Heuristic Self-Evaluation and Returns to STEM

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Abstract

This study investigates how uncertainty about own ability shapes human capital investments and career outcomes. It focuses on a pivotal economic decision young adults face: whether to apply to selective STEM degree programs. To isolate the role of perceived ability in these choices, I exploit a regression discontinuity design around a round-number test-score threshold. Although students scoring just above this threshold do not receive a direct admissions advantage, the left-digit bias appears to boost their self-perception, making them significantly more likely to apply to STEM. These marginal applicants achieve significant long-term earnings gains, similar to those of their higher-ability peers, with their early career wages nearly doubling. The findings highlight the vulnerability of major economic decisions to simple cognitive heuristics, suggesting that subtle changes in perceived ability can have profound and lasting effects on educational and career trajectories.

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1 Introduction

Young adults face considerable uncertainty when making pivotal life decisions. In modern economies, choosing a degree field carries significant implications (Hastings et al., 2013; Altonji et al., 2016; Kirkeboen et al., 2016; Kirkebøen et al., 2021; Heinesen et al., 2022; Bleemer and Mehta, 2022; Daly et al., 2022; Andrews et al., 2024; Ng and Riehl, 2024; Goldstein and Kolerman-Shemer, 2025). Reflecting the global demand for STEM skills (Deming and Noray, 2020), selective STEM fields often offer very high economic rewards early after graduation. Given these substantial opportunities, why do many students still avoid them? While some choose other fields for non-economic reasons and others may lack the necessary skills for success in math-intensive disciplines, an important question remains: Could uncertainty about their own abilities deter capable students from pursuing these opportunities?

This paper addresses this question by using a research design that exploits quasi-random boosts to perceived academic success. The analysis focuses on test scores as signals, leveraging left-digit bias—a well-documented tendency to overemphasize round-number thresholds. This bias influences human decisions in contexts ranging from consumer behavior (Strulov-Shlain, 2022) to expert judgments (Olenski et al., 2020). Because of this bias, scoring just above a round number may feel like a disproportionately strong indicator of success. Crucially, in our setting, crossing the specific round-number threshold in focus does not directly improve admission chances to selective fields, implying that any discontinuity around the threshold should reflect changes in perception rather than other factors. Thus, this research aims to answer two main questions: Does an enhanced ability perception influence decisions to pursue selective STEM fields, and can those who are uncertain about their ability still benefit by pursuing STEM?

The analysis uses a rich administrative dataset from Israel that links students' university entrance test scores, applications, degrees, and career outcomes. In Israel, as in many countries, students must select their fields of study in advance, and selective STEM fields yield substantially higher returns than others. The earnings disparity is striking: computer science and electrical engineering (CS and EE) graduates can earn 50–300 percent more than graduates from other fields. Consequently, deciding to pursue these fields is arguably one of the most consequential economic choices young adults face. For example, even in the early years following graduation, the average graduate from these fields earns more than 90% of all workers across all age groups.

Admission to these fields is competitive. While test scores range from 200 to 800, the median score for CS and EE admits is 681. This context makes the

600 score especially relevant: only about 20 percent of students initially score above 600, yet this threshold typically remains below the admissions bar for CS or EE. As a result, students scoring around 600 face a critical decision: whether to retake the test to improve their chances or settle for lower-paying alternatives. In contrast, lower thresholds are too far from the admissions cutoff to have an impact, while scores around 700 are only reached by top performers who can often guarantee admission to nearly all programs. Therefore, the 600 score serves as the focal cutoff in our analysis.[1] Left-digit bias suggests that a score of 600 may be perceived as significantly better than 599, motivating a regression discontinuity design (RDD) that isolates the impact of perceived ability. Moreover, because admissions in Israel are determined solely by test scores, there is no subjective component that might be influenced by bias.

The findings reveal that crossing the 600 threshold substantially increases the likelihood of applying to selective STEM fields by 1.7pp from a baseline of 8%. However, analysis of retake decisions uncovers substantial heterogeneity. On one hand, marginal STEM applicants retake the test before applying and significantly improve their scores, reaching an average of 650. On the other hand, scoring above 600 reduces the overall likelihood of retesting by 3.0pp from a 42% baseline and is associated with a noisy decrease in maximum scores (about 1 point from an average of 615). These findings suggest that perceived success can lead to diverse responses. While some students view it as a cue to aim even higher, others consider it sufficient and avoid further improvements.

To further explore which subgroups drive these diverse responses, I divide the sample by age. This split is motivated by Israel's mandatory military service, which forces most students to delay higher education until age 21 and above. Approximately half of the test-takers take the university entrance test during high school or shortly after (up to age 20, the "younger" group), while the rest take it after their service (the "older" group). Younger test-takers differ in a key aspect: they often have more time to improve their admission outcomes before applying to universities, a critical factor for potential application to STEM. Consistent with this, younger test-takers drive the increased applications to selective STEM fields, with a 3.8pp rise from a 9% baseline. Meanwhile, older test-takers exhibit the largest decline in retaking likelihood—a 3.1pp drop from a 25% baseline—and a 1.22-point decrease in maximum scores. Among younger test-takers, those with a relative advantage in quantitative skills respond most sharply, increasing their probability of applying by 9.4pp from a 22% baseline.

[1]The appendix also reports significant estimated impacts of crossing other round thresholds on various outcomes. However, the specific effects depend on the context. Focusing the main analysis on a particularly important decision and a specific round score cutoff thus provides a clearer view of the underlying mechanisms and the long-term consequences.

This increased ambition leads to substantial differences in potential earnings. Younger test-takers scoring just above 600 shift their applications away from lower-return fields such as humanities and business, while their overall application rate remains unchanged. As a result, crossing the threshold raises the expected annual early-career earnings by approximately 6,400 NIS (1,800 USD), driven solely by changes in field choice rather than by institution. Among quantitatively advantaged test-takers, the increase in expected earnings is even larger—around 18,100 NIS (5,000 USD). In contrast, older test-takers show no significant change in their predicted earnings.

One natural question is how these ambitious university decisions translate into long-term outcomes. One might suspect that the heuristic response to round numbers may lead students to make overambitious choices. However, our data suggest that the improvements among marginal applicants are real, as evidenced by their enrollment in these fields, graduation, and subsequent STEM-related careers. Among younger test-takers, those who score just above 600 are 3.4pp more likely to work in the tech sector at age 30 and have average annual earnings that are roughly 6,900 NIS (1,900 USD) higher. As expected, quantitatively advantaged test-takers drive these gains, with an earnings boost of approximately 16,700 NIS (4,700 USD). Furthermore, the results suggest that these students are more likely to reach the top tail of the wage distribution, consistent with the significant early-career earnings gains typically associated with STEM pathways. In contrast, older test-takers just above 600 show no labor-market benefits.

This setting also enables the estimation of returns to choosing more selective fields. While it is common to use admission cutoffs in a fuzzy RDD to estimate returns from pursuing specific fields (e.g., Bleemer and Mehta, 2022), this study employs a non-admission cutoff. I use earnings at age 30 as the outcome and predicted earnings based on university applications or degrees as the endogenous variable. This IV estimate can be interpreted as a forecast coefficient (see, e.g., Angrist et al., 2020), capturing the extent to which the observational earnings differences between these fields predict the local earnings gains from pursuing more selective fields among the compliers. This approach relies on additional assumptions—relevance, monotonicity, and the exclusion restriction—that empirical evidence supports for the specific subgroups of interest in our setting. Our results show that the local gains from choosing a more selective field are at least as large as the observational differences between these fields. This finding is particularly noteworthy given that the compliers in our setting likely have lower abilities than the average student.

Moreover, this study aims to quantify the returns to STEM for the marginal applicant in our setting. A naive fuzzy RD approach using a binary indicator for pursuing selective STEM may yield biased estimates—a common issue in

instrumental variable settings (Andresen and Huber, 2021). Specifically, if compliers shift not only to STEM fields but also to other programs that offer higher returns than their counterfactual choices, a fuzzy RD will fail to isolate the returns from STEM. To address this, I propose a solution based on the assumption that any movement between different selective STEM programs has negligible effects on earnings. This assumption is justified as the earnings gap between STEM and other programs is much larger than any variation within the STEM group. Under this assumption, the average treated complier mean is identified. Without further assumptions, the returns can be bounded based on the most extreme scenarios—where all compliers' earnings are either higher or lower than those of the never-takers. Although these initial bounds are relatively wide, under less restrictive yet conservative assumptions—such as assuming that untreated compliers' earnings are evenly distributed in the upper half of the untreated earnings distribution—we can derive informative bounds. Such bounds imply substantial returns from STEM in our setting—amounting to no less than 120K NIS (35,000 USD), which corresponds to almost a 100% increase.

Overall, this paper's findings show that uncertainty about one's own abilities can deter even capable students from pursuing the substantial economic opportunities available in selective STEM fields. In doing so, this study contributes to the literature on field-of-study choices (see a recent review by Patnaik et al., 2021) as well as to the broader literature on aspirations in economic behavior (see a recent review by Genicot and Ray, 2020). The evidence provided in this paper demonstrates that ability uncertainty plays a critical role in one of the most consequential economic decisions young adults make early in life—whether to invest in challenging educational paths that yield significant labor-market returns.

Our results provide two key contributions. First, prior work on ability uncertainty—spanning theoretical models (Altonji, 1993; Altonji et al., 2016), survey evidence (Zafar, 2011; Stinebrickner and Stinebrickner, 2012, 2014; Wiswall and Zafar, 2015), and observational studies of test score responses (Papay et al., 2016; Smith et al., 2017; Avery et al., 2018; Li and Xia, 2022; Graetz et al., 2023)—has not conclusively determined whether capable students are held back by misperceptions of their abilities, sometimes interpreting dropout patterns as signs of overconfidence. This gap may stem from the challenge of linking survey evidence on ability beliefs with long-term labor-market outcomes. Our unique research design, which isolates the role of perceived abilities using administrative data, allows us to address this issue more directly. Specifically, our findings indicate that

encouraging students to aim higher can benefit them, even if not all ultimately complete the targeted program.[2]

Second, our results reveal that students rely on heuristics when making high-stakes decisions, and these biases significantly shape their future trajectories. Prior research has documented that left-digit bias influences expert judgments (Olenski et al., 2020; Shurtz, 2022), consumer behavior (Lacetera et al., 2012; Strulov-Shlain, 2022), and responses to test scores (Pope and Simonsohn, 2011; Goodman et al., 2020; Li and Qiu, 2023). Yet, such biases are often considered minor and not expected to affect critical, life-altering decisions. In contrast, our findings show that even in one of the most consequential decisions faced by young adults in our setting, heuristics play a crucial role in determining their future educational and career trajectories. Special attention should be given to the specific studies on how students respond to round test scores. This paper distinguishes itself by linking these heuristic responses to long-term career outcomes and focusing on a highly consequential decision—the choice to pursue selective STEM fields.

This paper also contributes to the literature on the returns to university fields of study by focusing on a unique group: students who hesitate to apply to high-return fields. Previous research shows that marginal returns are high for students at the admission margin (Hastings et al., 2013; Altonji et al., 2016; Kirkeboen et al., 2016; Heinesen et al., 2022; Bleemer and Mehta, 2022; Daly et al., 2022; Andrews et al., 2024; Ng and Riehl, 2024). In contrast, our estimates capture returns along a different margin. Rather than comparing two applicants who differ solely in admission status, our setting allows us to compare individuals whose application decisions differ due to quasi-random signals. The closest work in the literature is Ng and Riehl (2024), which documents high returns for less-prepared students in selective STEM programs. Both studies imply that increasing the number of slots in selective STEM programs could yield significant welfare gains. However, this paper offers a novel insight: beyond expanding capacity, policymakers and educators might enable students to capture substantial long-term earnings gains by helping them recognize their suitability for selective fields.

The rest of the paper is organized as follows. Section 2 reviews the Israeli university system, Section 3 describes the data, and Section 4 outlines our empirical strategy. Section 5 presents our findings on university applications, while Section 6 examines long-term outcomes. Section 7 discusses the methodology for estimating returns to selective STEM fields, and Section 8 concludes.

[2]Evidence also suggests that within-class rankings influence students' decisions and outcomes (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020; Elsner et al., 2021; Denning et al., 2023), possibly by affecting how students or their social environments perceive their abilities.

2 Background

2.1 Higher Education in Israel

During the sample period, Israel had seven universities and dozens of colleges offering undergraduate degrees.[3] Colleges are lower-tier institutions, as reflected in their admission requirements, and also in the quality of academic teaching, and graduates' earnings (e.g., Achdut et al., 2019). The data include only university application decisions and not college applications. However, this is not a major limitation as university programs are typically more challenging and lucrative than those offered at colleges, which makes them a natural focus for our research. Also, the data include information on degree enrollment in both colleges and universities, which allows validating that the results are not driven by a shift from colleges to universities for students who would pursue lucrative fields anyway.

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 selective STEM fields, such as CS and EE. Figure 1a illustrates this by showing the average earnings and tech employment rates at age 30 across all fields of study in Israel. The figure shows circles for each field and mentions the names of the ten most common ones. Among the most common ones, CS and EE graduates earn much more than any other: approximately 220K NIS (60K USD) relative to 80–160K NIS. They also have the highest rate of tech employment, 60% relative to 1%-38%. Moreover, CS and EE graduates are very likely to become top earners. The likelihood of becoming top 5% earner among university graduates of the same cohort is about 35%. For comparison, among the most common fields, the next best are science and economics, with 19% and 12%.

Recognizing the need to attract more young adults to selective STEM fields, Israel's policy circles are actively exploring measures to encourage enrollment in these fields. For instance, Recently, the Israeli government allocated NIS 100 million for this purpose.[4] This is consistent with the growing demand for STEM skills in modern economies (see, e.g., Deming and Noray, 2020). Thus, understanding the decision-making process of young adults regarding applications to selective STEM fields is crucial, with significant policy implications in many other developed countries facing ongoing demand for high-skilled technology-oriented workers.

[3]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.

[4]Retrieved from https://che.org.il/hi-tech on November 21st, 2022).

2.2 University Admissions

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 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 (referred to as the "Sechem"). The weights and specific thresholds may vary between academic programs and over the years.

The University Psychometric Entrance Test (UPET). The UPET is a standardized test. Figure 1b presents the distribution of scores in the sample, ranging from 200 to 800.[5] 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 their first 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). Still, as can be seen in Appendix Figure A.1a, approximately half of the Jewish candidates take their first test during high school or just after graduation (age 20 and below), and the other half do so later. Arab candidates tend to take the UPET early 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 differences 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.

[5]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.

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. For more details on Israel's high school and matriculation system, see, e.g., Lavy and Goldstein (2022).

Admission to selective STEM programs. Admission requirements for selective STEM fields are higher than most other university fields. While the specific thresholds are not available for all years and institutions, we can analyze the admission-relevant (highest) scores for those who were admitted to each program. The median score for both CS and EE fields is 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.[6] 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.

The interpretation of results throughout this paper relies on the assumption that the only discontinuity at the 600-score cutoff is in how students perceive their scores. This assumption is supported by the fact that a score of 600 falls below the actual admissions cutoff for selective STEM programs. Moreover, admissions decisions in Israel depend strictly on objective criteria—typically a weighted average of the university entrance test and matriculation GPA—meaning left-digit bias should not directly affect admissions chances. Indeed, scores around 600 generally require students to retake the test for realistic chances of admission. To further validate this assumption, Appendix Figures A.4a and A.4b illustrate the low likelihood of admission to CS and EE for students scoring around 600. Additionally, Appendix Figures A.4c and A.4d confirm that the likelihood of attending these programs, conditional on applying, is continuous around the 600 threshold. Furthermore, as discussed in the next section, the data suggests that applicants are generally aware that 600 is insufficient for admission to selective STEM fields.

3 Data

3.1 Database and Sample

The analysis in this paper uses an administrative database from the Israeli Central Bureau of Statistics (CBS), which combines data from various sources. The sample

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

comprises individuals who first took the UPET between 2000 and 2009, allowing to examine effects up to 12 years after the test (labor market data are available up to 2021). For further details on the data, their sources, the baseline sample, and the sample restriction procedure see Appendix A.1.

3.2 Main Outcome Variables

University applications. To evaluate the effects on the likelihood of applying to selective STEM fields, I created an indicator variable set to 1 if an individual applies to CS or EE. This outcome focuses on applications within seven years post-test, though I validate that the results are consistent across other periods. I also explore alternative definitions for selective STEM fields, including any field where at least 40% of graduates are employed in tech at age 32. In addition, I analyze indicators for application to other fields (with less than 40% tech employment) 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 field at age 32 and assign this value to the corresponding application. When an individual applies to multiple programs, the highest value is selected. I refer to this outcome as the earnings associated with the application.

Additionally, to explore decisions related to retesting, I define an indicator variable with a value of 1 if an individual retakes the test within seven years of their first attempt. I also consider the highest score achieved during this period as the admission-relevant score.

Degree enrollment and attainment. 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 ensure that the observed effects do not STEM from students transferring from college STEM programs to university STEM programs.

Labor-market outcomes. To explore long-term effects, I analyze the early career outcomes of students, focusing on the 10—12th years after their first UPET, which are the latest 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 with and without zeros, earnings rank conditional on age, and indicators for becoming top earners. I also examine these outcomes at ages 30–32, a point by which nearly all (approximately

99%) individuals in my sample are observed. In future versions, I will update the labor-market outcomes so that earnings data at age 32 are available for all individuals, and the main outcome will be revised accordingly.

3.3 Descriptive Evidence

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 1c illustrates the relationship between first UPET scores and the probability of applying to a university high-earning field. It shows the average likelihood of applying to these fields in bins of 5-score points, which is similar but slightly smaller than what would been selected by the algorithm offered 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, etc. 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.[7]

The figure also provides further justification for focusing on the round score of 600 when analyzing university high-earning 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 Figure 1b), which limits the statistical power of analysis at this cutoff.

Finally, Figure 1d restricts the sample to university applicants choosing selective STEM fields and shows the share of retakes as a function of their first score. The figure demonstrates that most applicants scoring around 600—who eventually applied to these fields—did so only after retaking the test, indicating that they recognized their initial score was insufficient. In contrast, most applicants scoring around 700 did not retest before applying. This pattern suggests that applicants

[7]The figure also shows a jump at 690. Theoretically, this may reflect students' responses to a specific admission threshold at a particular institution during certain years. However, given the much steeper slope around this point, it is more likely due to noise.

are generally aware that a score of 600 is not competitive for selective STEM admission, and it implies that the discontinuous increase in applications is not driven by changes in admission likelihood or misperceptions about admission prospects. While the evidence discussed here is descriptive, the next subsection elaborates on how this study uses RDD to explore this more rigorously.

4 Empirical Design

This section describes the empirical design, which aims to isolate the role of perceived academic ability in students' decisions and outcomes. To achieve this, the study exploits an RDD around a round score cutoff of 600. Our identification strategy rests on the assumption that potential outcomes are continuous at 600, so that the only discontinuous change at the threshold is in the perception of the score. This assumption is plausible given the unlikelihood of cutoff manipulation and the stability of admission chances around this score, as well as supporting empirical evidence. First, the density of observations around the 600 cutoff is smooth (see Section 2.2) and predetermined outcomes are continuous at 600 (see Section 4), suggesting no manipulation. Second, the probability of admission to selective university STEM programs remains low and stable around 600, reinforcing that the cutoff itself does not directly affect admission chances (see Section 2.2).

To estimate the discontinuous change in outcomes at the cutoff, a local linear regression discontinuity approach is employed. Let s_i be the first UPET score of the individual i. Restricting the sample to scores in the range $s_i \in [580, 620]$, the following equation is estimated:

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

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).

Other specifications are also used to validate the robustness of the results. Specifically, the main results are robust to non-parametric RD models with different polynomial orders and kernel functions based on the algorithm developed by Calonico et al. (2014). The estimates appear to be stable across specifications, and the chosen bandwidths resemble those used in the main estimation.

If the identification assumption holds, predetermined outcomes should be continuous at the cutoff. To test this, Equation 1 is estimated, and the results are

presented in Table 1. In Panel A, individual characteristics—such as age at the time of the test and indicators for being Arab, female, attending a non-religious school, and being born in Israel—are used as outcome variables.[8] In Panel B, the year and month of the test, along with the scores in each of its three domains, are examined. Panel C focuses on family characteristics, including parental years of education, total annual income (measured at ages 14–16), and the number of siblings. Only two out of these 15 estimates are significant at the 90% level, none are significant at the 95% level, and all estimated discontinuities are small.[9]

For further validation, the main outcome—an indicator for selective university STEM applications—is predicted using all predetermined outcomes. Figure A.2 shows that these predicted values are continuous at the 600 score cutoff. Additionally, falsification tests using placebo cutoffs are conducted to estimate discontinuous changes in the main outcome at non-round score cutoffs. The results in Figure A.3 support the interpretation that the only significant discontinuity occurs precisely at 600.

5 Applications to Selective STEM Fields

Panel A of Table 2 presents the main estimation results. The table reports the estimates of τ from Equation (1), capturing the impact of crossing the 600-score cutoff in the first UPET on various outcomes. Column (1) shows that the likelihood of applying to any university field decreases by 2pp (3% relative to a baseline of 62%). In contrast, Column (2) indicates that the probability of applying to selective STEM programs increases by 1.7pp (17% relative to a baseline of 10%). Consistent with this, Column (3) reveals that the earnings associated with these applications rise by approximately 4,000 NIS. Columns (4) and (5) indicate that crossing the threshold decreases the likelihood of retaking the test by about 3pp (7% relative reduction), while the average maximum score achieved by these test-takers decreases insignificantly.

These results suggest that the effects of crossing the round score may be heterogeneous. Panels (B)–(D) of Table 2 report the results separately by ethnicity and age. Panel (B) shows that Arab test-takers increase their likelihood of applying to selective STEM programs by 9pp (32% relative to the baseline), with no other significant changes. However, the number of Arab students scoring around 600 is small, limiting statistical power for this subgroup. Panels (C) and (D) focus on

[8]The table also reports the baseline mean for each outcome, defined as the average below the cutoff within the estimation window (580 to 599). Note that all binary variables throughout the paper are multiplied by 100 to render the coefficients more informative.

[9]Given that many results in this paper focus on the subsample of younger test-takers, Table A.1 presents the falsification tests for this group.

Jewish test-takers, splitting the sample by age at the first test. The increase in selective STEM applications is driven entirely by the younger group, showing a 3.5pp increase (25% relative to a 14% baseline). Application-associated earnings also significantly increase only for younger test-takers, by approximately 6,400 NIS. Additionally, while both age groups reduce retaking, the relative effect is larger for older test-takers (12%) compared to younger test-takers (5%). Figure 2 illustrates these patterns graphically.

The results in Panel (D) suggest additional heterogeneity among younger test-takers. To investigate this further, we split the sample by relative quantitative advantage, estimating the effects separately for students with a quantitative advantage—defined as scoring at least 5 points higher in the quantitative domain than in both the qualitative and English domains—and those without such an advantage. Panel (E) presents results for the quantitatively advantaged subgroup, while Panel (F) shows findings for the remaining students. This stratification indicates that the effects of crossing the 600 cutoff differ substantially by quantitative advantage. For younger test-takers with a quantitative advantage, the probability of applying to selective STEM programs increases by nearly 50% (9pp relative to a 22% baseline). Additionally, this subgroup shows an insignificant increase in retaking (3pp, or 5%) and a significant improvement in maximum scores (4.4 points), consistent with efforts to gain admission into selective programs. In contrast, among those without a quantitative advantage, we observe only a marginally significant increase in applications to selective STEM programs, accompanied by a significant reduction in both retaking (5pp, or 9%) and maximum scores (2.6 points).

The results suggest that left-digit bias produces heterogeneous effects. For some students, the round-number score serves as a positive ability signal, motivating them to aim higher. In our setting, these students likely considered selective STEM programs beforehand; they tend to be younger, have more time to improve their admission-related outcomes before applying, and possess quantitative advantages that make them suitable candidates for math-intensive fields. Consequently, these students enhance their admission prospects and apply to challenging yet rewarding fields. Conversely, a second group—students who might not have initially considered selective STEM fields—appears satisfied upon reaching the round number, thus reducing their inclination to retake the test. This satisfaction effect aligns with the well-documented tendency to set round-number goals (see, e.g., Pope and Simonsohn, 2011). However, it might also reflect a belief that round scores could directly facilitate better academic admissions.[10] Appendix B

[10]This belief might occasionally be justified if specific academic programs use round UPET scores as admission thresholds. Although this is generally not the case, it could hold true for certain

presents a conceptual framework to reconcile both types of effects at the same cutoff.

5.1 Why do Students Apply More to Selective STEM Programs?

Throughout this paper, the increased applications to selective STEM programs are interpreted primarily through a perceived-ability channel. Specifically, some students may doubt their capability to succeed in these challenging programs—whether in gaining admission, managing demanding coursework, or succeeding in relevant career paths. However, since this analysis relies on administrative rather than survey data, it lacks direct measures of perceived ability. While administrative data enable the examination of long-term outcomes, the absence of direct perception measures limits our ability to precisely identify the underlying mechanisms. Therefore, it is important to discuss several alternative explanations for the increased applications to selective STEM fields.

First, we can rule out rational responses to admission thresholds, since, as demonstrated earlier, a score of 600 typically lies below actual admission cutoffs and does not confer a direct advantage. Nevertheless, it remains theoretically possible that students mistakenly perceive a 600 score as beneficial for admission prospects, independent of actual cutoffs. This explanation would imply that students interpret the threshold as important in terms of admissions rather than their own ability. However, empirical evidence rejects this possibility, too. As previously discussed, the subgroup driving increased applications to selective STEM programs simultaneously exhibits higher retake rates, indicating awareness that an initial score of 600 is insufficient for admission.

To further explore this, Table A.2 presents additional estimates of the impacts of crossing the 600 cutoff on relevant behaviors. Columns (1) and (2) report effects on retaking and maximum scores, each interacted with an indicator for applying to selective STEM fields. The positive estimate in Column (1) shows that increased applications primarily come from individuals who retake the test before applying rather than applying directly. This finding aligns with the descriptive evidence shown in Figure 1d, indicating that nearly all selective STEM applicants around the threshold retook the test before applying. Moreover, Column (2) allows calculation of the average score ultimately used in applications. Among quantitatively advantaged younger test-takers, the estimated increase in interacted maximum scores is 61 points, implying that the average application-relevant score

programs. For our purposes, we have ensured that round-number scores do not affect admissions to selective STEM programs, as discussed earlier.

among compliers is approximately 650 (61 divided by the share of compliers, 0.094).

These findings also align with the larger observed effects among younger test-takers. Unlike older individuals who may already be employed or have other commitments, younger test-takers can typically dedicate more time to improving their test scores and matriculation outcomes. This interpretation is supported by their higher baseline retake rates (55% compared to 25% among older test-takers) and substantially higher baseline rates of selective STEM applications (14% versus 4% among older test-takers).

Another potential strategy for improving admission chances is enhancing matriculation outcomes. Therefore, the analysis also examines these outcomes, focusing specifically on the total number of matriculation credits and the total number of STEM-related matriculation credits.[11] Columns (3)–(4) of Table A.2 show the corresponding estimates. For quantitatively advantaged younger test-takers, crossing the threshold increases their total credits by 0.7 from a baseline of 29.8, driven mostly by additional STEM credits (0.6 increase from 6.3 baseline). These results suggest that students who applied to selective STEM programs after scoring just above 600 did not only retake the UPET and significantly improve their scores but also actively worked to enhance their matriculation outcomes. While some of these individuals were still in high school and could adjust their matriculation coursework directly, others might have retaken matriculation exams after graduation—a common practice in Israel for applicants aiming to improve their admission prospects.

These findings allow us to rule out misperceptions about admission standards as a primary driver, since the applicants in our setting clearly recognize that their initial scores are insufficient. Although the absence of direct measures of perceived ability limits our ability to pinpoint a specific mechanism, the results suggest that uncertainty about academic ability is likely the relevant channel.

Additionally, young adults' uncertainty about their abilities may also be sensitive to social influences from family and peers. In our setting, family members and friends might similarly exhibit left-digit bias and encourage individuals scoring just above 600 to aim higher. Although we cannot directly test these social influences, indirect evidence supports their plausibility. Specifically, Column (5) of Table A.2 examines the testing behavior of younger siblings as an outcome. The estimates suggest that, on average, younger siblings' test-taking increases by 0.06 tests (7%). This finding aligns with interpreting a score of 600 as an influential ability signal that generates spillovers within families. It is also consistent with previous

[11] Data on matriculation test scores is available but excluded from this analysis due to substantial measurement noise for most students.

research showing 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; Avdeev et al., 2024).

5.2 Counterfactual Field Choices

An important point to consider is the counterfactual field choices of the affected students. First, we examine whether the increased applications to CS and EE are driven by a corresponding decline in applications to other selective STEM fields. Our main analysis focuses specifically on CS and EE, as these are the most lucrative among the common fields in our data. However, to validate our results, we also consider alternative definitions of selective STEM fields. Columns (1)–(3) of Table A.3 show estimates using three dummy outcomes: applying to CS, applying to EE, or applying to any field in which at least 40% of graduates are employed in tech by age 32. Table A.4 lists the fields included in this broader definition. The results indicate increased applications to both CS and EE, with a larger increase observed for CS. Additionally, there is no evidence that these increases are driven by decreases in applications to other selective STEM fields. Focusing on quantitatively advantaged younger students, applications to any selective STEM field increase by 9.9pp, nearly identical to the 9.4pp increase found when considering only applications to CS or EE.

This finding suggests that the observed increase in applications to selective STEM fields is driven primarily by a decrease in applications to less lucrative fields, consistent with the observed increase in application-associated earnings. To further validate this point, we consider two additional outcomes. First, we estimate the impact on application-associated earnings while imputing earnings for students who did not apply to any program. Column (4) of Table A.3 shows that this alternative definition yields similar estimates (a 13,300 NIS increase versus 18,100 NIS for quantitatively advantaged students). Second, we examine whether changes in institution, rather than changes in field choices, drive our results. Column (5) defines application-associated earnings based only on field averages rather than the specific field-institution combination used in the main analysis. The resulting estimate (16,400 NIS increase) closely resembles the main result, further supporting the interpretation that increased expected earnings primarily stem from students' decisions to apply to more selective STEM fields rather than from other channels.

Finally, to further investigate which specific fields students substitute away from when scoring just above 600, Tables A.5 and A.6 present additional estimates for the likelihood of applying to other university fields. The observed increase in applications to selective STEM programs does not appear to come at the expense

of less selective STEM fields. Instead, we observe declines primarily in non-STEM fields, such as humanities, business, and education.

5.3 Robustness of the Results

The two panels of Figure A.5 show that the main estimates are highly robust. Specifically, Figures A.5a and A.5b focus on applications to selective STEM fields and associated earnings. The figures present estimates based on alternative polynomial order (up to quadratic). Moreover, the figure shows the results based on multiple bandwidths for each polynomial order, with smaller bandwidths for lower polynomial orders. The figure also shows the results with and without controls. The results appear stable across specifications. Also, the results are robust to non-parametric estimation, following the algorithms provided by Calonico et al. (2015) and Kolesár and Rothe (2018). These results are shown in Table A.7. The chosen bandwidths are similar to those used in the main analysis.

5.4 Heterogeneity of the Effects

This section examines heterogeneity in the estimated effects by gender and socioeconomic status (SES), where SES is proxied by an indicator for having parental earnings above the median of NIS 250,000. Results are similar when using the median parental years of schooling (15 years) as an alternative measure. Defining Z_i as an indicator for individual i's gender or SES, we 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 Table A.8, focusing on the sample of younger test-takers. While results indicate slightly stronger effects for males and students from higher socio-economic backgrounds, differences in coefficients are not statistically significant 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.

6 Long-Term Outcomes

The previous section demonstrated that students respond heuristically to scoring just above a round-number threshold. Specifically, younger test-takers—particularly those with a quantitative advantage—interpret a score above 600 as an encouraging signal, prompting them to apply to selective STEM programs. In contrast, older test-takers exhibit no such increase and may even reduce their test retakes. This section investigates long-term outcomes related to degree attainment and labor-market success, focusing on individuals who shifted their applications toward more selective and rewarding programs. Analyzing these outcomes allows us to assess whether these marginal applicants were overly optimistic or, instead, successfully gained admission, graduated, and realized the career benefits typically associated with selective STEM fields.

6.1 Degree Outcomes

Columns (1)–(3) of Table 3 present estimates of the impact of crossing the 600-score threshold on university enrollment outcomes. Column (1) shows that scoring above 600 decreases the likelihood of enrolling in any university degree by 2.6pp, primarily driven by older test-takers and younger students without a quantitative advantage. Column (2) indicates a significant increase of 1.4pp in enrollment in selective university STEM programs, mainly among younger test-takers with a quantitative advantage (4.9pp increase from a baseline of 9.5%). Column (3) reveals no significant changes in overall degree attainment (universities or colleges).

Columns (4)–(6) extend the analysis by considering enrollment in either universities or colleges. The results are qualitatively similar. Notably, younger test-takers without a quantitative advantage exhibit a significant 5.0pp decrease in university enrollment. In contrast, younger test-takers with a quantitative advantage exhibit substantial positive shifts toward selective STEM fields, consistent with earlier results. Appendix Table A.9 shows similar patterns for overall degree attainment. Furthermore, even students who do not complete degrees in CS or EE frequently shift toward other tech-oriented fields, resulting in a significant 7.9pp increase in the attainment of degrees from tech-oriented programs.

These results indicate that while reduced effort leads some students toward less selective institutions, increased ambition motivates others to pursue the most selective and rewarding university programs. Among quantitatively advantaged younger test-takers, increased ambition substantially boosts enrollment in selective STEM programs, resulting in meaningful shifts in long-term expected earnings. Specifically, the expected earnings associated with the university degrees chosen by these students increase by approximately 15,600 NIS (over 4,000 USD). This

estimate closely matches the expected earnings increase based on earlier application decisions and remains stable when considering degrees obtained at any institution.

Appendix Table A.10 further explores the impact of scoring above 600 on enrollment at elite institutions—defined by the CBS as the Technion, Hebrew University, or Tel Aviv University—and on pursuing advanced degrees at any institution by type. The estimates are generally insignificant, suggesting no meaningful changes along these dimensions. Additionally, estimating the effects on the timing of enrollment or graduation similarly yields insignificant results.

6.2 Labor-Market Outcomes

Columns (1)–(4) of Table 4 report the estimated impacts of crossing the 600-score threshold on labor-market outcomes. Among younger test-takers, particularly those with a quantitative advantage, we find significant long-term benefits: expected annual earnings increase substantially, and the likelihood of employment in the tech industry rises by 3.3pp. Specifically, the earnings gains amount to approximately 6,100 NIS annually (excluding zeros), suggesting these gains directly result from increased enrollment in selective STEM fields. Conversely, older test-takers exhibit no significant effects on these outcomes. These patterns are illustrated graphically in Figure 3. Taken together, Panels (E)–(F) of Table 4 further highlight that these labor-market benefits are primarily driven by younger, quantitatively advantaged students, consistent with their increased selective STEM enrollment.

These results suggest that applying to selective STEM fields is indeed beneficial. One might question whether the observed earnings gains arise solely from the shift toward STEM or if they also reflect other factors—such as alternative educational or career decisions, or employer perceptions triggered by crossing the 600 cutoff. The evidence strongly supports the human-capital investment channel. First, the positive earnings and tech employment effects are concentrated among subgroups that significantly increased their applications to selective STEM fields, with no corresponding gains for other groups. Second, Figure 4 shows no immediate earnings effects around the threshold, only long-term gains. This pattern is consistent with a mechanism whereby students first invest in securing admission and completing their degrees, and subsequently realize career benefits. It refutes the idea that round-number test scores boost earnings immediately through short-term confidence or employer biases.[12] Third, a distinctive feature of STEM careers is their large early-career returns; for instance, 35% of STEM graduates become top-5% earners within their cohort. Consistent with this, Table A.11

[12]Employers could also exhibit left-digit bias; however, the predominance of test retakes suggests employers typically observe only applicants' highest scores, diminishing the relevance of initial UPET scores for long-term career outcomes.

reveals an average increase of approximately 2 percentile points in earnings rank, driven primarily by improvements at the top of the earnings distribution—a characteristic pattern of STEM careers. Similar results emerge when examining earnings outcomes from ages 30 to 32.

Overall, these results indicate that the increased applications to selective STEM fields yield substantial benefits for the marginal applicant, implying sizable returns at the application margin. The next section further explores these returns by estimating fuzzy RD models and discussing their interpretation.

6.3 Heterogeneity of the Long-Term Effects

Estimates for the heterogeneity of the effects are displayed in Table A.13, focusing on the sample of younger Jewish test-takers. Results indicate that the long-term benefits are driven by males. While these estimates are only marginally significant, they may suggest that the effects maintain the gender gaps in STEM careers.

6.4 Robustness of the Long-Term Results

The two panels of Figure A.6 show that the main estimates are highly robust. Specifically, Figures A.6a and A.6b focus on tech employment and annual earnings. The figures present estimates based on alternative polynomial order (up to quadratic). Moreover, the figure shows the results based on multiple bandwidths for each polynomial order, with smaller bandwidths for lower polynomial orders. The figure also shows the results with and without controls. The results appear stable across specifications. Table A.12 also shows that results are robust to non-parametric estimation, following the algorithms provided by Calonico et al. (2015) and Kolesár and Rothe (2018).

6.5 Other Round Scores

While the main analysis focuses on the 600-score threshold—where decisions to pursue selective STEM fields are most relevant—Table A.14 reports additional results for the highest round-number cutoff at 700. The only significant finding at this cutoff concerns maximum test scores: students scoring just above 700 further improve their scores. One potential explanation is that these individuals aim for medical school, which typically requires scores above 700 in Israel. Additionally, Table A.15 shows some heterogeneous long-term effects. Older test-takers scoring just above 700 are slightly less likely to pursue any degree (a 1pp decrease from a 97.3% baseline), whereas younger test-takers exhibit a notable increase in the likelihood of attending graduate school (an 8.1pp increase from a 50.8% baseline).

However, the relatively small sample size near this threshold limits our ability to clearly identify the underlying mechanisms.

Estimating effects at lower round-number thresholds also yields several significant outcomes. However, these results are more difficult to interpret since our data do not include college applications, which are likely more relevant for students scoring near these lower cutoffs. Overall, these findings reinforce the importance of left-digit bias in shaping perceptions of test scores and influencing student decisions, but also highlight that the impacts of crossing round-number thresholds remain context-specific and exhibit substantial heterogeneity across different populations and settings.

7 Returns to Field Choices

Previous sections document that some young adults significantly alter their university field-of-study decisions if they score just above a round-number threshold on their university tests. This leads them to apply to, enroll in, and graduate from selective STEM programs, ultimately resulting in substantial career improvements. This section explains how this setting can be used to estimate the returns from pursuing selective STEM fields through a fuzzy RD design. We first estimate the average returns from choosing more selective fields. We then discuss specific challenges related to isolating the returns to STEM and propose a methodology to address these challenges.

7.1 Returns Relative to the Average Student

Let $Z_i = \mathbf{1}_{\{s_i \geq 600\}}$ be a dummy indicating student i scoring above 600, D_i^z the student's chosen academic program if $Z_i = z$, and $Y_i^{d,z}$ the student's potential earnings at age 30 for $Z_i = z$ and $D_i = d$. Defining D_i^z is challenging, as the choice of an academic program is naturally a multi-valued, unordered treatment. However, for this analysis, it is reasonable to treat it as an ordered treatment by ranking programs based on average graduate earnings at age 32.[13] This simplifying assumption may not hold if program returns are heterogeneous and students select programs based on individual-specific gains. Indeed, Kirkeboen et al. (2016) show evidence supporting selection on gains in Sweden. Nevertheless, this assumption is more plausible in our setting, since descriptive analysis indicates that the returns

[13]In future versions, I will update the labor-market outcomes so that earnings data at age 32 are available for all individuals, and the main outcome will be revised accordingly. Preliminary analyses indicate that the results are very similar when using earnings or expected earnings at age 30 versus 32.

from selective STEM programs in Israel substantially exceed those from all other programs.

More importantly, this simplifying assumption implies a positive monotonicity condition, i.e., $Pr(D_1 \geq D_0) = 1$ and $Pr(D_1 > D_0) > 0$. While this condition might not hold for the entire sample, it is plausible in certain subsamples, particularly among younger test-takers and those with a quantitative advantage. To support this plausibility, Figures A.7 and A.8 present stochastic dominance tests. The results indicate that crossing the round-number threshold shifts both the application- and degree-based earnings distributions upward across all quantiles.[14] Although violations of this condition cannot be entirely ruled out, these findings suggest that the treatment variation induced by the instrument is primarily driven by students selecting programs with higher associated earnings, which supports the ordered-treatment assumption. Nonetheless, the next subsection relaxes this assumption by imposing less restrictive conditions.

Beyond monotonicity, this analysis also requires that the potential outcomes, $Y_i^{d,z}$ and D_i^z, are continuous at s_i. This continuity assumption is likely to hold given the evidence and discussion in Section 4. Additionally, the analysis relies on an exclusion restriction, which requires that the instrument does not directly affect the outcome, i.e., that $Y_{d,0} = Y_{d,1}$. In our setting, this means that round-number scores affect earnings only through their impact on field choices, and not via other channels. Empirical evidence supports this assumption, as the earnings gains are concentrated among subgroups that alter their field decisions and emerge gradually—consistent with a human-capital investment channel.

Given these assumptions, we can estimate the following set of fuzzy RD equations:

$$D_i = \psi + \kappa \times Z_i + \lambda \times (s_i - 600) + \omega \times (s_i - 600) \times \mathbf{1}_{\{s_i \geq 600\}} + \nu_i \tag{3}$$

$$Y_i = \theta + \delta \times D_i + \eta \times (s_i - 600) + \zeta \times (s_i - 600) \times \mathbf{1}_{\{s_i \geq 600\}} + \xi_i \tag{4}$$

Where the indicator $Z_i = \mathbf{1}_{s_i \geq 600}$ for scoring just above the cutoff serves as an instrumental variable for the endogenous variable D_i. We use application- (or degree-) associated earnings as the endogenous variable and actual earnings at age 30, Y_i, as the outcome. Consequently, the coefficient of interest, δ, captures the extent to which the returns from choosing better fields differ relative to the average earnings in these fields. These estimates—often referred to as the forecast coefficient (see, e.g., Angrist et al., 2020)—quantify how local gains are predicted by the observational differences.

Results are shown in Table 5 for both subsamples of interest. When using application-based associated earnings, the estimated coefficient is 1 for both

[14] A.9 shows the corresponding figures for actual earnings.

samples. When using degree-based associated earnings, the coefficient is 2 for the subsample of younger test-takers and 1.2 for quantitatively advantaged younger test-takers. However, these estimates are noisier, given the lower first-stage F-statistic, and they are not statistically different from 1. All estimates support the interpretation that the local average gains from pursuing more selective and rewarding fields in our sample are at least as high as those of the average student in these fields. These results suggest that even students with lower ability relative to the average—those who doubt their likelihood of success—can benefit in terms of career outcomes by aiming higher in their field-of-study decisions.

7.2 Returns to Selective STEM Fields

The results indicate that returns from pursuing selective STEM fields are very large in our setting. Most of the variation in D_i induced by changes in Z_i is driven by students selecting into STEM, and the observational differences between these fields and the counterfactual choices (e.g., humanities or business) are substantial—often amounting to dozens of percentage points and, in some cases, exceeding 100%. Combined with the large forecast coefficient, these findings suggest that the returns from STEM for students of lower ability, who doubt their likelihood of success, are very high. In this subsection, we quantify these returns.

To quantify these returns, we follow the definitions in the previous subsection and redefine the treatment variable as an indicator for pursuing selective STEM fields. In this case, the previous version of the exclusion restriction is insufficient. Some students' earnings may be affected by their choice among better fields even within the same treatment category. For example, some students may choose business instead of humanities after crossing the round-number threshold. Since business typically offers higher returns than humanities, the round score can affect earnings directly, even when $D_i = 0$. This issue is common when binarizing multivalued treatments in IV settings (Andresen and Huber, 2021). In our setting, it implies that the estimated LATE will be upward biased because our binary indicator may overlook "more ambitious" choices that yield additional earnings gains.

To make progress, we note that although the LATE may be biased in our setting, the treated complier mean remains identifiable under weaker assumptions. Recall that by using the modified outcome $\widetilde{Y}_i = Y_i D_i$, we can estimate the treated complier mean (Imbens and Rubin, 1997; Abadie, 2003). In this specification, the exclusion restriction is more plausible because it requires that STEM students' earnings are unaffected by crossing the round-number threshold. We assume this holds in our setting, given the large earnings differences between STEM graduates and graduates from other fields and the much smaller variation among programs within the STEM group. In contrast, the same restriction does not hold for the

untreated complier mean, as variations in field choices outside the selective STEM group (e.g., business versus humanities) may still affect earnings. These shifts within the $D_z = 0$ group alter only the estimate of the untreated complier mean. Therefore, the LATE in our case is biased primarily due to bias in the untreated complier mean rather than in the treated complier mean.

The estimated LATE reported in Table 5 using the binary treatment for either applying to or enrolling in STEM is consistent with this discussion. The untreated complier mean is very low, with average earnings below 70,000 NIS or even negative in some cases. This implies that the untreated earnings of compliers are much lower than those of never-takers in our setting. Although this scenario is theoretically possible, it is unlikely given that compliers are plausibly self-selected within the estimation sample.

In contrast, the treated complier mean is less likely to be biased because the identifying assumptions for the modified outcome are more plausible. Although we cannot fully rule out violations of the exclusion restriction for this modified outcome, it appears more credible in our context. Table 5 shows that the treated complier mean for those who enroll in STEM is 290,000 NIS for younger test-takers and 270,000 NIS for quantitatively advantaged younger test-takers.

The treated complier mean is particularly relevant. Our descriptive analysis shows that STEM graduates earn significantly more than other university graduates. A heuristic way to assess the returns from pursuing STEM is to compare the average earnings among treated compliers with the average earnings in the field. Interestingly, the estimated complier mean is similar to the average earnings of STEM graduates and slightly higher than those of always-takers near the round-number cutoff, while it is substantially higher than the average earnings in any other field.

Building on the heuristic argument, we propose a formal approach to bind the treatment effect. By imposing assumptions on the location of compliers within the earnings distribution of untreated individuals, we can bind the returns to STEM. A zero-assumption approach relies on extreme cases where all compliers earn either above or below all never-takers. Given that the compiler share is identified as 10% in our setting, we can construct such zero-assumptions bounds by taking the difference between the estimated treated compiler mean and the average earnings among the top and bottom 10% of untreated individuals. Although these bounds are relatively wide—ranging from 250 NIS (i.e., 270 minus 20) to 30 NIS (i.e., 270 minus 240)—imposing slightly more restrictive yet conservative assumptions yields more informative bounds.

Figures 5a and 5b illustrate this argument and the returns implied by different assumptions. Specifically, Figure 5b shows that by using any decile of the untreated

earnings distribution as a counterfactual, the estimated returns are large. The figure highlights two points that can serve as conservative bounds. The lower bound assumes that compliers are similar to never-takers, so their average should be near the median of the untreated distribution. The upper bound assumes that compliers are only distributed above the median, with their average around the 80th percentile. Although more extreme cases are theoretically possible, these assumptions remain quite conservative. Under these assumptions, the bounded returns range from 120,000 to 180,000 NIS (approximately 30,000 to 50,000 USD). These bounds imply very large relative returns of around 100% for the marginal student in our setting.

Taking into account the estimation variance of the treated complier mean, these differences are statistically significant at conventional levels. However, when more restrictive assumptions are imposed—such as comparing to the ninetieth percentile of the untreated earnings distribution—the estimated returns, while still positive and large (around 80,000 NIS, or 23,000 USD), become statistically insignificant. In future versions of this work, I will support the assumptions used to construct these bounds by providing evidence on compliers' pre-test characteristics. Moreover, given the estimated forecast coefficient of 1, any scenario suggesting lower returns from STEM necessarily implies that the returns from non-STEM fields are exceptionally high—well above those of the average student. I will formalize this argument in subsequent versions of the paper.

8 Conclusion

This paper examines how ability perceptions and cognitive heuristics shape one of the most critical decisions young adults face: investing in their future through education. Focusing on the choice to pursue selective STEM programs—fields that are both challenging and highly financially rewarding—it shows that subtle shifts in test score perceptions, driven by left-digit bias, can significantly boost the likelihood of applying to these fields. The findings further reveal that while crossing the threshold motivates some to retake the test and pursue more ambitious paths, others settle once they reach the round score. These insights suggest that perceived success can lead to diverse responses. While some students view it as a cue to aim even higher, others consider it sufficient and avoid further improvements.

Importantly, the heuristically driven increased ambition when making university decisions leads to substantial differences in potential earnings between those who score just above and just below the round score cutoff. Examining the long-term consequences of crossing the round-score cutoff indicates that these decisions indeed translate into significant earnings benefits years after the test.

By implication, individuals in our sample who do not attempt to pursue selective STEM programs may lack ambition in their academic choices, potentially missing out on more rewarding opportunities. This result highlights the potential adverse consequences of underestimating one's abilities when making pivotal educational decisions and demonstrates that perceived abilities may act as a barrier for some students from pursuing highly rewarding fields.

Moreover, our results suggest that the returns from pursuing STEM are very large for less prepared students who initially doubt their ability to succeed. With the growing demand for STEM skills in the labor market, there is an opportunity to encourage more students to acquire these high-demand skills, ultimately unlocking better economic opportunities.

In summary, this study shows that uncertainty and simple cognitive biases can significantly influence major economic decisions, shaping educational and career trajectories over the long term. These findings underscore the need for transparent communication about self-assessment and test score interpretation. Policymakers and educators can use these insights to help students recognize their strengths, choose programs that better match their potential, and ultimately achieve improved long-term outcomes.

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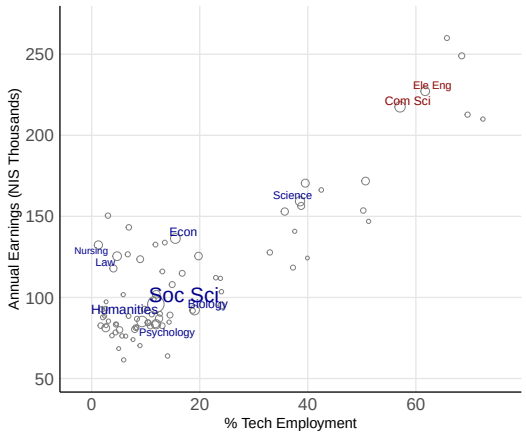
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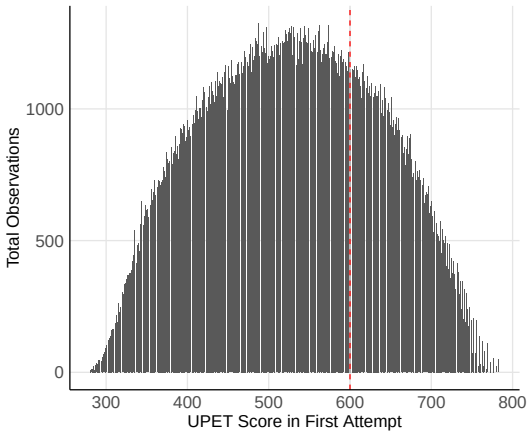
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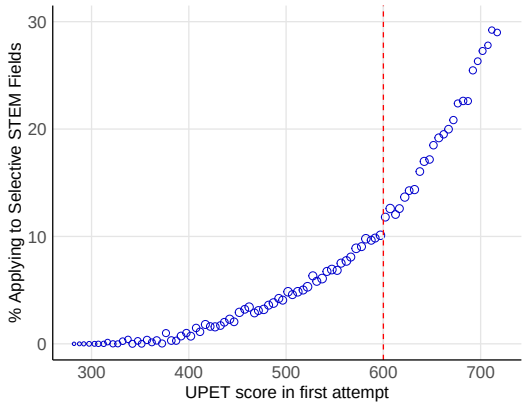
Figure 1: Descriptive Evidence on Selective STEM Fields and UPET Testing



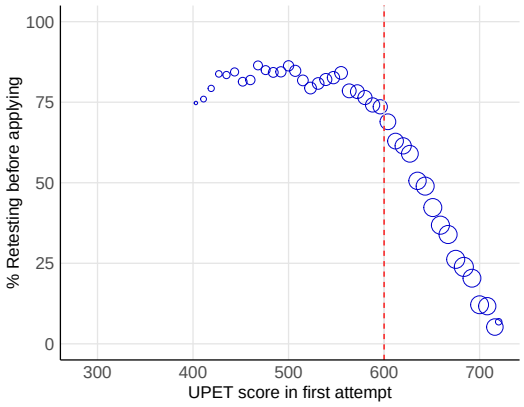
(a) Labor-Market Outcomes by Field



(b) First UPET Score Distribution



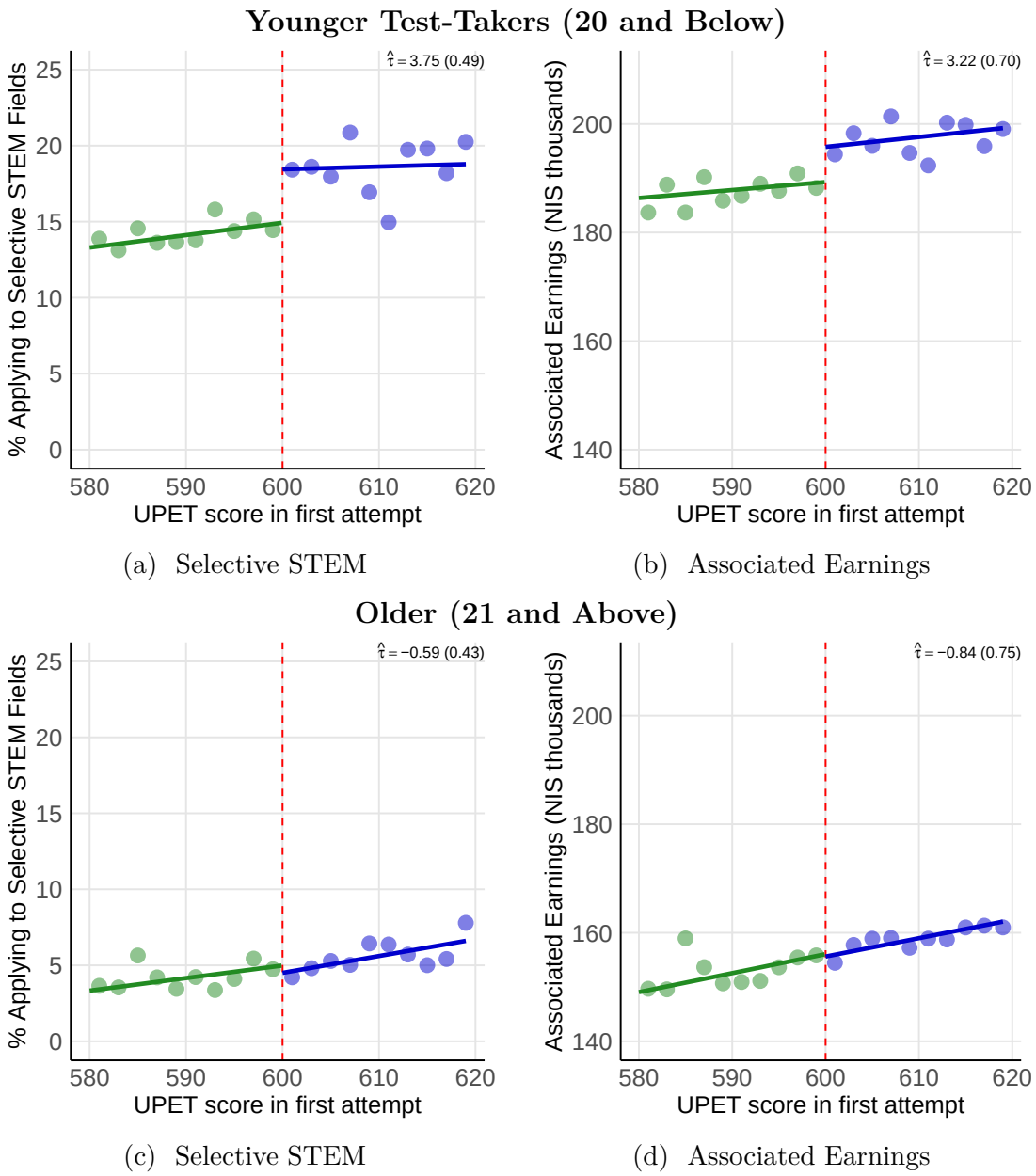
(c) Applying to Selective STEM Field



(d) Retesting (Among Applicants)

Notes: The figures provide descriptive evidence on selective STEM fields and UPET testing. Panel (a) shows labor-market outcomes at age 30 for 153,124 Israeli university graduates in our sample. The y-axis measures average annual earnings, and the x-axis measures the share employed in tech. Circle size is proportional to the number of graduates in each field; red circles mark selective STEM fields (computer science and electrical engineering). Panel (b) shows the distribution of first UPET scores for 347,511 individuals tested between 1999 and 2008. Panel (c) shows the share of individuals who apply to selective STEM fields, binned by first UPET score (5-point bins). Panel (d) shows the rate of retaking the test among those who initially applied to selective STEM fields. The red dashed lines mark the 600 cutoff.

Figure 2: Effects of Crossing 600 on University Applications

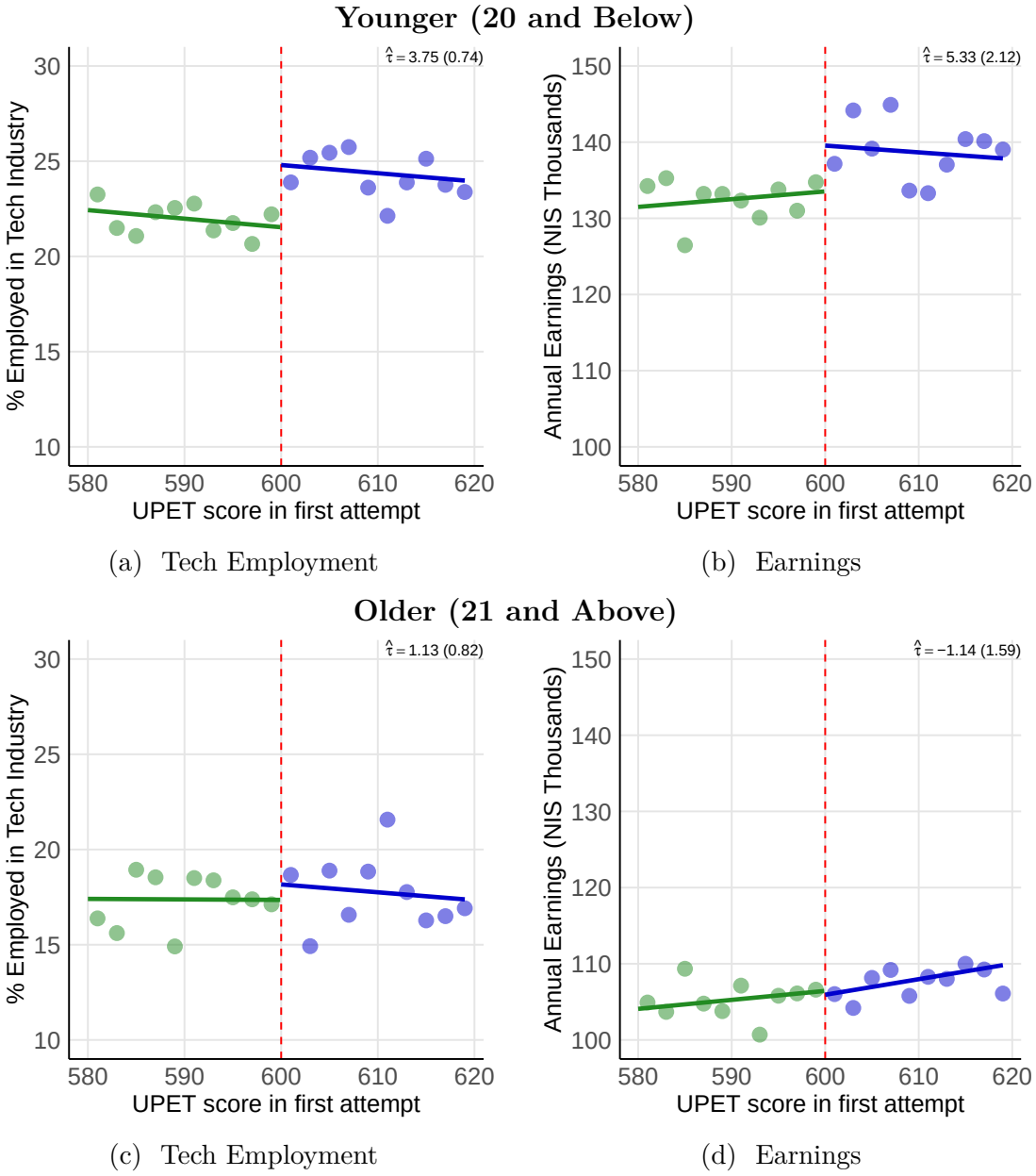


(a) Selective STEM (b) Associated Earnings

(c) Selective STEM (d) Associated Earnings

Notes: The figures display the impact of crossing a 600 UPET score on university application outcomes, split by age group at the first test. Younger test-takers (20 or below) appear in panels (a) and (b), while older test-takers (21 and above) appear in panels (c) and (d). The x-axes show first UPET scores in two-point bins; the y-axes show the probability of applying to selective STEM fields (panels a and c) and the potential earnings associated with the applications in thousands of NIS (panels b and d). The sample consists of 39,608 Jewish test-takers who first took the UPET between 1999 and 2008 (18,629 younger and 20,979 older). The sample in panels b and d is further restricted to those who applied to any university field (12,814 younger and 11,493 older). The red dashed vertical line marks the 600 cutoff. The blue and green fitted lines are based on Equation 1. The coefficient τ is the estimated effect of crossing 600, with standard errors clustered by score.

Figure 3: Effects of Crossing 600 on Labor-Market Outcomes at Age 30

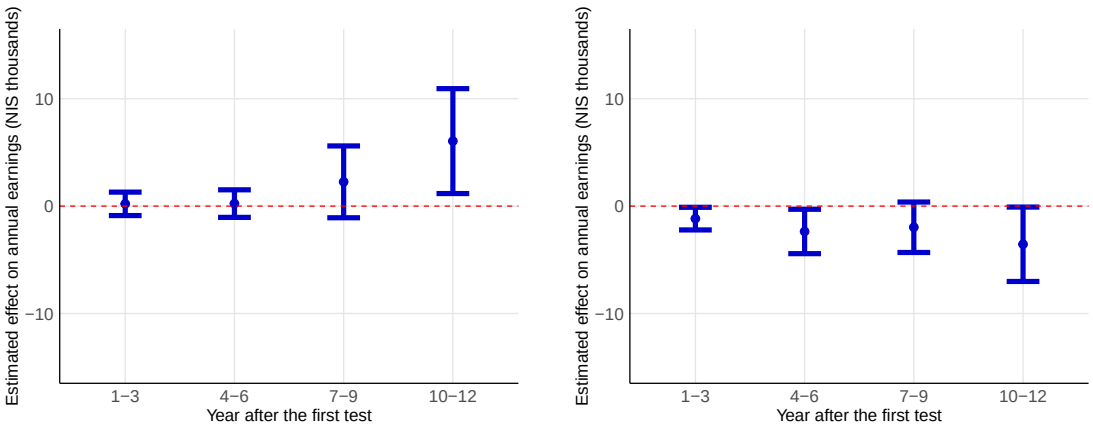


(a) Tech Employment (b) Earnings

(c) Tech Employment (d) Earnings

Notes: The figures display the effect of crossing the 600 UPET score on labor-market outcomes at age 30, split by age group at the first test. Younger test-takers (20 or below) appear in panels (a) and (b), while older test-takers (21 and above) appear in panels (c) and (d). The x-axes show first UPET scores in two-point bins; the y-axes show the probability of being employed in the tech industry (panels a and c) or annual earnings conditional on being employed at any sector in thousands of NIS (panels b and d). The sample consists of 18,629 Jewish test-takers who took their first UPET between 1999 and 2008. The red dashed vertical line marks the 600 cutoff. The blue and green fitted lines come from estimating Equation 1, and the coefficient τ (with standard errors clustered at the score level) is the estimated jump at 600.

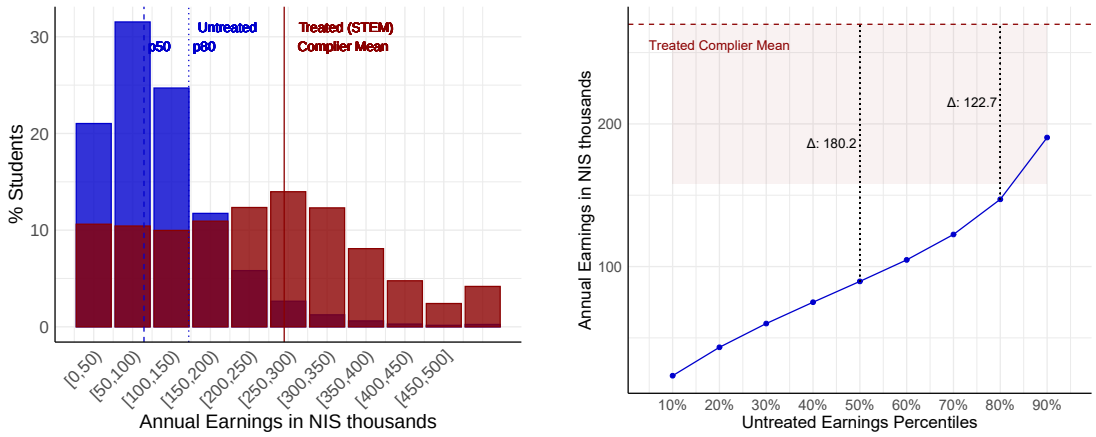
Figure 4: Effects of Crossing 600 on Earnings, by Year After the Test



(a) Younger (20 and Below) (b) Older (21 and Above)

Notes: These panels display the year-by-year impact of crossing the 600 UPET score on average annual earnings, conditional on being employed at any sector, in thousands of NIS. Younger test-takers (20 or below) appear in panel (a), while older test-takers (21 and above) appear in panel (b). The x-axis shows the number of years since the first test, and the y-axis shows the estimated coefficient τ from Equation 1. Dots mark point estimates and lines show 95% confidence intervals, with robust standard errors clustered at the score level. The sample consists of 39,608 Jewish test-takers who first took the UPET between 1999 and 2008 (18,629 younger and 20,979 older).

Figure 5: Constructing Bounds on the Returns to Selective STEM Fields



(a) Earnings Distributions (b) Bounds

Notes: The figure presents bounds for the returns to pursuing selective STEM fields in our setting. Panel A displays the earnings distributions for students enrolled in selective STEM fields (treated, red) and for those not enrolled (untreated, blue). A vertical red line marks the estimated treated complier mean, while the 50th and 80th percentiles of the untreated group's earnings are shown as counterfactual benchmarks. Panel B plots the earnings gap between the average treated complier and various points in the untreated distribution, emphasizing the gaps at the 50th and 80th percentiles. The shaded red area represents the 95% confidence interval for the estimated complier mean. The sample consists of test-takers who first took the UPET between 1999 and 2008 at ages 20 and below and who scored at least 5 points higher in the quantitative domain than in the other domains. Earnings are measured at age 30 in NIS thousands.

Table 1: Falsification Tests: "Effects" of Crossing 600 on Basline Characteristics

	(1)	(2)	(3)	(4)	(5)
A. Individual					
	Age	% Female	% Israeli	% Regular	Order
	-0.01	-0.02	-0.49	-0.18	-1.15
	(0.08)	(0.01)	(0.54)	(0.86)	(0.90)
Mean	20.23	0.56	84.51	82.21	151.96
N	40,383	40,383	40,383	40,383	40,383
B. Test					
			Score by domain		
	Year	Month	Quantitative	English	Qualitative
	-0.04	-0.05	-0.15	0.45*	-0.01
	(0.03)	(0.08)	(0.20)	(0.26)	(0.18)
Mean	2004.63	7.07	116.83	117.19	113.81
N	40,383	40,383	40,383	40,383	40,383
C. Family					
	Mother		Father		
	Educ	Income	Educ	Income	Siblings
	0.07	-3.22*	-0.01	0.57	-0.01
	(0.06)	(1.85)	(0.07)	(5.03)	(0.04)
Mean	14.05	88.13	13.61	191.91	2.42
N	40,383	40,383	40,383	40,383	40,319

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

Notes: This table reports estimated discontinuous changes in baseline characteristics at the 600 cutoff on the first UPET. Columns (1)–(5) present estimates of τ from Equation 1, with robust standard errors in parentheses. The baseline sample consists of all individuals who took their first UPET between 1999 and 2008. The estimation sample is restricted to those scoring between 580 and 620 on their first test. Earnings are in thousands of NIS. "Regular school" refers to non-religious school attendance.

Table 2: Effects of Crossing 600 on University Applications

	Any Field	STEM	Earnings	Retaking	Max Score
	(1)	(2)	(3)	(4)	(5)
A. All					
	-2.03**	1.70***	3.97**	-2.99**	-1.00
	(0.94)	(0.56)	(1.58)	(1.29)	(0.81)
Mean	62.11	9.90	174.93	41.50	615.29
N	40,383	40,383	25,959	40,383	40,383
B. Arabs					
	0.46	9.36*	11.06	-2.21	0.42
	(3.02)	(4.96)	(7.73)	(3.91)	(4.25)
Mean	90.14	28.69	218.17	84.52	649.23
N	1,799	1,799	1,652	1,799	1,799
C. Older (21 and Above)					
	-2.45*	-0.48	-0.47	-3.09**	-1.22
	(1.27)	(0.42)	(1.94)	(1.34)	(0.90)
Mean	53.13	4.21	152.74	25.08	601.30
N	20,672	20,672	11,493	20,672	20,672
D. Younger (20 and Below)					
	-1.66	3.52***	6.41***	-2.81*	-0.83
	(1.24)	(0.83)	(1.70)	(1.66)	(1.14)
Mean	68.96	14.12	187.63	54.96	627.06
N	17,912	17,912	12,814	17,912	17,912
E. Younger, Quant Advantage					
	-0.03	9.36***	18.07***	2.99	4.44**
	(1.38)	(2.61)	(4.93)	(4.62)	(2.21)
Mean	69.27	22.09	213.97	59.70	629.25
N	4,623	4,623	3,347	4,623	4,623
F. Younger, Non-Quant Advantage					
	-2.21	1.69*	2.56	-4.65***	-2.57**
	(1.43)	(0.97)	(2.42)	(1.42)	(1.26)
Mean	68.85	11.26	178.11	53.25	626.27
N	13,289	13,289	9,467	13,289	13,289

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

Notes: This table reports the estimated effect of crossing the 600-point cutoff on university applications and admission-relevant outcomes. Columns 1–5 display the estimated coefficients τ from Equation 1 along with robust standard errors (in parentheses), the baseline mean for each outcome, and the sample size. Outcome names, provided in the column headers, include indicators for applying to any university field and for selective STEM fields, the expected annual earnings associated with the application (in NIS thousands), an indicator for UPET retesting, and the highest UPET score achieved by the individual. For dummy outcomes, the estimated coefficients are presented in percentage points. The baseline sample comprises all first-time UPET takers in Israel between 1999 and 2008, while the effective sample is restricted to scores between 580 and 620. Panels *B–F* report results for subsamples based on ethnicity, age, and relative academic advantage. In the table, "STEM" refers to selective STEM fields (CS and EE) and "Earnings" refers to the average earnings at age 30 associated with the application field.

Table 3: Effects of Crossing 600 on Degree Enrollment

	Any Field	STEM	Earnings	Any	STEM (Any)	Earnings (Any)
	(1)	(2)	(3)	(4)	(5)	(6)
A. All						
	-2.64***	0.55*	2.22	0.16	0.91***	1.05
	(0.73)	(0.32)	(1.62)	(0.27)	(0.24)	(0.89)
Mean	61.91	6.34	154.81	94.72	10.71	149.81
N	40,383	40,383	25,624	40,383	40,383	38,462
B. Arabs						
	0.38	0.83	-2.79	2.42	1.93	-3.40
	(2.43)	(3.27)	(7.16)	(2.08)	(3.68)	(7.45)
Mean	80.81	13.21	180.11	90.41	14.48	174.11
N	1,799	1,799	1,490	1,799	1,799	1,640
C. Older (21 and Above)						
	-2.15*	-0.53	-0.12	0.09	-0.28	-0.16
	(1.14)	(0.36)	(1.74)	(0.53)	(0.68)	(0.69)
Mean	51.44	2.53	136.68	94.39	6.82	137.40
N	20,672	20,672	10,983	20,672	20,672	19,642
D. Younger (20 and Below)						
	-3.43***	1.84***	4.73***	0.04	2.23***	2.85**
	(1.29)	(0.55)	(1.54)	(0.28)	(0.78)	(1.42)
Mean	71.47	9.80	166.14	95.56	14.61	160.88
N	17,912	17,912	13,151	17,912	17,912	17,180
E. Younger, Quant Advantage						
	1.35	5.55**	15.54***	0.57	5.20**	12.78***
	(2.86)	(2.19)	(4.25)	(0.98)	(2.20)	(3.26)
Mean	73.80	16.21	189.08	96.54	23.05	182.34
N	4,623	4,623	3,535	4,623	4,623	4,465
F. Younger, Non-Quant Advantage						
	-5.00***	0.65	0.57	-0.14	1.31	-0.29
	(1.10)	(0.62)	(1.25)	(0.42)	(1.18)	(1.74)
Mean	70.63	7.50	157.51	95.21	11.58	153.06
N	13,289	13,289	9,616	13,289	13,289	12,715

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

Notes: This table reports the estimated effect of crossing the 600-point cutoff on degree enrollment outcomes. Columns 1–4 present the estimated coefficients τ from Equation 1, along with robust standard errors (in parentheses), the baseline mean for each outcome, and the sample size. Outcome names, provided in the column headers, include indicators for attending selective STEM field degrees, and the expected annual earnings associated with the degree (in NIS thousands) in universities (columns 1-2) and in any institution (columns 3-4). For dummy outcomes, the estimated coefficients are presented in percentage points. The baseline sample includes all first-time UPET takers in Israel between 1999 and 2008, while the effective sample is restricted to scores between 580 and 620. Panels *B–F* report results for subsamples by ethnicity, age, and relative academic advantage. In the table, "STEM" refers to selective STEM fields (CS and EE), "Earnings" refers to the average earnings at age 30 associated with the application field, and "Any refer" to any institution (universities and colleges).

Table 4: Effects of Crossing 600 on Labor-Market Outcomes

	Employement	Tech Employement	Earnings	Earnings (No Zeros)
	(1)	(2)	(3)	(4)
A. All				
	-0.04	1.82***	2.47	2.46
	(0.90)	(0.47)	(2.34)	(1.51)
Mean	82.43	18.87	102.46	119.16
N	40,383	40,383	39,941	34,351
B. Arabs				
	3.33	-0.58	4.25	-1.35
	(4.79)	(2.76)	(11.85)	(10.11)
Mean	66.33	7.42	114.21	150.64
N	1,799	1,799	1,630	1,250
C. Older (21 and Above)				
	-1.54	0.81	-1.37	-0.50
	(1.04)	(0.95)	(1.30)	(0.87)
Mean	86.60	17.18	93.98	105.34
N	20,672	20,672	20,671	18,493
D. Younger (20 and Below)				
	1.38	3.27***	6.94*	6.11**
	(1.51)	(1.06)	(4.08)	(2.74)
Mean	79.59	22.04	110.83	132.93
N	17,912	17,912	17,640	14,608
E. Younger, Quant Advantage				
	2.46	6.07***	16.70**	14.44**
	(3.00)	(1.91)	(7.24)	(6.06)
Mean	77.64	27.66	128.80	157.00
N	4,623	4,623	4,520	3,703
F. Younger, Non-Quant Advantage				
	0.98	2.41*	4.01	3.52
	(1.27)	(1.36)	(4.69)	(3.85)
Mean	80.29	20.02	104.45	124.57
N	13,289	13,289	13,120	10,905

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

Notes: This table reports the estimated effect of crossing the 600-point cutoff on labor-market outcomes at age 30. Columns 1–4 present the estimated coefficients τ from Equation 1, along with robust standard errors (in parentheses), the baseline mean for each outcome, and the sample size. Outcome names, provided in the column headers, include indicators for employment and for employment in the tech industry, and annual earnings with and without zeros (in NIS thousands). For dummy outcomes, the estimated coefficients are presented in percentage points. The baseline sample includes all first-time UPET takers in Israel between 1999 and 2008, while the effective sample is restricted to scores between 580 and 620. Panels *B–F* report results for subsamples by ethnicity, age, and relative academic advantage.

Table 5: Returns to Selective STEM Fields

	Never	Compliers		Always	
	E[Y(0)]	E[Y(0)]	E[Y(1)]	E[Y(1)]	LATE
	(1)	(2)	(3)	(4)	(5)
A. Sample: Younger (20 and Below)					
Endogenuous Variable: Applications					
Associated Earnings					1.06***
N=10,577, F=8.2					(0.37)
Selective STEM	123.8	12.7	189.4	207.7	176.73**
N=14,608, F=10.7	(1.2)	(71.4)	(24.3)	(2.9)	(74.40)
Endogenuous Variable: Degrees					
Associated Earnings					2.03**
N=14,204, F=3.3					(0.79)
Selective STEM	125.8	-184.7	293.8	228.8	478.52*
N=14,608, F=2.0	(1.3)	(230.3)	(87.9)	(6.0)	(263.21)
B. Sample: Younger, Quantitatively-Advantaged					
Endogenuous Variable: Applications					
Associated Earnings					0.97**
N= 2,712, F=16.0					(0.36)
Selective STEM	144.2	63.9	220.7	218.7	156.80**
N= 3,703, F=13.4	(2.9)	(61.4)	(35.9)	(5.0)	(66.63)
Endogenuous Variable: Degrees					
Associated Earnings					1.17***
N= 3,611, F=12.9					(0.37)
Selective STEM	147.7	-9.7	269.8	241.7	279.52**
N= 3,703, F=5.4	(2.7)	(114.3)	(56.9)	(8.4)	(105.13)

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

Notes: The table shows the estimated returns to pursuing selective STEM fields. Note that in the binary version, the LATE estimates, untreated complier mean, and never takers' mean are biased. See a discussion and proposed solution in the main text.

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 selective STEM fields. I have predicted the main outcome (applications to selective STEM 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

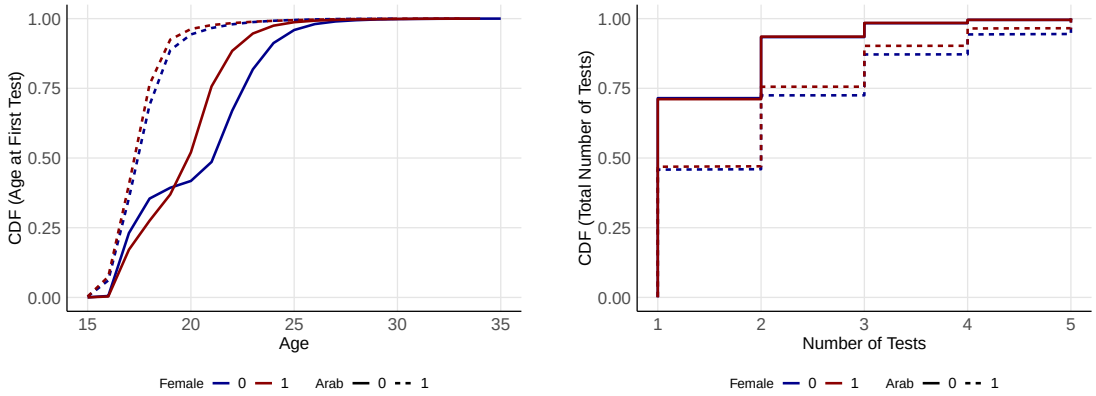
[15]These numbers are larger than 100 due to the GPA calculation method. These methods give extra 10-30 points for test scores in some high school programs (e.g., programs with five credits).

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

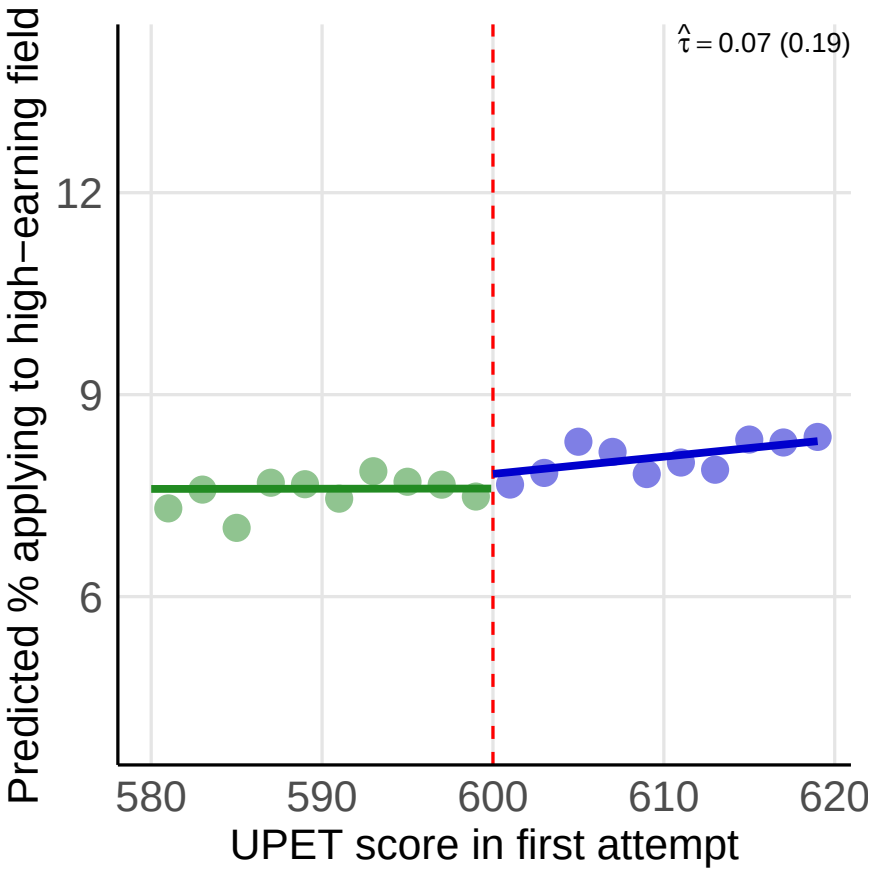


(a) Age at First Test

(b) Number of Tests

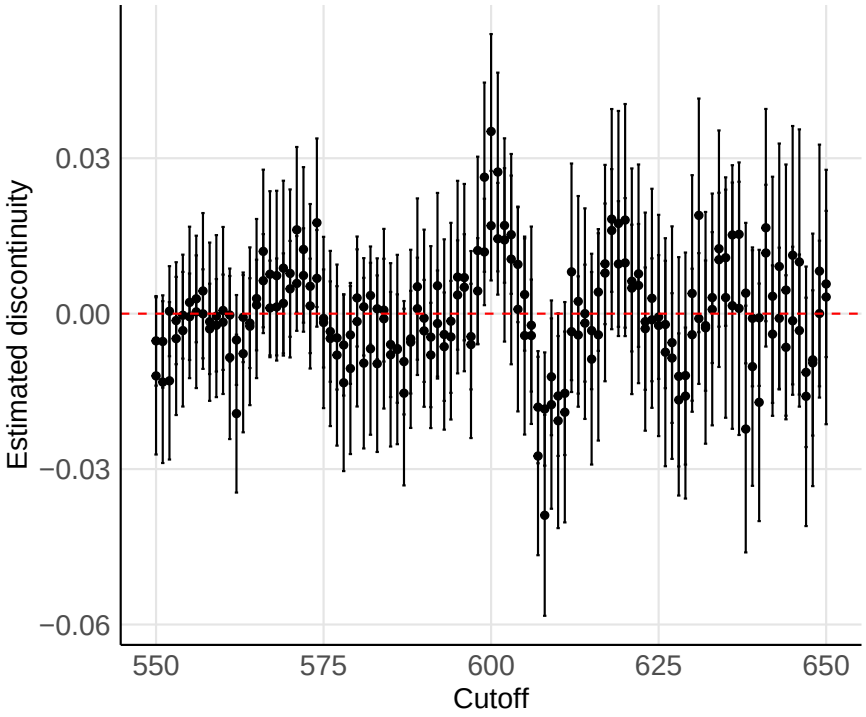
Notes: The figures present the testing regularities of Jews and Arabs in Israel. The sample includes all individuals in Israel who participated in their first UPET during 1999–2008 (347,511 observations). The figure in the upper panel (a) shows the cumulative distribution of ages at the first test. The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



Notes: The figure shows the estimated discontinuity in the predicted likelihood of applying to selective STEM 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 selective STEM fields, based on background characteristics. 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.

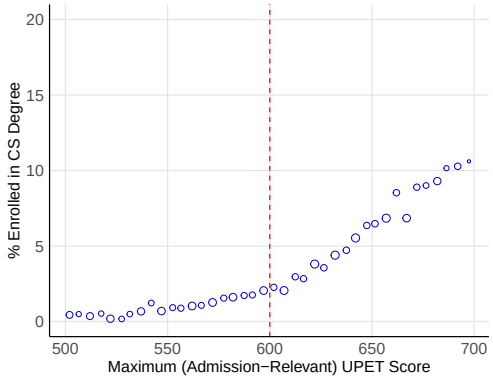
Figure A.3: The "Impact" of Crossing Non-Round Scores on the Likelihood of Applying to Selective STEM fields



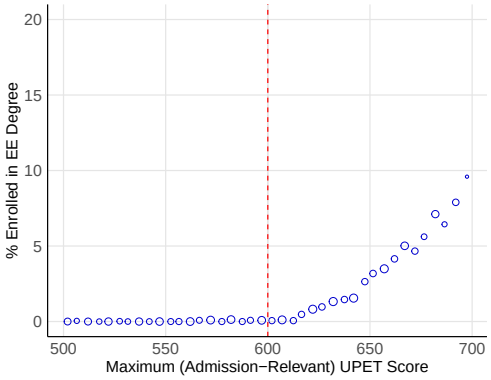
Notes: This figure displays the results of a falsification test, estimating the "impact" of crossing non-round score cutoffs. The y-axis illustrates estimated discontinuities (τ in equation 1), with an indicator for applying to selective STEM fields as the outcome. The x-axis indicates the RD cutoff used for estimation. 95% 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: Selective STEM Fields Admission

Unconditional

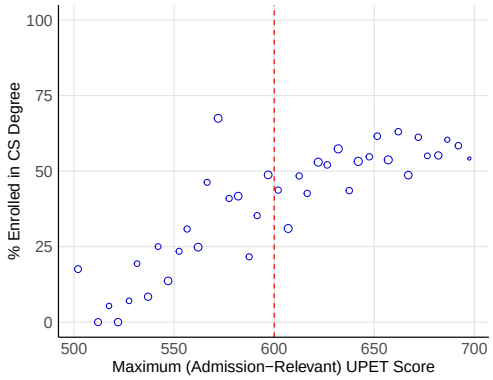


(a) CS

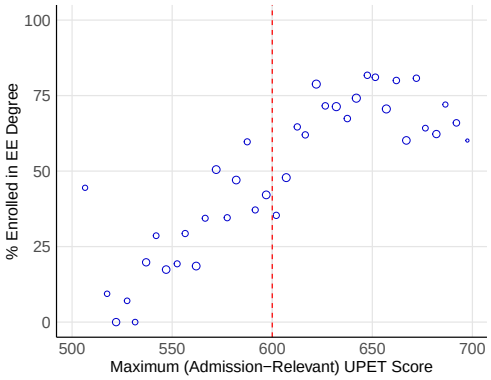


(b) EE

Conditional on Applying



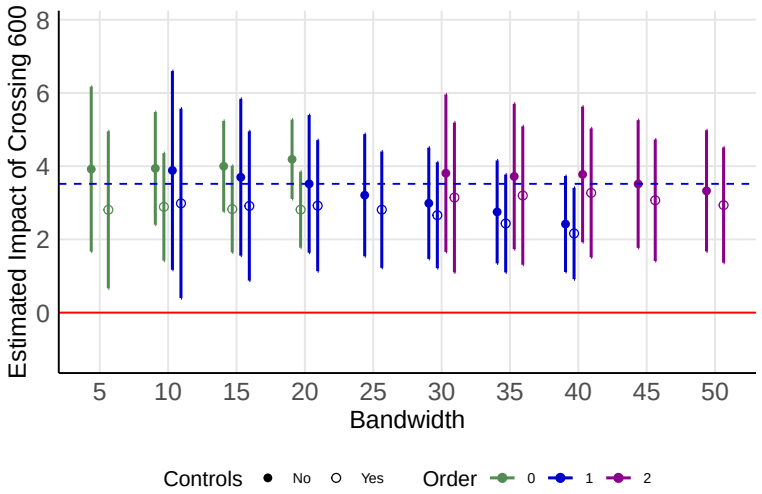
(c) CS



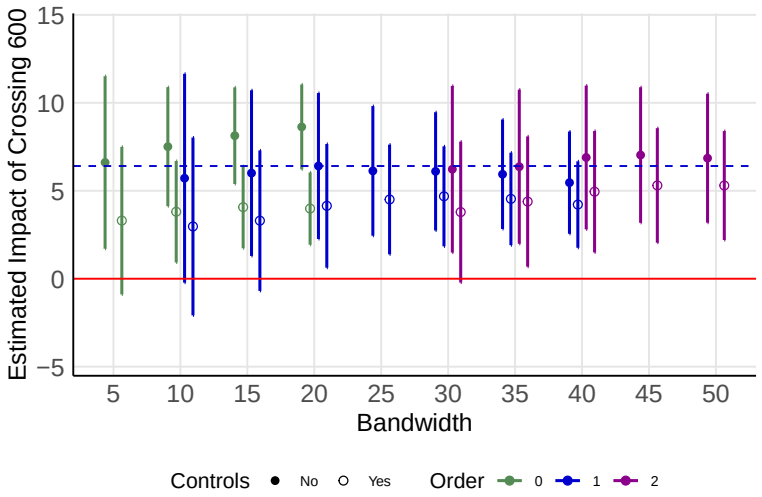
(d) EE

Notes: The figures in panels (a) and (b) show the relationship between selective STEM 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.5: Robustness of the Estimated Effects of Crossing 600 on University Applications (Sample of Younger Test-Takers)



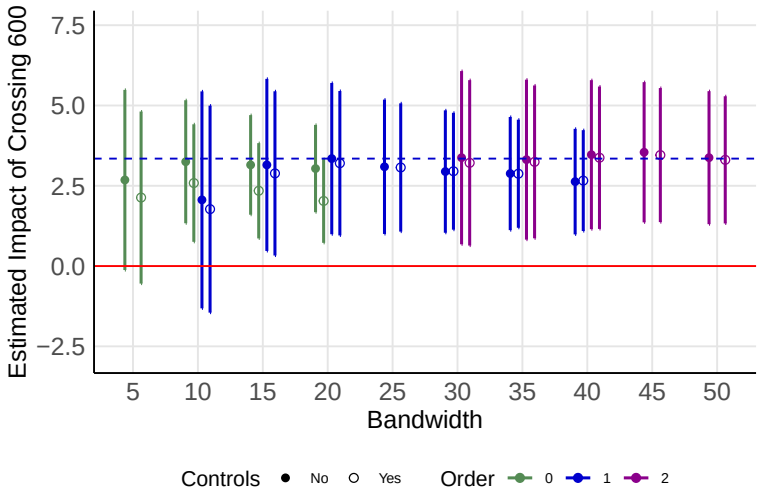
(a) % Selective STEM



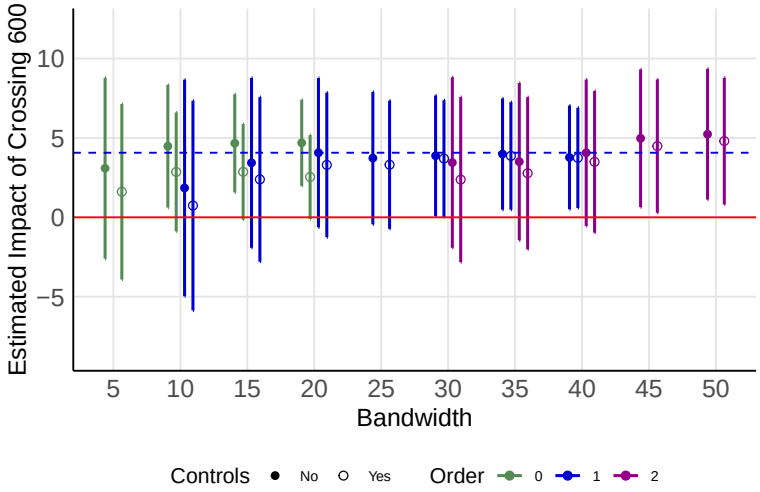
(b) Associated Earnings

Notes: This figure displays estimates for the impact of crossing the 600 UPET score threshold using various specifications. Each point represents the estimated coefficient τ from Equation 1 for a given bandwidth (displayed on the x-axis), polynomial order, and control variable inclusion, as described below the figure. The sample consists of 18,629 Jewish test-takers who first took the UPET between 1999 and 2008 at age 20 or younger.

Figure A.6: Robustness of the Estimated Effects of Crossing 600 on Labor-Market Outcomes (Younger Test-Takers)



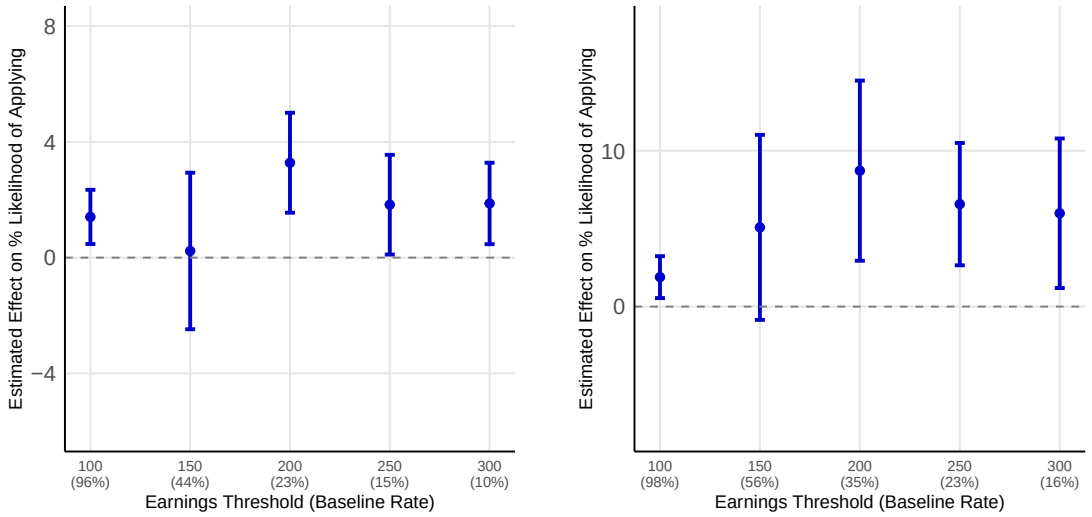
(a) % Tech Employed



(b) Earnings

Notes: This figure displays estimates for the impact of crossing the 600 UPET score threshold using various specifications. Each point represents the estimated coefficient τ from Equation 1 for a given bandwidth (displayed on the x-axis), polynomial order, and control variable inclusion, as described below the figure. The sample consists of 18,629 Jewish test-takers who first took the UPET between 1999 and 2008 at age 20 or younger.

Figure A.7: Effects of Crossing 600 on Applications to University Programs by Associated Earnings Threshold

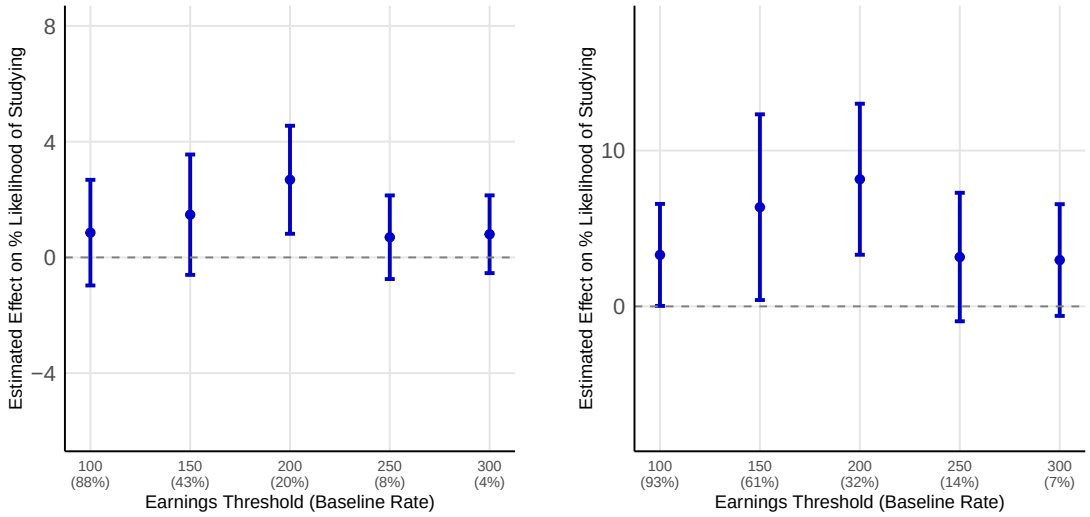


(a) Younger (20 and Below)

(b) Quantiatively-Advantaged Younger

Notes: This figure displays the impact of crossing a 600 UPET score on applications to university fields by associated earnings thresholds. Each point represents the estimated coefficient τ of Equation 1, when the outcome variable is an indicator for applying to any program with earnings above the (appears on the x-axis). Estimates are measured in percentage points (y-axis) representing the impact of crossing 600. The sample in panel (a) consists of 18,629 Jewish test-takers who first took the UPET between 1999 and 2008 at ages 20 and below. The sample at panel b is further restricted to the 4,623 students with quantitative advantage within this sample.

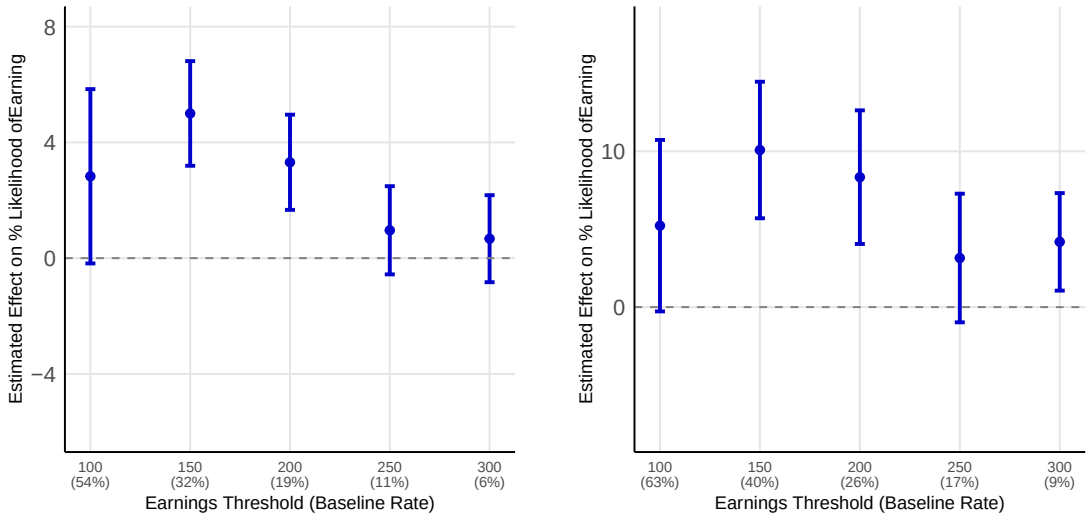
Figure A.8: Effects of Crossing 600 on Applications to University Programs by Associated Earnings Threshold



(a) Younger (20 and Below) (b) Quantiatively-Advantaged Younger

Notes: This figure displays the impact of crossing a 600 UPET score on academic degrees by associated earnings thresholds. Each point represents the estimated coefficient τ of Equation 1, when the outcome variable is an indicator for enrolling in any degree program with earnings above the (appears on the x-axis). Estimates are measured in percentage points (y-axis) representing the impact of crossing 600. The sample in panel (a) consists of 18,629 Jewish test-takers who first took the UPET between 1999 and 2008 at ages 20 and below. The sample at panel b is further restricted to the 4,623 students with quantitative advantage within this sample.

Figure A.9: Effects of Crossing 600 on Actual Earnings, by Threshold



(a) Younger (20 and Below) (b) Quantiatively-Advantaged Younger

Notes: This figure displays the impact of crossing a 600 UPET score on academic degrees by associated earnings thresholds. Each point represents the estimated coefficient τ of Equation 1, when the outcome variable is an indicator for enrolling in any program with earnings above the (appears on the x-axis). Estimates are measured in percentage points (y-axis) representing the impact of crossing 600. The sample in panel (a) consists of 18,629 Jewish test-takers who first took the UPET between 1999 and 2008 at ages 20 and below. The sample at panel b is further restricted to the 4,623 students with quantitative advantage within this sample.

Appendix Tables

Table A.1: Falsification Tests: "Effects" of Crossing 600 on Basline Characteristics (Sample of Younger Test-Takers)

	(1)	(2)	(3)	(4)	(5)
A. Individual					
	Age	% Female	% Israeli	% Regular	Order
	-0.02	-0.02	-0.83	-0.82	0.06
	(0.04)	(0.02)	(0.99)	(1.13)	(1.06)
Mean	18.18	0.61	76.78	75.82	154.54
N	17,912	17,912	17,912	17,912	17,912
B. Test					
			Score by domain		
	Year	Month	Quantitative	English	Qualitative
	0.10	-0.13	0.23	0.25	-0.29
	(0.07)	(0.09)	(0.17)	(0.47)	(0.25)
Mean	2003.66	8.34	118.04	117.29	112.55
N	17,912	17,912	17,912	17,912	17,912
C. Family					
	Mother		Father		
	Educ	Income	Educ	Income	Siblings
	0.02	-4.26*	-0.02	1.33	-0.02
	(0.08)	(2.23)	(0.15)	(3.80)	(0.06)
Mean	14.51	94.70	13.90	196.95	2.31
N	17,912	17,912	17,912	17,912	17,891

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

Notes: This table reports estimated discontinuous changes in baseline characteristics at the 600 cutoff on the first UPET. Columns (1)–(5) present estimates of τ from Equation 1, with robust standard errors in parentheses. The sample consists of Jewish test-takers who took their first UPET between 1999 and 2008 at ages 20 and below, restricted to those scoring between 580 and 620 on their first test. Earnings are in thousands of NIS. "Regular school" refers to non-religious school attendance.

Table A.2: Effects of Crossing 600 on UPET and Matriculation Outcomes

	STEM × Retaking	STEM × Max score	Total Credits	STEM Credits	Siblings Tests
	(1)	(2)	(3)		
A. All					
	1.13**	11.01***	0.06	0.00	0.06**
	(0.57)	(3.61)	(0.10)	(0.06)	(0.03)
Mean	8.01	63.57	27.20	4.10	0.88
N	40,383	40,383	39,894	39,894	24,186
B. Arabs					
	7.53*	63.33*	0.42	0.73**	0.34**
	(4.32)	(32.74)	(0.36)	(0.32)	(0.15)
Mean	27.42	189.45	32.00	8.05	1.99
N	1,799	1,799	1,749	1,749	1,433
C. Older (21 and Above)					
	-0.37	-2.98	-0.25	-0.14**	0.03
	(0.48)	(2.61)	(0.16)	(0.07)	(0.03)
Mean	2.59	26.37	25.22	2.71	0.78
N	20,672	20,672	20,317	20,317	12,312
D. Younger (20 and Below)					
	2.28***	22.36***	0.41***	0.11	0.06
	(0.83)	(5.37)	(0.11)	(0.08)	(0.05)
Mean	11.87	90.88	28.85	5.18	0.82
N	17,912	17,912	17,828	17,828	10,441
E. Younger, Quant Advantage					
	6.61**	61.11***	0.69***	0.56***	0.14
	(2.57)	(16.92)	(0.26)	(0.21)	(0.09)
Mean	18.25	141.07	29.80	6.34	0.82
N	4,623	4,623	4,613	4,613	2,836
F. Younger, Non-Quant Advantage					
	0.93	10.18	0.32***	-0.03	0.03
	(0.75)	(6.37)	(0.12)	(0.07)	(0.04)
Mean	9.57	72.84	28.51	4.76	0.82
N	13,289	13,289	13,215	13,215	7,605

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

Notes: This table reports the estimated effect of crossing the 600 UPET cutoff on university applications, separately by ethnicity and age. Columns (1)–(3) show the coefficient τ from Equation 1, with robust standard errors in parentheses. The baseline sample includes all first-time UPET takers in Israel between 1999 and 2008; the effective sample is restricted to scores between 580 and 620. Column (1) includes Jewish test-takers aged 20 or below, Column (2) includes Jewish test-takers aged 21 or above, and Column (3) includes Arab test-takers.

Table A.3: Effects of Crossing 600 on University Applications, Alternative Outcomes

	CS	EE	Tech > 40%	Imputed	Field only
	(1)	(2)	(3)	(4)	(5)
A. All					
	1.51***	0.45	1.17*	1.49	3.32**
	(0.45)	(0.60)	(0.61)	(1.27)	(1.51)
Mean	6.63	5.16	15.85	155.58	171.75
N	40,383	40,383	40,383	40,383	25,959
B. Arabs					
	7.41*	3.98*	2.60	10.40	7.69
	(4.01)	(2.34)	(4.50)	(9.27)	(6.71)
Mean	22.08	15.02	44.07	208.87	208.30
N	1,799	1,799	1,799	1,799	1,652
C. Older (21 and Above)					
	-0.37	-0.26	-0.88	-1.04	-1.59
	(0.35)	(0.49)	(0.69)	(1.31)	(1.97)
Mean	2.85	1.98	7.83	139.21	151.47
N	20,672	20,672	20,672	20,672	11,493
D. Younger (20 and Below)					
	3.19***	0.94	3.47***	3.61**	6.55***
	(0.79)	(0.95)	(0.98)	(1.48)	(1.72)
Mean	9.10	7.59	21.61	167.84	183.80
N	17,912	17,912	17,912	17,912	12,814
E. Younger, Quant Advantage					
	6.71***	3.69*	9.94***	13.28***	16.41***
	(1.85)	(2.11)	(3.21)	(3.92)	(5.39)
Mean	13.56	13.41	31.66	186.28	209.81
N	4,623	4,623	4,623	4,623	3,347
F. Younger, Non-Quant Advantage					
	2.08**	0.10	1.48	0.64	3.30
	(1.05)	(0.76)	(1.04)	(1.86)	(2.29)
Mean	7.50	5.50	18.00	161.21	174.39
N	13,289	13,289	13,289	13,289	9,467

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

Notes: This table reports the estimated effect of crossing the 600 UPET cutoff on university applications, separately by ethnicity and age. Columns (1)–(3) show the coefficient τ from Equation 1, with robust standard errors in parentheses. The baseline sample includes all first-time UPET takers in Israel between 1999 and 2008; the effective sample is restricted to scores between 580 and 620. Column (1) includes Jewish test-takers aged 20 or below, Column (2) includes Jewish test-takers aged 21 or above, and Column (3) includes Arab test-takers.

Table A.4: University Fields with the Highest Tech Employment Likelihood

Field	Students (1)	% Tech (2)	Earnings (3)
Comp. Elec. Engineering	1144	64.87	326.05
Computer Engineering	2385	67.07	302.41
Electrical Engineering	8320	62.52	287.65
Communications Engineering	702	75.98	267.42
Systems Engineering	1372	67.98	266.51
Computer Science	13779	55.86	264.32
Bio-Med Engineering	1619	51.74	191.44
Computer Systems	703	52.08	182.50

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.5: Effects of Crossing 600 on Applications to Alternative Fields (Sample of Younger Test-Takers)

	(1)	(2)	(3)	(4)	(5)
A.					
	Any	Other STEM	Medicine	Law	Business
	-5.14***	-0.00	-0.59	-1.63	-2.02**
	(1.16)	(1.15)	(0.51)	(1.18)	(0.85)
Mean	47.35	27.57	4.13	8.23	11.33
N	17,912	17,912	17,912	17,912	17,912
B.					
	Para-Med	Health	Social	Education	Humanities
	-1.12	-0.68	-2.38	-1.22***	-1.99**
	(1.22)	(0.54)	(2.64)	(0.39)	(0.96)
Mean	12.67	4.77	32.07	4.49	13.63
N	17,912	17,912	17,912	17,912	17,912

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

Notes: This table reports the estimated impact of crossing the 600 UPET score cutoff on university applications. Columns (1)–(5) report the RD estimates of τ from Equation 1, with robust standard errors in parentheses. The sample consists of younger test-takers who took their first UPET between 1999 and 2008, restricted to those scoring between 580 and 620 on their first test. Each outcome is measured as a percentage (multiplied by 100). CS stands for Computer Science; EE stands for Electrical Engineering.

Table A.6: Effects of Crossing 600 on Applications to Alternative Fields (Sample of Quantitatively Advantaged Younger Test-Takers)

	(1)	(2)	(3)	(4)	(5)
A.					
	Any	Other STEM	Medicine	Law	Business
	-9.97***	-0.77	-1.67	-0.29	0.24
	(3.02)	(1.81)	(1.75)	(1.88)	(1.48)
Mean	37.61	29.35	4.57	6.34	12.64
N	4,623	4,623	4,623	4,623	4,623
B.					
	Para-Med	Health	Social	Education	Humanities
	-1.80	-1.16	-3.79	-1.45	-2.55*
	(1.42)	(1.74)	(3.57)	(1.03)	(1.52)
Mean	9.45	5.19	25.16	2.61	6.84
N	4,623	4,623	4,623	4,623	4,623

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

Table A.7: Robustness of the Main Estimation Results

	(1)	(2)	(3)	(4)
	3.59***	6.35***	3.72**	6.07*
	(0.83)	(1.66)	(1.37)	(2.84)
Outcome	STEM	Ass Earnings	STEM	Ass Earnings
Bandwidth	17	21	14	16
N	16317	14346	13769	10984
Method	MSE-opt	MSE-opt	Honest	Honest
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$				

This table shows the estimates of τ from Equation 1, with robust standard errors in parentheses. The baseline sample consists of all Jewish individuals who took their first UPET between 1999 and 2008 at ages 20 or below. The estimation sample is restricted to those scoring between 580 and 620 on their first test. Estimation is based on the algorithms developped by Calonico et al. (2015) and Kolesár and Rothe (2018).

Table A.8: Heterogeneity of the Impact of Crossing 600 on University Applications (Sample of Younger Test-Takers)

	Difference	Z=0	Z=1
	(1)	(2)	(3)
Z: High-SES			
Earnings	3.02	5.01**	8.04**
	(5.58)	(2.36)	(4.04)
		190.20	188.33
Max Score	-2.04	0.29	-1.75
	(2.58)	(1.42)	(1.99)
		631.51	639.88
Retaking	0.72	-3.02	-2.30
	(3.06)	(2.32)	(2.19)
		53.38	59.47
STEM	1.41	2.88**	4.28**
	(3.01)	(1.46)	(1.96)
		15.23	14.57
Z: Female			
Earnings	-7.54	9.72**	2.18
	(5.17)	(3.93)	(2.33)
		227.08	169.02
Max Score	-1.82	-0.01	-1.83
	(3.27)	(2.18)	(1.68)
		643.80	630.34
Retaking	-3.04	-1.27	-4.31*
	(3.09)	(1.74)	(2.42)
		64.79	50.96
STEM	-3.64*	5.32***	1.68**
	(2.19)	(1.90)	(0.75)
		25.77	8.14

Notes: The table shows the estimated heterogeneity of the impact of crossing the 600 score on the first UPET. 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.9: Effects of Crossing 600 on Degree Attainment

	Any	STEM	Tech > 40%	Any	STEM (Any)	Tech > 40% (Any)
	(1)	(2)	(3)	(4)	(5)	(6)
A. All						
	-1.25	0.30	1.33***	-0.34	0.42	1.55**
	(1.18)	(0.19)	(0.45)	(0.63)	(0.32)	(0.61)
Mean	49.40	3.41	7.15	83.42	6.58	13.76
N	40,383	40,383	40,383	40,383	40,383	40,383
B. Arabs						
	2.22	-2.90**	-0.20	5.09	-1.79	1.10
	(3.33)	(1.28)	(2.44)	(3.11)	(1.84)	(2.76)
Mean	66.43	5.43	9.86	76.74	6.15	10.95
N	1,799	1,799	1,799	1,799	1,799	1,799
C. Older (21 and Above)						
	-0.58	-0.04	0.60	-0.97	-0.13	0.59
	(1.14)	(0.23)	(0.42)	(1.04)	(0.61)	(0.90)
Mean	38.69	1.07	2.90	82.40	4.21	10.50
N	20,672	20,672	20,672	20,672	20,672	20,672
D. Younger (20 and Below)						
	-2.32	1.05***	2.39***	-0.17	1.30	2.73***
	(1.82)	(0.40)	(0.91)	(0.77)	(0.84)	(0.78)
Mean	59.43	5.79	11.58	85.30	9.27	17.71
N	17,912	17,912	17,912	17,912	17,912	17,912
E. Younger, Quant Advantage						
	1.53	4.24**	7.93***	-2.21	4.36**	7.34***
	(3.30)	(1.87)	(2.88)	(1.80)	(1.92)	(2.60)
Mean	62.81	10.60	19.55	87.48	15.98	28.58
N	4,623	4,623	4,623	4,623	4,623	4,623
F. Younger, Non-Quant Advantage						
	-3.54*	0.04	0.65	0.53	0.36	1.32
	(1.83)	(0.73)	(0.70)	(1.06)	(1.30)	(0.87)
Mean	58.21	4.06	8.72	84.51	6.85	13.80
N	13,289	13,289	13,289	13,289	13,289	13,289

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

Notes: This table reports the estimated effect of crossing the 600-point cutoff on degree enrollment outcomes. Columns 1–4 present the estimated coefficients τ from Equation 1, along with robust standard errors (in parentheses), the baseline mean for each outcome, and the sample size. Outcome names, provided in the column headers, include indicators for attending selective STEM field degrees, and the expected annual earnings associated with the degree (in NIS thousands) in universities (columns 1-2) and in any institution (columns 3-4). For dummy outcomes, the estimated coefficients are presented in percentage points. The baseline sample includes all first-time UPET takers in Israel between 1999 and 2008, while the effective sample is restricted to scores between 580 and 620. Panels *B–F* report results for subsamples by ethnicity, age, and relative academic advantage.

Table A.10: Effects of Crossing 600 on Degree Enrollment

	BA, Elite	MA, Elite	MA, Uni	MA, Any
	(1)	(2)	(3)	(4)
A. All				
	-1.77**	-0.46	-0.80	-1.03*
	(0.71)	(0.90)	(0.72)	(0.59)
Mean	26.51	13.28	28.88	37.36
N	40,383	40,383	40,383	40,383
B. Arabs				
	0.16	-0.99	-1.75	-0.38
	(4.85)	(4.19)	(4.21)	(5.15)
Mean	60.36	12.76	25.34	30.32
N	1,799	1,799	1,799	1,799
C. Older (21 and Above)				
	-0.97	-1.22	-1.02	-1.10
	(0.67)	(0.74)	(1.21)	(1.26)
Mean	16.59	10.57	24.77	34.38
N	20,672	20,672	20,672	20,672
D. Younger (20 and Below)				
	-2.80**	0.47	-0.41	-1.00
	(1.41)	(1.43)	(1.30)	(1.52)
Mean	33.76	16.36	33.85	41.45
N	17,912	17,912	17,912	17,912
E. Younger, Quant Advantage				
	2.48	2.57	-0.39	-2.00
	(3.15)	(1.69)	(2.05)	(2.30)
Mean	34.08	16.56	33.92	40.76
N	4,623	4,623	4,623	4,623
F. Younger, Non-Quant Advantage				
	-4.54**	-0.24	-0.41	-0.66
	(1.83)	(1.87)	(1.22)	(1.76)
Mean	33.65	16.29	33.83	41.70
N	13,289	13,289	13,289	13,289

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

Notes: This table reports the estimated effect of crossing the 600-point cutoff on degree enrollment outcomes. Columns 1–4 present the estimated coefficients τ from Equation 1, along with robust standard errors (in parentheses), the baseline mean for each outcome, and the sample size. Outcome names, provided in the column headers, include indicators for attending selective STEM field degrees, and the expected annual earnings associated with the degree (in NIS thousands) in universities (columns 1-2) and in any institution (columns 3-4). For dummy outcomes, the estimated coefficients are presented in percentage points. The baseline sample includes all first-time UPET takers in Israel between 1999 and 2008, while the effective sample is restricted to scores between 580 and 620. Panels *B–F* report results for subsamples by ethnicity, age, and relative academic advantage.

Table A.11: Effects of Crossing 600 on Labor-Market Outcomes (Sample of Younger Test-Takers)

	(1)	(2)	(3)	(4)
	Age 30		Ages 30-32	
A. By Age				
	Rank	Top 5%	Rank	Top 5%
	1.99	1.95**	2.16*	1.13
	(1.53)	(0.86)	(1.27)	(0.98)
Mean	59.61	13.08	54.59	10.07
N	17,910	17,910	17,912	17,912
	12 Years After		10-12 Years After	
B. By Year				
	Rank	Top 5%	Rank	Top 5%
	1.52	1.82**	2.27*	1.44*
	(1.45)	(0.87)	(1.23)	(0.77)
Mean	57.90	13.45	57.01	10.61
N	17,912	17,912	17,912	17,912

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

Notes: This table reports the estimated impact of crossing the 600 UPET score cutoff on labor-market and degree outcomes at ages 28–30. Columns (1)–(5) present the RD estimates of τ from Equation 1, with robust standard errors in parentheses. The baseline sample includes all younger Jewish (age 20 or below) first-time UPET takers from 1999–2008; the effective sample is restricted to those scoring between 580 and 620 on their first test. Earnings are reported in thousands of NIS.

Table A.12: Robustness of the Main Long-Term Estimation Results

	(1)	(2)	(3)	(4)
	6.08**	3.19***	5.70	3.31**
	(2.70)	(0.98)	(4.55)	(1.51)
Outcome	Earnings	Tech	Earnings	Tech
Bandwidth	19	21	14	15
N	14608	20036	11250	14257
Method	MSE-opt	MSE-opt	Honest	Honest
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$				

This table shows the estimates of τ from Equation 1, with robust standard errors in parentheses. The baseline sample consists of all Jewish individuals who took their first UPET between 1999 and 2008 at ages 20 or below. The estimation sample is restricted to those scoring between 580 and 620 on their first test. Estimation is based on the algorithms developped by Calonico et al. (2015) and Kolesár and Rothe (2018).

Table A.13: Heterogeneity of the Impact of Crossing 600 on Long-Term Outcomes (Sample of Younger Test-Takers)

	Difference	Z=0	Z=1
	(1)	(2)	(3)
Z: High-SES			
Earnings	2.63	4.97	7.60**
	(7.94)	(5.60)	(3.70)
		133.28	133.69
Earnings (Degree)	2.42	1.71	4.13**
	(3.51)	(2.39)	(2.06)
		163.31	162.58
STEM	3.54	0.19	3.73***
	(2.41)	(1.46)	(1.13)
		11.40	9.82
Tech	1.57	2.55	4.12***
	(2.16)	(1.78)	(1.10)
		22.14	20.81
Z: Female			
Earnings	-11.69*	12.09**	0.39
	(6.87)	(5.72)	(3.47)
		173.62	111.45
Earnings (Degree)	-6.69**	5.88**	-0.81
	(3.34)	(2.94)	(1.42)
		194.19	144.04
STEM	-2.09	2.76*	0.67
	(1.87)	(1.49)	(0.65)
		20.37	4.59
Tech	-2.04	4.16	2.12*
	(3.20)	(2.63)	(1.26)
		31.19	15.48

Notes: The table shows the estimated heterogeneity of the impact of crossing the 600 score on the first UPET. 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.14: Effects of Crossing 700 on University Applications

	Any	STEM	Earnings	Retaking	Max Score
	(1)	(2)	(3)	(4)	(5)
A. All					
	-0.11	-0.47	-0.41	1.72	1.22**
	(0.39)	(1.12)	(2.07)	(1.18)	(0.50)
Mean	97.37	24.48	203.05	16.47	694.31
N	22,236	22,236	19,442	22,236	22,236
B. Jews, Old					
	-1.00***	-2.24	-4.55	1.10	0.93***
	(0.38)	(1.41)	(3.03)	(1.02)	(0.35)
Mean	97.31	17.79	190.39	11.30	692.14
N	12,473	12,473	10,819	12,473	12,473
C. Jews, Young					
	1.33*	1.48	3.65	0.93	0.97
	(0.69)	(1.24)	(2.76)	(1.79)	(0.77)
Mean	97.64	32.84	218.34	21.72	696.58
N	9,503	9,503	8,371	9,503	9,503

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

Notes: This table reports the estimated effect of crossing the 700 UPET cutoff on long-term outcomes Columns (1)–(3) show the coefficient τ from Equation 1, with robust standard errors in parentheses. The baseline sample includes all first-time UPET takers in Israel between 1999 and 2008; the effective sample is restricted to scores between 580 and 620.

Table A.15: Effects of Crossing 700 on Long-Term Outcomes

	BA	BA Earnings	MA	Employed	Tech Emp.	Earnings
	(1)	(2)	(3)	(4)	(5)	(6)
A. All						
	-0.11	-0.03	2.61*	-1.19	-2.75**	-1.63
	(0.39)	(1.40)	(1.48)	(1.02)	(1.20)	(3.30)
Mean	97.37	178.47	46.17	82.04	27.09	142.67
N	22,236	21,736	22,236	22,236	22,236	18,696
B. Jews, Old						
	-1.00***	-2.25	-0.84	-0.33	-2.70*	-2.00
	(0.38)	(2.26)	(1.59)	(1.40)	(1.44)	(3.26)
Mean	97.31	165.02	42.95	87.02	24.85	125.23
N	12,473	12,175	12,473	12,473	12,473	11,123
C. Jews, Young						
	1.33*	1.41	8.06***	-1.91	-2.78**	-3.89
	(0.69)	(2.05)	(2.36)	(1.38)	(1.40)	(4.85)
Mean	97.64	195.34	50.85	75.98	30.38	166.62
N	9,503	9,321	9,503	9,503	9,503	7,403

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

Notes: This table reports the estimated effect of crossing the 700 UPET cutoff on long-term outcomes Columns (1)–(3) show the coefficient τ from Equation 1, with robust standard errors in parentheses. The baseline sample includes all first-time UPET takers in Israel between 1999 and 2008; the effective sample is restricted to scores between 580 and 620.

Appendix B Conceptual Framework

The goal of this framework is to complement the empirical analysis discussed throughout the paper and to provide a formal discussion that helps reconcile the main findings. Recall that in Section 5 it has been shown that crossing the round score cutoff of 600 in the first UPET induces some students to decrease their effort in retaking the test, and other students to increase their effort in retaking the test and improving their scores significantly such that they can pursue the most challenging and rewarding fields in our setting. Thus, I sketch here a simple conceptual framework to illustrate how left-digit bias can induce such diverse responses to test scores among different students.

Assume that individuals value scoring above round numbers due to left-digit bias. Let their baseline utility, after taking their first university tests, be a function of scoring above the round number, $V_0 = \mathbf{1}_{s \geq 600}$, where s is their score on the first test attempt. Students can value scoring above the round number for many reasons, such as ego-utility, social comparisons, or the belief that round scores will improve their admission opportunities.[16]

Additionally, assume that students can retake the test at a cost c, and if they do, they will certainly cross the round number. Thus, their utility for retaking the test is $V_1 = 1 - c$.[17] Furthermore, assume that there is also an option to aim higher when retaking the test, and invest additional efforts in improving their scores to gain admission to selective STEM fields. The returns for this option vary by the student's abilities, such that $V_2 = 1 + f(a) - e$. This value is the sum of three parts, 1 for scoring above 600 which is certain in this case, $f(a)$ which represents the returns for pursuing challenging and rewarding fields as a function of the student's ability $a \in \{0, 1\}$, and $-e$ which represents the effort cost of retaking and aiming higher ($e > c$).

To fit the empirical analysis, we can think of two types of students. Students of the first type have lower abilities $a = 0$ and they are certain about it, and those of the second type are uncertain about their ability type. Assume that these students learn about their ability from the score on their first attempt, and this learning process is completely heuristic: if they score above the round number, they believe they are of high ability type, and otherwise, they believe they are of lower ability type. Furthermore, we can specify the function f such that the

[16] However, note that in our setting, scoring just above 600 is insufficient to get admission into the most challenging fields, which are the focus of this research. Therefore, all students who score just around 600 need to retake their tests and significantly improve their scores to get into these fields.

[17] This assumption simplifies the model but is justified by our empirical setting: nearly all students (90% or more) who retake the test after initially scoring just below 600 will score 600+ on their second attempt.

returns from pursuing STEM are null for students with lower ability and high for those with high ability, for example:

$$f(a) = \begin{cases} 0 & \text{if } a = 0 \\ 5 & \text{if } a = 1 \end{cases}$$

Now we can analyze how crossing the round score will affect both types of students. Starting with students who are certain about their low ability, we can conclude that they will never choose to aim high as they will not get any positive returns from these fields (note that $V_1(a = 0) = 1 - c > 1 - e = V_2(a = 0)$ by assumption). Therefore, they only consider retaking and getting the value $V_1 = 1 - c$ versus remaining with their baseline value, $V_0 = \mathbf{1}_{s \geq 0}$. They will retake the test only if the value of retaking is higher than the baseline value, $\mathbf{1}_{s \geq 0} < 1 - c$. It follows that for students who are certain of their lower ability types, crossing the round score induces a discontinuous decrease in the probability of retaking the test (in non-trivial cases where $1 > c$) due to an increase in their baseline value from 0 to 1. This can explain the discontinuous decrease in retaking shown in Section 5, which is concentrated among students with lower baseline aspirations.

Now, consider the second type, who are uncertain about their ability type. These students will aim high if the expected value of retaking and aiming high ($E(V_2) = 1 + 5 \cdot \mathbf{1}_{s \geq 0} - e$) is higher than the expected values of the alternatives, or formally, $1 + 5 \cdot \mathbf{1}_{s \geq 0} - e > \mathbf{1}_{s \geq 0} = V_0$ and $1 + 5 \cdot \mathbf{1}_{s \geq 0} - e > 1 - c = V_1$. It follows that for students who are uncertain about their ability types, crossing the round score may induce a discontinuous increase in the probability of aiming higher (in non-trivial cases where $e - c < 5$), due to a boost to their perceived abilities, which increases the expected value of aiming higher. This can explain the discontinuous increase in the likelihood of applying to challenging and rewarding fields, shown in Section 5, which is concentrated among students with higher baseline aspirations.