sample includes all individuals in Israel who took their first UPET in 1999–2008. The effective sample is restricted to individuals with first test scores within the window of 580–620. The sample in Column (1) includes only Jewish test-takers who were aged 20 or below when first tested. The sample in Column (2) includes only Jewish test-takers who were aged 21 or above when first tested. The sample in Column (3) includes only Arab test-takers.

Table 5: Long-Term Effects of Crossing 600, Heterogeneity by Ethnicity and Age

	Jews		Arabs
	Age < 21	Age > 20	
	(1)	(2)	(3)
% Tech employment, age 30	3.01***	0.46	-0.12
	(1.03)	(0.97)	(3.52)
Mean	23.27	16.98	9.64
N	17,957	20,979	1,496
Annual earnings, age 30	7.37**	-0.67	1.12
	(3.18)	(1.73)	(11.71)
Mean	114.60	93.33	133.17
N	17,957	20,979	1,496
% Tech employment, 12 years after	3.08***	1.06	-1.22
	(0.93)	(0.85)	(2.91)
Mean	23.04	18.25	10.64
N	18,629	20,979	1,814
Annual earnings, 12 years after	8.63**	-3.00	-4.85
	(3.68)	(2.37)	(10.27)
Mean	110.53	137.52	118.95
N	18,629	20,979	1,814

Notes: The table shows the estimatedimpact of crossing the 600 cutoff score on the first UPET on long-term outcomes, among different groups of test-takers by ethnicity and age. Columns (1), (2), and (3) show the estimates for au in Equation efeq:rdd (and their robust standard errors). The baseline sample includes all individuals in Israel who took their first UPET in 1999–2008. The effective sample is restricted to individuals with first test scores within the window of 580–620. The sample in Column (1) includes only Jewish test-takers who were aged 20 or below when first tested. The sample in Column (2) includes only Jewish test-takers who were aged 21 or above when first tested. The sample in Column (3) includes only Arab test-takers.

For Online Publication

Appendix A Supplementary Materials

Data and Definitions

A.1 Data Sources

I use an administrative database from the Central Bureau of Statistics of Israel (CBS), which allows restricted access to this data in their protected research lab. Data are available for all students in Israeli high schools (tenth grade) between 1995 and 2016. The data include merged datasets from multiple sources: 1) The National Institution for Testing and Evaluation provides information on the University Psychometric Entrance Test (UPET); It includes the scores and timing of all tests ever taken by each individual in the sample since 1995. 2) Higher Council of Education records of post-secondary completed degrees, the institution of study (colleges and universities), the field of study (one or two), and completion year; essential additional features of these data are the university application information. I observe these data for universities in all years and colleges in 2009 and later only. I also observe partial data on the admission decisions made for each application. 3) Israel Tax Authority (ITA) provides data on the earnings of employees and self-employed individuals from 2000-2018 and a three-digit code of industry of employment. 4) The population registry data includes a fictitious individual national ID number that appears in all the data sets described below and enables the matching and merging of the files at the personal level. It also contains information on the following student's family background variables: birth year, sex, locality, number of siblings, country of birth, and parental countries of birth. 5) The Ministry of Education has provided administrative data on Israeli high schools' universe since 1995. It provides data on students' matriculation programs and test scores (test scores are shown in groups).

A.2 Sample Restrictions

The analysis focuses on students who participated in their first tests during the ten years from 1999 to 2008. The exclusion of tests after 2008 enables long-term analysis, facilitating the observation of outcomes up to twelve years after the test. Similarly, excluding tests before 1999 serves the purpose of validating that the observed test is indeed the individual's first test. Additionally, this restriction results in a minimal reduction of less than 5% in the sample size, and importantly, the results remain consistent even without this exclusion. Finally, I also focus on tests made in Hebrew or Arabic, excluding tests made in other languages (less than 1% of the sample).

A.3 Variables Definitions

University applications. In this study, I utilize the university application dataset to create indicators for university application behavior. These indicators represent the likelihood of applying to different academic fields within three years after the test and in any year. The academic fields are classified using three-digit codes based on the CBS classification. For instance, the fields of CS and EE are identified by codes 900 and 1020, respectively. Moreover, I employ the CBS definitions to categorize degrees and applications into STEM and non-STEM fields. STEM fields encompass disciplines such as Mathematics, Statistics, Computer Science, Engineering, and Physical and Biological Sciences. On the other hand, non-STEM fields include all other academic disciplines not falling within the STEM classification.

The application dataset used in this study also contains partial information on admission decisions for each application. It also includes valuable data on individuals who were admitted and subsequently started their degree programs. However, the admission decisions data is limited as it only provides binary indicators for first-choice field admissions and admissions to other fields. Given these limitations, the analysis in this study primarily focuses on applications and university enrollment.

Degree enrollment. The university enrollment dataset includes some missing information on fields of study for certain individuals. To address this, I combine information from the university degree attainment dataset and the applications dataset. The enrollment indicator is assigned a value of one if an individual is marked as enrolled in a university CS degree program in the enrollment dataset *or* completed a university CS degree program in the degrees dataset *or* marked as starting a university CS degree program in the application decisions dataset. This comprehensive approach ensures an accurate examination of enrollment patterns in CS degree programs. Importantly, the results remain consistent even when excluding the application decisions dataset.

Tech employment. The definition of the tech industry is based on working in services or manufacturing tech companies. According to the CBS definition, these include the following industries: Pharmaceutical products for human and veterinary uses, Office and accounting machinery and computers, Electronic components, Electronic communication equipment, Industrial equipment for control and supervision, medical and scientific equipment, Aircraft (manufacturing); Telecommunications, Computer, and related services, Research and Development (services).

Earnings outliers. To handle earnings outliers, I apply a restriction in the primary analysis, capping each earnings observation at a maximum of six or more standard deviations from the mean. This restriction has minimal impact, affecting only a small number of observations, and does not alter the results.

Missing parental education and earnings. There are a few missing values in the parental education and income data. I used the partner's education income to impute a value in cases of missing values. If both parents had missing values, I assigned the average value in my sample.

Predicted likelihood of applying to high-tech fields. I have predicted the main outcome (applications to high-tech fields) by fitting a logistic regression of the pre-determined variables on the outcome. The estimation sample includes all individuals in Israel who participated in their first UPET during 1999–2008, with UPET scores between 500 and 699. The following explanatory variables are included: Gender, an indicator for taking the first est after the age of 20, an indicator for Arabs, an indicator for individuals who were born in Israel, an Indicator for studying in non-religious school, an indicator for parental earnings above the 250K NIS, an indicator for parental post-high school education, the number of siblings (indicators for one or two siblings and for more than two). In this estimation, I used a standard 2-fold cross validation procedure.

A.4 Information on Official Admission Thresholds

The interpretation of the results in this paper relies on institutional details that university CS degree admission chances do not increase at the 600 cutoff, which is supported by the empirical analysis presented throughout the paper. The admission threshold for CS is typically very high, making it nearly impossible to gain admission with a UPET score of 600. For instance, in 2012, a candidate with a UPET score of 600 needed a matriculation GPA of 114 to enter a CS program at Tel Aviv University, which is exceptionally high and rare.[15] Similar requirements exist in other universities and years.

Some programs may have additional requirements beyond Sechem, such as a minimum UPET score or matriculation score in specific subjects. For instance, admission to CS programs in some cases requires participation in 5 or 4 credits matriculation programs in math or other scientific fields, with a minimum score. At Ben Gurion University in 2013, all scientific programs, including CS, required a UPET score of at least 600 in addition to the Sechem requirement, but this did

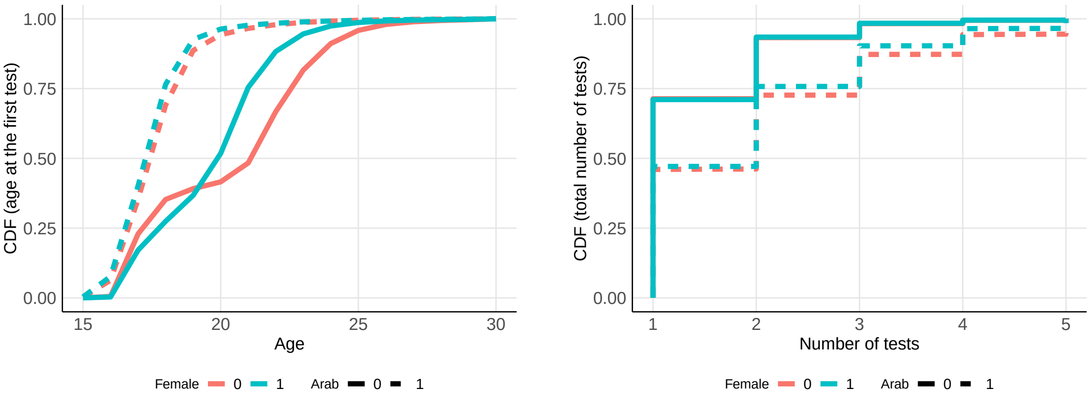
[15] These numbers are larger than 100 due to the GPA calculation method. These methods give extra 10-30 points for test scores in some high school programs (e.g., programs with five credits).

not applying to CS applicants due to the higher Sechem requirement. Additionally, there are various indirect pathways to enter university programs in Israel, including pre-academic programs that help students improve their admission chances and the possibility for students to switch fields after completing one year of university.

Unfortunately, I lack information on colleges' applications and admission decisions during the data period. However, it is worth noting that college admission requirements are typically lower compared to universities. Therefore, it is plausible that a UPET score of 600 is sufficient for enrollment in college CS programs.

Appendix Figures

Figure A.1: Testing in the UPET, by Population Group

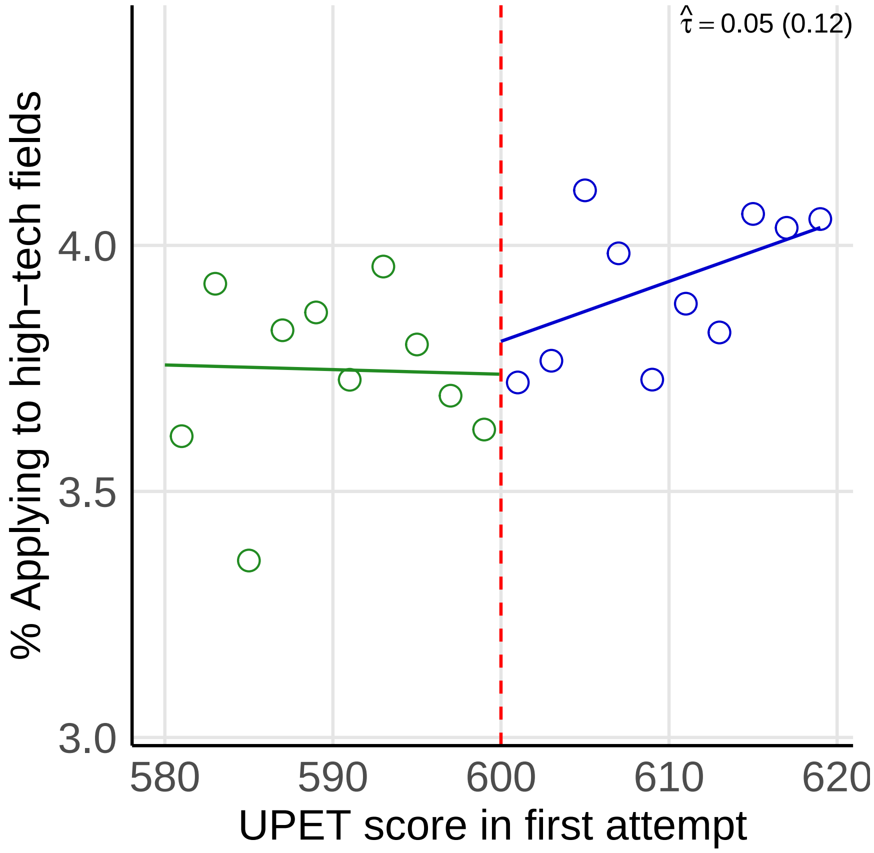


(a) Age at First Test

(b) Number of Tests

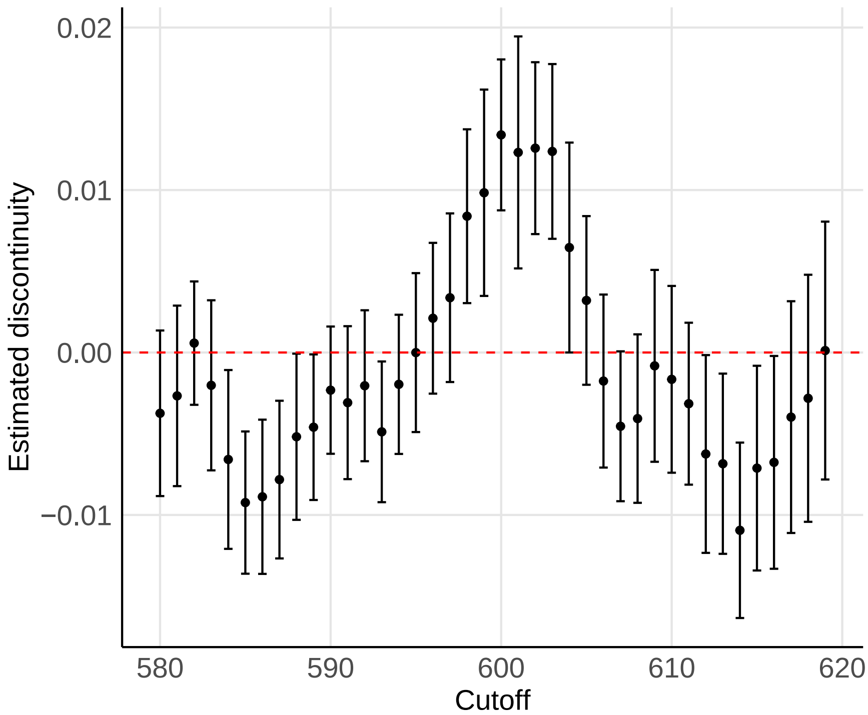
Notes: The figures present the testing regularities of Jews and Arabs in Israel. The sample includes all individuals in Israel who participated in their first UPET during 1999–2008 (347,511 observations). The figure in the upper panel (a) shows the cumulative distribution of ages at the first test. The lower panel (b) figure shows the cumulative distribution of the number of tests taken.

Figure A.2: The "Impact" of Crossing 600 on the Predicted Likelihood of Applying to High-Tech Fields



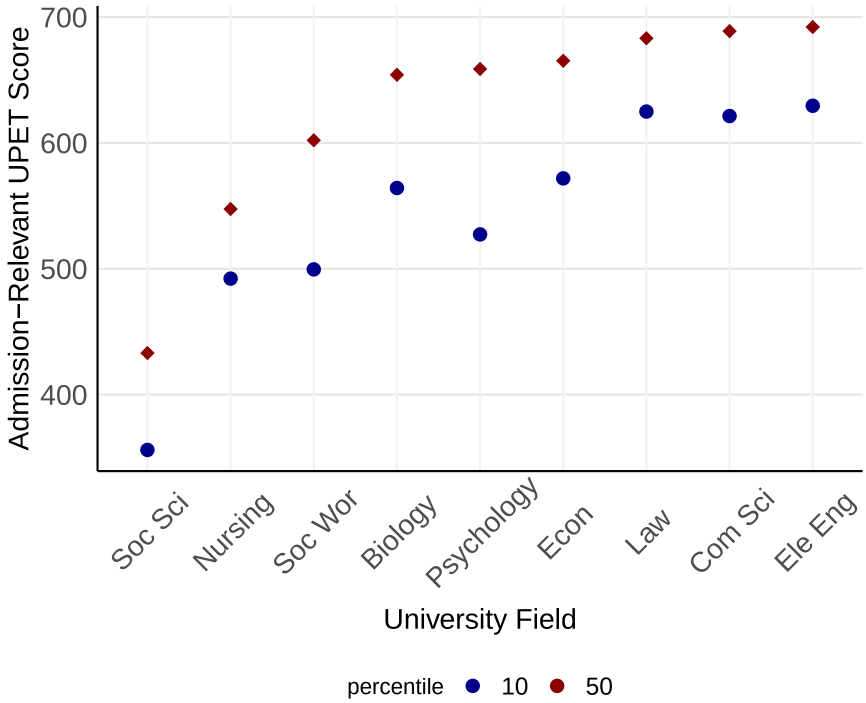
Notes: The figure shows the estimated discontinuity in the predicted likelihood of applying to high-tech fields at the score cutoff of 600 in the first UPET. The x-axis shows the first UPET score (in bins of two points). The y-axis shows the predicted likelihood of applying to high-tech fields within five years after the test, based on pre-determined outcomes. The sample includes all individuals in Israel who participated in their first UPET during 1999–2008 (39,140 effective observations). The red dashed vertical line represents the score cutoff of 600. The blue and green solid lines are based on the estimation of equation 1. The figure also reports the estimate (and its robust standard errors clustered at the score level) for the coefficient of interest, τ, which represents the impact of crossing 600 on the outcome variable.

Figure A.3: The "Impact" of Crossing Non-Round Scores on the Likelihood of Applying to High-Tech Fields



Notes: This figure displays the results of a falsification test, estimating the "impact" of crossing non-round score cutoffs. The y-axis illustrates estimated discontinuities (τ in equation 1), with an indicator for applying to high-tech fields as the outcome. The x-axis indicates the RD cutoff used for estimation. 90% confidence intervals, based on robust standard errors clustered at the score level, are also shown. The baseline sample comprises all individuals in Israel who took the UPET between 1999 and 2008, with first test scores within 20 points below and above the cutoff. The estimation focuses on a 20-point window both above and below each cutoff.

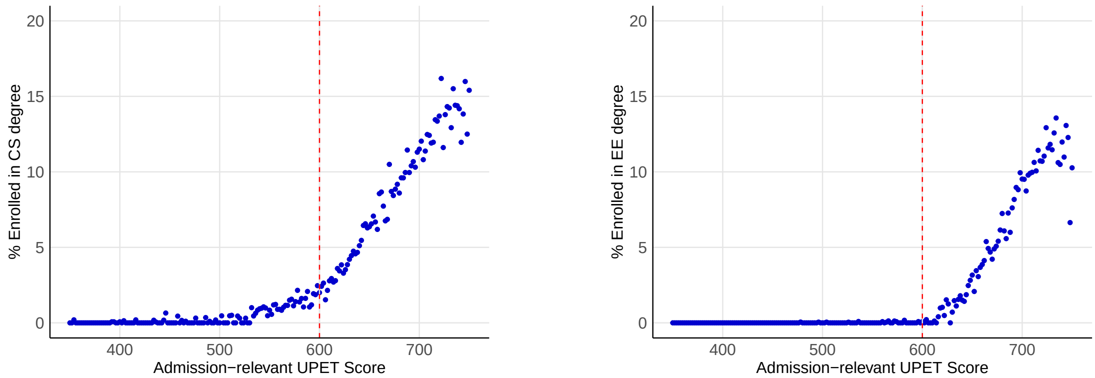
Figure A.4: University Students' Admission-Related UPET Scores, by Field of Study



Notes: This figure displays the admission-relevant UPET scores of university graduates in Israel, grouped by field of study. The y-axis represents the median and the tenth percentile in the distribution of admission-relevant UPET scores, while the x-axis indicates the field. The figure included the most prevalent fields (with at least 5,000 observations). Abbreviations used: Com Sci for computer science and Ele Eng for electrical engineering. The sample encompasses all university graduates from these fields in our sample, totaling 65,243 students.

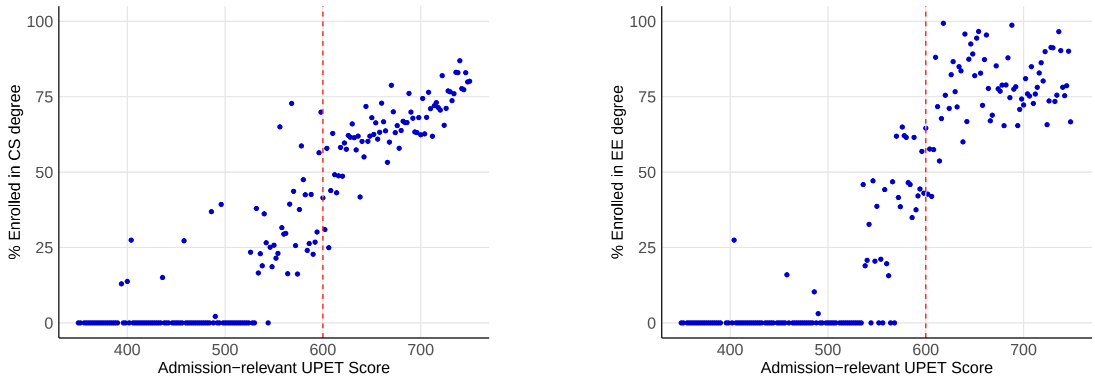
Figure A.5: High-Tech Fields Admission

Unconditional



(a) CS (b) EE

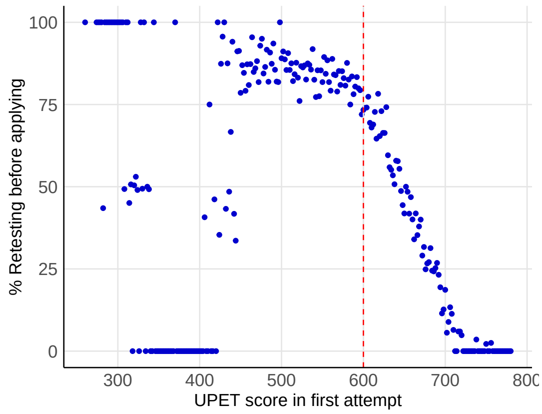
Conditional on Applying



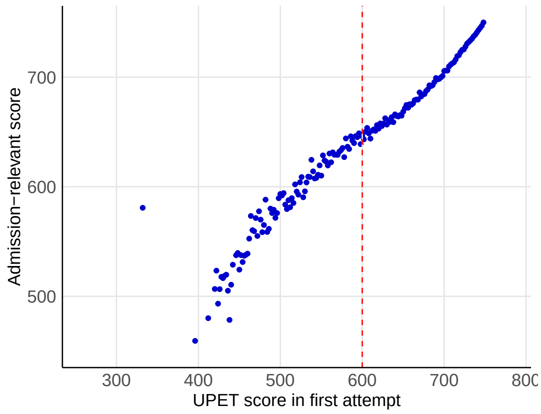
(c) CS (d) EE

Notes: The figures in panels (a) and (b) show the relationship between high-tech field university degree attendance (y-axis) and *admission-relevant* UPET scores (x-axis). The figures in panels (c) and (d) show the likelihood of attending the degree, conditional on applying. The samples in panels (a) and (b) include all individuals in Israel who participated in their first UPET from 1999–2008 (347,511 observations). The samples in panels (c) and (d) are restricted to those who applied to CS and those who applied to EE. The figures group observations into bins selected using an evenly-spaced mimicking variance method. CS stands for Computer Science and EE stands for Electrical Engineering.

Figure A.6: Retaking Patterns Among High-Tech Applicants



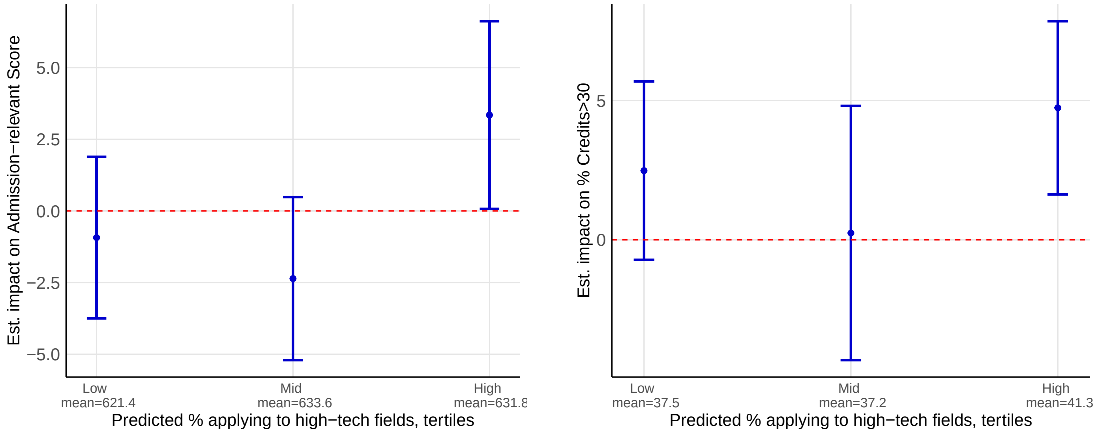
(a) % Retaking



(b) Admission-relevant Score

Notes: The figures show the relationship between scores on the first UPET attempt and UPET retaking decisions among those who apply to high-tech field degrees in universities. The x-axis shows the first UPET score in bins of two score points each. The y-axis shows the share of individuals who retook the UPET (a) and their average admission-relevant UPET score (b). The sample includes all individuals in Israel from cohorts 1979 and later who participated in their first UPET during 1999–2008 and applied to computer science (22,505 observations). The red dashed vertical line represents the score cutoff of 600.

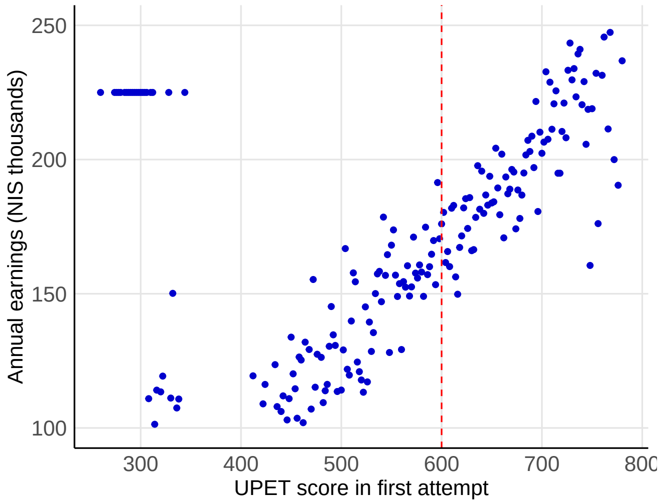
Figure A.7: Heterogeneous Effects of Crossing 600 on Admission-Relevant Outcomes, Endogenous Stratification



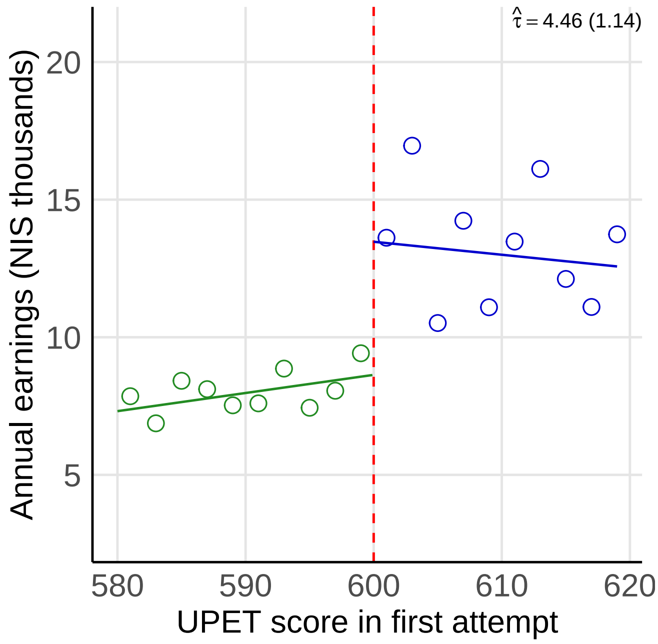
(a) UPET Score (b) Matriculation Credits 30+

Notes: The figures present the estimated effects of crossing 600 in the first UPET and their 90% confidence intervals, stratified by the individual's baseline predicted likelihood of applying. The estimates are based on the estimation of Equation 2, adjusted such that Z_i includes dummies for each tertile in the distribution of predicted values. The x-axis represents these tertiles. The y-axes display the estimated effect on the admission-relevant (highest) UPET score (a) and on the likelihood of achieving 30 or more total matriculation credits. The analysis includes all individuals in Israel who took their first UPET by age 20 (18,629 observations). UPET stands for University Psychometric Entrance Test.

Figure A.8: Analyzing earnings among high-tech applicants



(a) Average earnings among applicants



(b) Impact of crossing 600 on earnings × applying

Notes: The figures analyze the average annual earnings 12 years after the test among those who apply to high-tech fields. The x-axis shows the first UPET score in bins of two score points each. The y-axis shows the average annual earnings in NIS thousands (a) and the average of the interaction of earnings with the indicator for applying to high-tech fields (b). The sample includes all individuals in Israel from cohorts 1979 and later who participated in their first UPET during 1999–2008 when they were at ages 20 and below. The sample in panel (a) is further restricted to those who applied to high-tech fields (xxx observations). The red dashed vertical line represents the score cutoff of 600.

Appendix Tables

Table A.1: University Fields with the Highest Tech Employment Likelihood

Field	Students (1)	% Tech (2)	Earnings (3)
Computer Engineering	1676	81.03	251.83
Comp. Elec. Engineering	884	77.60	248.85
Computer Science	7089	73.62	231.36
Communications Engineering	648	80.86	216.34
Electrical Engineering	6963	69.98	211.34
Systems Engineering	796	75.75	199.31
Industrial Engineering	4871	56.00	167.59
Math	2097	40.92	150.55
Bio-Med Engineering	836	62.08	148.48
Physics	2855	43.12	130.28
Aerospace Engineering	760	44.74	125.70
Bio-Tech Engineering	531	43.13	114.18
Materials Engineering	584	41.78	113.34

This table presnents information on tech-related fields of study in Israel (with 40% tech employment or more at age 30). The sample encompasses all university graduates from these fields in our sample.

Table A.2: Heterogeneity of the Impact by Gender

	Difference (1)	Males (2)	Females (3)
% Applying	-3.28*	4.17***	0.90**
	(1.74)	(1.47)	(0.39)
Baseline Mean		10.34	2.89
% Retaking	-4.66	0.26	-4.40**
	(2.96)	(2.28)	(2.15)
Baseline Mean		50.69	47.99
Admission-relevant score	-3.78	2.32	-1.46
	(2.66)	(2.06)	(1.40)
Baseline Mean		630.91	627.69
Matriculation credits > 30	-2.54	4.03**	1.49
	(2.52)	(1.89)	(1.80)
Baseline Mean		40.26	37.64
N	18,545		

Notes: The table shows the estimated heterogeneity of the impact of crossing the 600 score on the first UPET by gender. Columns (1) shows the estimates for au_1 in Equation 2, along with robust standard errors in parentheses, capturing the estimated difference in the effects between females and males. Columns (2)-(3) shows the estimated impacts for males and females, seperately. The baseline sample comprises all individuals in Israel who took their first UPET by age 20 in 1999–2008. The effective sample is further narrowed to individuals with first test scores falling within the window of 580–620.

Table A.3: Heterogeneity of the Impact by Socio-Economic Status

	Difference (1)	Low (2)	High (3)
% Applying	1.77	1.63**	3.41***
	(1.33)	(0.65)	(0.92)
Baseline Mean		6.40	4.53
% Retaking	0.62	-2.50	-1.88
	(3.19)	(2.07)	(2.52)
Baseline Mean		47.56	51.79
Admission-relevant score	1.28	-0.07	1.21
	(2.61)	(1.42)	(1.98)
Baseline Mean		626.89	632.79
Matriculation credits > 30	3.72	1.32	5.04**
	(2.36)	(1.53)	(2.20)
Baseline Mean		38.34	39.32
N	18,545		

Notes: The table shows the estimated heterogeneity of the impact of crossing the 600 score on the first UPET by socio-economic status,roxied by whether parents' earnings and years of schooling are above the median of NIS 250,000 and 15 years. Columns (1) shows the estimates for au_1 in Equation 2, along with robust standard errors in parentheses, capturing the estimated difference in the effects between students from high- and low- SES backgrounds. Columns (2)-(3) shows the estimated impacts for students from low- and high-SES backgrounds, seperately. The baseline sample comprises all individuals in Israel who took their first UPET by age 20 in 1999–2008. The effective sample is further narrowed to individuals with first test scores falling within the window of 580–620.

Table A.4: Long-Term Effects of Crossing 600, Sample of Younger Jewish Test-Takers

	(1)	(2)	(3)	(4)
A. Employment, 12 years after				
	% Employed	% Self employed	Earnings rank	Log earnings
	1.08	1.03	2.01	4.02
	(1.16)	(0.80)	(1.31)	(2.61)
Mean	83.26	8.28	63.53	1142.46
N	18,629	18,629	18,629	15,964
B. Employment, age 30				
	% Employed	% Self employed	Earnings rank	Log earnings
	1.33	0.71	2.03*	3.86
	(1.12)	(0.71)	(1.19)	(2.99)
Mean	84.10	8.76	61.57	1143.74
N	17,957	17,957	18,629	15,486
C. Degree Attendance				
	Hi-tech, uni.	Hi-tech, any	Any, uni.	Any
	1.51**	2.12**	-3.06***	0.19
	(0.68)	(0.92)	(1.16)	(0.35)
Mean	9.63	14.41	71.49	95.56
N	18,629	18,629	18,629	18,629
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$				

Notes: The table shows the estimatedimpact of crossing the 600 cutoff score on the first UPET on Labor-Market and Degree Outcomes. Columns (1)-(5) show the estimates for τ in Equation 1, along with robust standard errors in parentheses. The baseline sample comprises all individuals in Israel who took their first UPET by age 20 in 1999–2008. The effective sample is further narrowed to individuals with first test scores falling within the window of 580–620. Earnings are measured in NIS thousands.

Table A.5: MSE-optimal Estimates of the Effects of Crossing 600, Sample of Younger Jewish Test-Takers

Kernel	Triangular		Uniform	
Pol. degree	1	2	1	2
	(1)	(2)	(3)	(4)
% High-tech application				
	2.29***	2.42***	2.29***	2.49***
	(0.47)	(0.49)	(0.51)	(0.51)
	[16]	[26]	[12]	[23]
N	15,025	24,265	11,549	21,761
% Tech employment				
	3.12***	3.39**	3.07***	3.94***
	(0.95)	(1.46)	(1.05)	(1.51)
	[22]	[25]	[17]	[23]
N	19,964	22,348	15,461	20,965
Earnings (1,000NIS)				
	7.49**	7.79*	9.22**	8.55*
	(3.70)	(4.43)	(3.92)	(4.70)
	[19]	[29]	[14]	[21]
N	16,969	25,846	13,046	18,986

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Notes: The table presents robust bias-corrected estimates of the effects of crossing 600 in the first UPET, utilizing MSE-optimal bandwidths based on the algorithm developed by Calonico et al. (2014). The baseline sample includes all Jewish test-takers from 1999–2008 who were aged 20 or below when first tested. Columns (1)-(2) display the results using a triangular kernel, while Columns (3)-(4) show the results using a uniform kernel with polynomial orders between 1–2. The optimal bandwidth chosen is indicated in squared parentheses.

Table A.6: MSE-optimal Estimates of the Effects of Crossing 600, Sample of Older Jewish Test-Takers

Kernel	Triangular		Uniform	
Pol. degree	1	2	1	2
	(1)	(2)	(3)	(4)
% High-tech application				
	0.27	0.22	-0.16	0.03
	(0.23)	(0.31)	(0.34)	(0.39)
	[21]	[21]	[11]	[17]
N	22,153	22,153	11,761	18,054
% Tech employment				
	0.86	0.99	0.27	0.86
	(0.97)	(1.06)	(1.15)	(1.23)
	[18]	[31]	[13]	[23]
N	19,199	32,637	14,013	24,440
Earnings (1,000NIS)				
	-1.10	-6.26***	-0.73	-5.32***
	(1.56)	(1.34)	(1.75)	(1.55)
	[26]	[19]	[18]	[18]
N	27,376	19,817	19,199	19,199

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

Notes: The table presents robust bias-corrected estimates of the effects of crossing 600 in the first UPET, utilizing MSE-optimal bandwidths based on the algorithm developed by Calonico et al. (2014). The baseline sample includes all Jewish test-takers from 1999–2008 who were aged 21 or above when first tested. Columns (1)-(2) display the results using a triangular kernel, while Columns (3)-(4) show the results using a uniform kernel with polynomial orders between 1–2. The optimal bandwidth chosen is indicated in squared parentheses.

Table A.7: MSE-optimal Estimates of the Effects of Crossing 600, Sample of Arabs

Kernel	Triangular		Uniform	
Pol. degree	1	2	1	2
	(1)	(2)	(3)	(4)
% High-tech application				
	6.01	6.86	6.83*	4.83
	(3.94)	(4.18)	(3.94)	(4.47)
	[22]	[23]	[21]	[21]
N	2,008	2,109	1,906	1,906
% Tech employment				
	-2.12	-4.89	-0.12	-2.11
	(3.24)	(3.61)	(3.47)	(3.88)
	[18]	[23]	[20]	[27]
N	1,361	1,737	1,496	2,051
Earnings (1,000NIS)				
	-1.82	-6.44	-7.04	-2.55
	(10.37)	(12.65)	(12.28)	(13.40)
	[28]	[27]	[17]	[28]
N	2,117	2,051	1,261	2,117

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Notes: The table presents robust bias-corrected estimates of the effects of crossing 600 in the first UPET, utilizing MSE-optimal bandwidths based on the algorithm developed by Calonico et al. (2014). The baseline sample includes all Arab test-takers from 1999–2008. Columns (1)-(2) display the results using a triangular kernel, while Columns (3)-(4) show the results using a uniform kernel with polynomial orders between 1–2. The optimal bandwidth chosen is indicated in squared parentheses.

Appendix B Other Round Score Cutoffs

The main analysis of this study focuses on the round score cutoff of 600, a critical decision point for students contemplating applications to university high-tech fields. For completeness, this section also briefly discusses the effects of crossing other round score cutoffs. While these findings provide an initial overview, they suggest that further detailed investigation is warranted. This is due to the heterogeneous nature of the effects and the range of outcomes that may vary in importance around each cutoff, which could reveal additional insights not captured by this analysis's limited scope.

Tables B.1, B.2 and B.3 present the results, showing no change on average in the likelihood of applying to any university field or to high-tech fields. However, it's important to note that our data do not include information on college applications, which may be more relevant for students scoring around the lower round score cutoffs.

The estimates for UPET retaking show varying signs at different round score cutoffs. There is no significant discontinuous change at 400, a significant decrease at 500 (as found also at 600), and an insignificant increase at 700, suggesting heterogeneous effects across scores. The testing of younger siblings increases at 400 and 500, similar to what is observed around 600, but not at 700 where effects are null.

Interestingly, there is an average earnings gain of 400, possibly reflecting students' decisions to pursue more rewarding educational paths than those scoring 399. There is also an increase in the likelihood of pursuing advanced degrees. At 500, there is no average change in these outcomes, while at 700, there is an increase in pursuing advanced degrees but no change in earnings.

Therefore, crossing round scores appears to be meaningful overall, but the specific impacts vary by population and context. Further research could shed light on the heterogeneity and mechanisms taking play at different round scores.

Table B.1: MSE-Uptimal Estimates of the Effects of Crossing 400 in the First UPET

Kernel	uniform		Uniform	
Pol. degree	1	2	1	2
	(1)	(2)	(3)	(4)
% Young Siblings' Test				
	2.51**	3.06**	2.90**	3.34**
	(1.27)	(1.40)	(1.21)	(1.46)
	[16]	[28]	[14]	[22]
N	18,416	32,119	15,823	24,714
% Applying to High-Tech Field				
	-0.21	-0.28	-0.21	-0.27
	(0.18)	(0.20)	(0.20)	(0.22)
	[15]	[20]	[13]	[17]
N	24,520	33,615	20,908	28,137
% UPET Retaking				
	-0.19	-0.13	0.57	-0.24
	(0.94)	(1.13)	(0.85)	(1.24)
	[19]	[29]	[23]	[19]
N	31,735	47,911	37,208	31,735
Earnings (1,000NIS)				
	2.74***	3.48**	2.53**	2.14
	(1.05)	(1.35)	(1.23)	(1.48)
	[23]	[25]	[14]	[27]
N	35,720	39,049	21,793	42,561
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$				

Notes: The table presents robust bias-corrected estimates of the effects of crossing 400 in the first UPET, utilizing MSE-optimal bandwidths based on the algorithm developed by Calonico et al. (2014). The baseline sample includes all individuals in Israel who took their first UPET between 1999–2008. Columns (1)-(2) display the results using a triangular kernel, while Columns (3)-(4) show the results using a uniform kernel with polynomial orders between 1–2. The optimal bandwidth chosen is indicated in squared parentheses.

Table B.2: MSE-Uptimal Estimates of the Effects of Crossing 500 in the First UPET

Kernel	uniform		Uniform	
Pol. degree	1	2	1	2
	(1)	(2)	(3)	(4)
% Young Siblings' Test				
	1.24**	1.86**	0.50	0.74
	(0.63)	(0.83)	(0.69)	(0.84)
	[21]	[26]	[23]	[28]
N	29,381	36,236	32,407	38,605
% Applying to High-Tech Field				
	-0.01	0.04	0.18	0.24
	(0.25)	(0.32)	(0.28)	(0.37)
	[23]	[30]	[19]	[22]
N	50,687	65,173	41,065	48,256
% UPET Retaking				
	-2.74***	-2.81**	-2.95***	-2.87*
	(0.98)	(1.18)	(0.96)	(1.30)
	[25]	[37]	[20]	[24]
N	54,242	79,265	43,498	53,104
Earnings (1,000NIS)				
	0.72	0.53	0.36	0.26
	(0.84)	(1.01)	(1.00)	(1.15)
	[26]	[31]	[23]	[27]
N	54,863	65,347	49,050	56,087

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Notes: The table presents robust bias-corrected estimates of the effects of crossing 500 in the first UPET, utilizing MSE-optimal bandwidths based on the algorithm developed by Calonico et al. (2014). The baseline sample includes all individuals in Israel who took their first UPET between 1999–2008. Columns (1)-(2) display the results using a triangular kernel, while Columns (3)-(4) show the results using a uniform kernel with polynomial orders between 1–2. The optimal bandwidth chosen is indicated in squared parentheses.

Table B.3: MSE-Uptimal Estimates of the Effects of Crossing 700 in the First UPET

Kernel	uniform		Uniform	
Pol. degree	1	2	1	2
	(1)	(2)	(3)	(4)
% Young Siblings' Test				
	-1.36	-1.99	-1.01	-1.58
	(1.10)	(1.94)	(1.42)	(1.88)
	[25]	[19]	[18]	[17]
N	17,170	13,449	12,690	11,911
% Applying to High-Tech Field				
	-0.28	-0.38	-0.03	-0.19
	(0.83)	(1.01)	(0.77)	(1.08)
	[15]	[18]	[16]	[17]
N	16,657	20,347	17,895	19,098
% UPET Retaking				
	0.45	1.74*	0.40	1.50
	(0.92)	(1.15)	(0.89)	(1.24)
	[25]	[20]	[20]	[17]
N	27,578	22,830	22,830	19,098
Earnings (1,000NIS)				
	-3.88	-4.19	-2.60	-3.80
	(3.24)	(5.12)	(3.34)	(4.85)
	[19]	[19]	[15]	[18]
N	21,186	21,186	16,378	19,997

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Notes: The table presents robust bias-corrected estimates of the effects of crossing 700 in the first UPET, utilizing MSE-optimal bandwidths based on the algorithm developed by Calonico et al. (2014). The baseline sample includes all individuals in Israel who took their first UPET between 1999–2008. Columns (1)-(2) display the results using a triangular kernel, while Columns (3)-(4) show the results using a uniform kernel with polynomial orders between 1–2. The optimal bandwidth chosen is indicated in squared parentheses.