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# Family background, education, and earnings: The limited value of "test-score transmission" * 

Naomi Friedman-Sokuler ${ }^{\dagger}$ and Moshe Justman ${ }^{\ddagger}$

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#### Abstract

Even the most egalitarian education systems employ high-stakes tests to regulate the transition from universal secondary education to selective academic programs that open doors to skilled, well-paid professions. This gives parents a strong incentive to invest substantial resources in improving their children's' achievement on these tests, thus reinforcing dynastic socioeconomic advantage through "test-score transmission". Using longitudinal administrative data to follow Israeli students in Hebrew-language schools from eighth grade to age 29, we provide evidence that despite Israeli schools being publicly financed and tuition-free, test-score transmission is very much prevalent. Second-generation (SG) students with more educated and affluent parents do much better on the screening tests that regulate access to the most selective tertiary academic programs than first-generation ( FG ) students with similar eighth-grade test score ranks. Yet this advantage does not manifest itself in earnings differentials at age 29, controlling for eighth grade achievement, which are statistically insignificant or even reversed. This is consistent with eighth-grade test scores reflecting individual human capital; SG parents investing in their children's test-taking abilities and improving their access to selective tertiary programs; and employers not valuing these skills and compensating employees according to their observed productivity. Both men and women exhibit these patterns.


Keywords: Intergenerational mobility; test-score transmission; human capital; parental education.

JEL Classification Numbers: I24, I26, J24, J62

[^2]
## 1 Introduction

Universal public education goes only so far in equalizing educational opportunity. Even the most egalitarian education systems restrict access to higher education through the use of high stakes tests that regulate admission to selective academic programs, which open doors to prestigious, well-paid professions, and it is at this point that highly educated, well informed and affluent parents have the motive, means and opportunity to invest substantial resources in improving their children's' access to opportunities through achievement on these tests (Lee and Suen, 2023). To the extent that these efforts are narrowly focused on improving test-taking skills, they add little to the stock of productive human capital. These findings are consistent with Rothstein (2019), who finds that the substantial geographical variation in "test-score transmission" across the United States-variation in the dynastic perpetuation of educational achievement-is only weakly correlated with observed variation in "income transmission"; and with the findings of Chetty et al. (2023), that high-SES children gain access to selective academic institutions based on characteristics that do not have strong predictive power vis-á-vis labor market outcomes. ${ }^{1}$ These patterns highlight the need for a better understanding of the nature and scope of test-score transmission and through it, the role of educational institutions in determining inter-generational mobility (Bukodi and Goldthorpe, 2018; Salvanes, 2023).

This paper investigates the relationship between test-score transmission on high-stakes screening tests and income transmission. We ask, what does test-score transmission actually achieve? To what extent does it afford socioeconomically advantaged students better access to selective tertiary academic programs, and subsequently, higher earnings in the labor market? To answer these questions, we track a representative cohort of Israeli men and women, from eighth grade to age 29, using parental education as the distinguishing socioeconomic feature, comparing the outcomes of "first-generation" (FG) students, neither of whose parents has more than 12 years of schooling, to

[^3]those of "second generation" (SG) students whose parents have at least some tertiary education. ${ }^{2}$ Israel's education system is an apt setting for this purpose, as nearly all elementary and secondary school students in Israel attend publicly financed, tuition-free schools, and virtually all the competitive, sought-after tertiary education programs are publicly provided and heavily subsidized. ${ }^{3}$ Consequently, high-stakes tests play a key role in regulating admissions to a limited number of places in these high-demand programs.

Identifying the role of test-score transmission in perpetuating socioeconomic gaps is complicated by the fact that test scores serve both as measures of human capital, which drives labor market productivity and earnings, and as social instruments that directly regulate access to educational opportunities at elite institutions and in selective disciplines, which generally lead to higher earnings. The relative importance of these two functions in determining actual socioeconomic gaps in achievement depends on the institutional features of testing schemes, specifically on the long term stakes attached to observed test scores. To disentangle these two functions we present a stylized conceptual model of the relationships between family background, human capital accumulation, test scores and earnings, and use it to interpret observational estimates of the evolution of socioeconomic gaps from eighth grade standardized test scores through end-of-high-school screening tests that regulate entry to tertiary education, to earnings around age 29. Our empirical approach takes advantage of differences in testing schemes at different stages of the educational pipeline in Israel, using rankings on eighth grade no-stakes tests to capture socioeconomic gaps in relative human capital accumulation as a baseline.

Our measure of baseline human capital is derived from a nationwide standardized testing scheme in fifth and eighth grade, Growth and Effectiveness Measures for Schools (GEMS). First

[^4]implemented in 2002 and 2003, when the students we observe attended eighth grade, it covered half of all (non-ultra-orthodox) schools in the country in each year. The stated goal of this scheme was to evaluate schools and not individual students, and so in the early years of its inception, neither students nor schools were informed of individual GEMS scores. ${ }^{4}$ For the purpose of our analysis, eighth grade is an opportune moment in the educational pipeline to measure human capital, as students have already accumulated substantial human capital but the screening tests that determine access to higher education are still several years down the road, so parents have little or no interest in artificially boosting their children's scores on these tests. We therefore use percentile ranks on GEMS mathematics tests as our ordinal measure of human capital, and find a substantial SG rank advantage, which we interpret as reflecting an SG advantage in human capital. It may be driven by differences in endowments, resources or direct parental investment in their children's education (for a review, see Mogstad and Torsvik (2023)).

First, we find that this advantage is amplified in the screening tests that regulate access to higher education: matriculation tests, the Israeli counterpart of the GCSE in the UK or Abitur in Germany, and the Psychometric Entrance Test (PET), the Israeli counterpart of the SAT in the US. The SG average advantage grows substnatially within each eighth grade achievement percentile, ranging from a 10 percentile ranks increase among top eight achievers to 23 percentiles among median eighth grade achievers, giving virtually all SG students a substantial advantage in admission to academic programs. However, the SG gains observed from eighth grade to the end of secondary education do not carry over to early labor market outcomes. We see little or no advantage for SG students in earnings at age 29 within eighth-grade percentiles. These general patterns apply to both men and women though a separate analysis by gender reveals an interesting mirror image: a weaker SG advantage among women in educational achievement; but a weaker SG advantage among men in earnings at age 29 conditioned on eighth-grade achievement. These findings suggest that while socioeconomic gaps in earning maybe at least partially driven by differences in the endowment and accumulation of human capital up to middle school, high school achievement gains as reflected in

[^5]achievement on high-stakes screening tests do not reflect underlying gains in skills that are valued in the labor market.

Second, we examine the relationship between SG gains in screening tests and access to selective tertiary education. To capture selectivity we sort the observed 157 programs, defined by institution type and specific field, into five levels of selectivity using a k-means algorithm over the levels of achievement in matriculation and PET of students in each program. Conditional on eighth grade achievement, SG students are 23 percentage points more likely to enter tertiary education; are at least twice as likely to study in university (the more selective type of institution); and are three times more likely to enter the most selective programs. If some of the greater success of SG students in gaining access to selective tertiary education can be attributed to superior test-taking skill, our conceptual framework predicts that, conditioned on admission to similarly selective tertiary education programs, FG students enter with higher level of human capital than SG students. Indeed, we find that in the selective clusters, conditional on eighth grade achievement, FG students exhibit higher earnings than SG students.

Additionally, we see that beyond the most selective cluster, which is associated with higher average earnings at age 29 , there is no clear relationship between selectivity and observed earnings. We also examine the hypothesis suggested by Leighton and Speer (2023) that due financial constraints, FG students favor majors with strong early-career returns, forgoing steeper earnings trajectories. However, using external data to characterize the earnings trajectories of different study fields, we do not find a relationship between expected earnings growth and the share of FG students in a study field, in our sample. Together, these patterns relate to research showing little to no returns to selectivity in tertiary education in the US context (Dale and Krueger, 2002; Mountjoy, 2022).

Our results beg the question, why do educated parents invest in their children's end-of-highschool achievement if it does not result in higher earnings? We explore one possible explanation, that guaranteeing access to selective tertiary programs conveys other non-pecuniary benefits, which educated parents enjoy and wish to pass on. We explores this hypothesis by estimating SG-FG gaps
with respect to study field and employer characteristics. To test this we cluster study fields by earnings, rather than selectivity, and find that the conditional SG-FG gap shrinks from 6.5 percentage points with respect to the most selective programs to 1.6 percentage points for programs characterized by highest earnings at age 29 . We also find that SG students are substantially more likely to choose public sector jobs, generally associated with lower earnings but better amenities. These patterns suggest that SG students are more inclined to forgo earnings for non-pecuniary advantages such as prestige, job security and access to policy making, reflecting some inter-generational persistence of class, defined not only by income levels but also by the characteristics of employment relations (Hérault and Kalb, 2013; Bukodi and Goldthorpe, 2018).

Understanding what screening tests do, and specifically the extent to which they reflect human capital accumulation vis-á-vis test-specific preparation, is crucial for designing policies that foster social mobility. To the extent that screening test scores are predominantly measures of human capital, socioeconomic gaps in test scores reflect productivity differences, which drive dynastic economic inequalities (Barrios Fernández et al., 2023; Markussen and Røed, 2023) implying a need to invest more in the education of FG children from an early age, in order to close gaps in human capital accumulation. However, to the extent that test scores are imperfect screening devices that can be manipulated by socially advantaged parents investing unproductively in their children's test-taking skills to perpetuate dynastic advantage (Fang and Noe, 2022; Lee and Suen, 2023; Posso et al., 2023), this suggests a need to re-examine the screening systems that regulate access to higher education. Our findings indicate that the naïve view of high stakes test scores as merely a noisy but reliable indicator of human capital, overlooks the fact that they already embody socioeconomic disparities that allow more educated parents with greater resources to secure advantages for their children beyond their children's actual skills and abilities. Helping lower-ability students from wealthier families crowd out less advantaged higher-ability students from the competitive degree programs that potentially lead to the jobs for which they are better suited, is also likely to have an adverse impact on efficiency (Hoxby and Avery, 2013; Fang and Noe, 2022; Black et al., 2023; Chetty et al., 2023).

The structure of the paper is as follows. Section 2 describes our conceptual framework and estimation strategy, and sets out our main hypotheses. Section 3 describes our data. Section 4 presents estimates of raw and conditional gaps in test scores and earnings between FG and SG rankings, from age 14 to age 29. Section 5 further explores gaps in tertiary admissions to different study fields, and in associated earnings, and considers suggestive evidence on alternative hypotheses for the patterns we observe. Section 6 concludes.

## 2 Conceptual framework and empirical strategy

To motivate our empirical analysis, we set out our main hypotheses within a simple formal framework that illustrates the relationships between ability, socio-economic background, human capital, test scores, and earnings.

Consider an economy with a continuum of households indexed by $i$, each comprising a parent and child. Households are characterized by the unobserved innate ability of the child, $a_{i}$, and by their parents' income and education. A proportion $\theta$ of these households are "first-generation" (FG) households in which the parent has no post-secondary education, and the rest are "second generation" (SG) households, with SG parents also having higher incomes than FG parents. To simplify the analysis, we assume that parents are uniform within each group and denote the two groups by $g=f$, $s$. We assume that FG and SG children's innate abilities are sampled from the same distribution, but that differences in parental education and income lead SG parents to invest more in their children's education than FG parents at each stage, as we elaborate below.

There are three levels of education in the model. In the first stage, all children are enrolled in a basic tier of free, uniform, compulsory primary education, from which they emerge with a basic level of human capital. It is a function of individual innate ability $a_{i}$, which is similarly distributed among FG and SG children; uniform public spending per pupil in compulsory education, $c_{1}$; and parents' private investment in their children's basic education, $p_{g 1}$, which we assume is higher for

SG parents, $p_{f 1}<p_{s 1}$. To fix ideas, we write, for the human capital of child $i$ in group $g$ at the end of stage 1 :

$$
\begin{equation*}
h_{i g 1}=a_{i}+c_{1}+p_{g 1} \tag{1}
\end{equation*}
$$

Human capital is not directly observed but students take standardized "no-stakes" tests at the end of period 1, yielding ordinal test scores that stochastically reflect their human capital. Test rankings, $R_{i g 1}$, are an increasing function of a child's human capital stock, $h_{i g 1}$, and of factors affecting test scores that are orthogonal to the child's' human capital, $\epsilon_{i 1}$ :

$$
\begin{equation*}
R_{i g 1}=f_{1}\left(h_{i g 1}, \epsilon_{i 1}\right) \tag{2}
\end{equation*}
$$

In the second stage, students participate in compulsory secondary education, which prepares them for an advanced tier of optional tertiary education that leads to occupation-specific accreditation. As the fixed measure of places in tertiary education, $\phi<1$, is less than the full measure of students, entry is contingent on performance on a high-stakes screening test taken at the end of secondary education, with the top $\phi$ scores gaining entry. In this second stage, students benefit from uniform public investment in their human capital $c_{2}$, and from additional private investment, which takes two forms: further investment in their human capital, $p_{g 2}$, and investment in their testtaking skills, $m_{g}$. We assume again that private investment is uniform within student type, with SG parents investing more than FG parents, $p_{s 2}>p_{f 2}$ and $m_{s}>m_{f}$. Students' end of period human capital is then:

$$
\begin{equation*}
h_{i g 2}=h_{i g 1}+c_{2}+p_{g 2} \tag{3}
\end{equation*}
$$

Their ranking on the screening tests that determines entry to tertiary education is a function of their human capital, $h_{i g 2}$, of their test-taking skills, $m_{g}$, and of test-specific measurement error $\epsilon_{i 2}$ :

$$
\begin{equation*}
R_{i g 2}=f_{2}\left(h_{i g 2}, m_{g}, \epsilon_{i 2}\right) \tag{4}
\end{equation*}
$$

In the third stage, the top $\phi$ share of students on the screening test are admitted to tertiary education. We assume there is only one tertiary education program and denote admission to tertiary education by $j(j=0,1) .{ }^{5}$ We assume that all who are admitted to tertiary education choose to attend, successfully graduate, and go on to work in better-paying jobs that require an academic degrees, while those without a tertiary degree work in non-academic occupations that pay less. ${ }^{6}$ Labor market earnings of an individual $i$ in group $g$ with tertiary education $j$ are then a function of their human capital at the end of secondary education, $h_{i g 2}$, further occupation-specific human capital obtained in tertiary education, $k_{j}$, where $k_{1}>0=k_{0}$, and a stochastic error term $\epsilon_{i j}^{w}$ :

$$
\begin{equation*}
w_{i g j}=h_{i g 2}+k_{j}+\epsilon_{i j}^{w} \tag{5}
\end{equation*}
$$

We apply this model empirically to gauge the extent of test-score transmission in post-primary education and its impact on earnings. We use ranks in no-stakes eighth-grade mathematics tests as a baseline measure of human capital, our empirical counterpart of $R_{i g 1}$. We expect SG students to have, on average, higher levels of human capital than FG students, and hence higher scores, because of differences in private investment from early childhood. We then estimate the difference between FG and SG students in their rankings on two high-stakes screening tests-high school matriculation tests in mathematics and the mathematical component of the Psychometric Entrance Test (PET)—and compare it to the difference in their earnings ranks, $R\left(w_{i g j}\right)$, both conditioned on students' eighth-grade ranks. Thus, we first estimate equation 6, separately regressing high school matriculation and PET ranks on eighth-grade ranks and an SG indicator ; then estimate equation 7 , regressing earnings ranks on eighth-grade ranks and an SG indicator; and compare $\delta_{2}$ to $\delta_{w}$.

$$
\begin{equation*}
R_{i g 2}=\beta_{02}+\beta_{12} R_{i g 1}+\delta_{2} S G+\epsilon_{i 1}^{s} \tag{6}
\end{equation*}
$$

[^6]\[

$$
\begin{equation*}
R\left(w_{i g j}\right)=\beta_{0 w}+\beta_{1 w} R_{i g 1}+\delta_{w} S G+\epsilon_{i 1}^{w} \tag{7}
\end{equation*}
$$

\]

We posit several testable hypotheses within this conceptual framework. The first of these is that SG students' advantage on eighth-grade tests is amplified on high-stakes tests by their parents' greater investment in their human capital and test-taking skills, so that SG students achieve stochastically higher scores on matriculation and PET tests than FG students with similar eighth grade scores:

Hypothesis 1. $\delta_{2}>0$
This leads automatically to a higher share of SG students admitted to selective degree programs than FG students with similar eighth-grade test-ranks. However, to the extent that some of this advantage is due to SG parents investing more than FG parents not only in human capital but also in test-taking skills-skills not valued in themselves in the labor market-the conditional advantage of SG students in tertiary admissions should not carry over fully to the labor market. The advantage in earnings rankings of SG students over FG students with similar eighth-grade scores should be less pronounced than their similarly conditioned advantage in matriculation or PET rankings. This is our second hypothesis:

Hypothesis 2. $\delta_{2}>\delta_{w}$
Finally, if some of the greater success of SG students in gaining access to selective tertiary education can be attributed to superior test-taking skills, it follows that comparing FG and SG students with the same screening test scores, and ignoring measurement error, the FG student should have a higher level of human capital, and therefore higher earnings in the labor market. As selective tertiary education programs admit a range of screening scores, and employers take time to discover the true measure of an employee's human capital, we posit the weaker hypothesis, that conditioned on admission to similarly selective tertiary education programs, FG students earn more than SG students with the same stage 1 test rank, $R_{i g 1}$ :

Hypothesis 3. $E\left(w_{i s j} \mid R_{i s 1}=R, k_{j}=1\right)<E\left(w_{i f j} \mid R_{i f 1}=R, k_{j}=1\right)$

## 3 Construction of the data set and descriptive statistics

We form a representative cohort of all Hebrew-language, non-ultra-orthodox students in Israel's public education system from two half cohorts of eighth grade students (aged 13-14), in 2001/2 and $2002 / 3$, and follow them, respectively, to 2017 and 2018, when they are about 29 years old and the large majority will have accumulated a few years of experience in the labor market. We draw data from several administrative data sets, merged for our study by Israel's Central Bureau of Statistics (ICBS) using national identity numbers: the population registry; the Ministry of Education's registry of student enrollment, and its eighth-grade and matriculation test-score records; the ICBS registry of higher education; the National Institute for Testing and Evaluation (NITE) PET database; and the Tax Authority database.

### 3.1 Baseline human capital

Our measure of baseline human capital is the student's score on the mathematics section of the Growth and Effectiveness Measures for Schools (GEMS) tests-a standardized eighth grade "nostakes" testing scheme. Schools are not informed of students' individual scores on these tests. Hence they cannot be used for screening, and the screening tests that determine access to higher education are still several years down the road, so parents have no incentive to invest in their children's test-taking skills for this test. This is supported by data from the ICBS Social Survey for 2007, which asked households whether they used additional private educational resources such as tutoring or preparatory courses. Table A1 in the appendix shows that use of such resources is more than twice as frequent in secondary school as in primary school, and increases markedly with parents' education and family income.

In 2001 all schools in Israel with an eighth grade, except most ultra-orthodox schools, were split into two balanced samples of equal size, with half the schools participating in GEMS tests in 2001/2 and the other half in 2002/3. ${ }^{7}$ Pooling these two half cohorts together yields a representative

[^7]cohort of 76,054 students attending schools in which GEMS tests were administered, reflecting the entire population of non-ultra-orthodox Hebrew language schools in Israel. ${ }^{8}$ GEMS comprises four tests: mathematics, literacy (Hebrew), English, and science and technology, taken on different days over a two-week period. Just over 15 percent of test-takers missed at least one of these tests, and 14 percent missed the mathematics test (Appendix Table A2).

Students' ranks on the GEMS mathematics test serve as our measure of their baseline human capital. We chose the mathematics component as our measure, as all three tests we observe include a mathematics section, mathematics shows the strongest correlation across the three outcomes, and mathematics scores are key selection criteria for the more selective tertiary programs. We restrict the data set to students with at least two GEMS scores, and impute missing mathematics scores by regressing the mathematics score on the other scores and on all available background characteristics for students with all scores. Comparing the students with two GEMS scores, in column (2) of Table 1 , to the entire population in column (1), we see that they are very similar in terms of parental education, family income, retention to twelfth-grade and high school matriculation. ${ }^{9}$ Among students with at least two GEMS scores, missing a mathematics score is uncorrelated with other observed student characteristics, and individuals are as likely to miss the mathematics test as any of the other subjects.

### 3.2 Socioeconomic background

The two indicators we use to characterize students socioeconomic status are their parents' selfreported years of education and their family income quintile, calculated from tax records when the child is in eighth grade. We are able to calculate income quintiles for all children in our sample, but for a small fraction of these children we do not have information on either parent's

[^8]years of schooling. In column (3) of Table 1 we keep only students for whom we have information on years of schooling for at least one parent, and define parents' education as the greater of the parents' reported years of schooling. This removes 5 percent of the sample but has little impact on the distribution of family income, suggesting that missing information on both parents' schooling levels is not substantially correlated with socio-economic status.

We define students as "first-generation" (FG) if neither parent has more than 12 years of schooling, and find that half of the students for whom we have SES data are FG. The other half are students with at least one parent with more than 12 years of schooling. We want to focus on comparing families with and without the experience of a college education, but observe only years of parents' schooling, not the nature of their post-secondary education. To sharpen the comparison, we define a "second-generation" (SG) student as a student with at least one parent with more than 12 years of schooling and whose family income is in the top two income quintiles. We drop from our analysis the remaining third of non-FG students whose parents have some post-secondary education but whose family income is in the bottom three quintiles.

We follow these students through their secondary and tertiary education and track their employment and earnings from the end of secondary school to 2018. In column (4) we drop a further $10 \%$ of our sample who do not appear in the tax records in 2017 or 2018, when they are around age 29. Appendix Table A3 estimates the probability of appearing in the tax registry in either 2017 or 2018. We find less than a one percent difference in the probability of appearing in the tax registry between FG and SG students, and even this difference disappears when we condition on attending twelfth grade. Moreover, conditional on attending twelfth grade we find no relationship between a students' GEMS score percentile and their appearing in the tax records. These findings indicate that individuals not appearing in earnings records are not necessarily unemployed. They are more likely to be absent for other reasons: they may have moved abroad, continue full-time studies, or are prevented from working due to disability. We therefore drop individuals who do not appear in the tax registry in either of these years from the sample rather than including them with zero earnings, leaving us with a final sample of 44,316.

### 3.3 Descriptive statistics

The right hand panel of Table 1 presents descriptive statistics comparing FG and SG students in our sample on baseline measures and outcomes of interest. The share of women among FG students is slightly higher than among SG students, presumably reflecting the greater vulnerability of male children to socioeconomic disadvantage in education The greater share of immigrants among FG students reflects migration patterns to Israel in the relevant years. On average, parents of FG students have 11.36 years of education, indicating that most FG students have at least on parent with a full high school education. SG parents have an average of 16.5 years of schooling, where 15 or 16 years are typically needed to obtain an undergraduate degree; 36 percent of FG students come from families in the top two income quintiles.

Following these students through the educational pipeline we see already in the eighth-grade, a gap of 18 percentile points between the median ranks of FG and SG students on the GEMS mathematics test. Two sets of optional tests then serve to screen applicants to tertiary education: matriculation tests taken during high school grades 10 to 12 ; and the Psychometric Entrance Test (PET; the Israeli counterpart of the SAT) usually taken a few years later. Matriculation is a precondition for most tertiary programs, and the PET is required for all the more selective programs. From these we take the mathematics matriculation test scores (a passing score in mathematics is required for matriculation), and the quantitative analysis score from the PET. Mathematics matriculation exams are administered at different levels of difficulty and we adjust scores to account for this, using the bonus system applied in tertiary applications. Table 1 shows that 83 percent of FG students sit for the mathematics matriculation test, and SG students are 12 percentage points more likely to do so. This gap increases with respect to the PET, which SG students are almost twice as likely to take. This has direct implications for participation in tertiary education. While SG students are only 6 percent more likely to attend twelfth grade than FG students, they are almost twice as likely to enroll in tertiary education, and three time more likely to enroll in a university program. SG students' earnings are 10.5 percent higher at the median and 17.4 percent higher at the mean than FG students.

Our empirical analysis aims to compare the advantage of SG students on high-stakes tests to their advantage in labor market earnings, both conditioned on eight-grade achievement. The challenge in comparing gaps across these different domains is that the three types of tests are not vertically aligned in terms of content matter, do not use the same scales for scoring, and have no such interval scales. Matriculation and PET scores especially are used primarily as ordinal indicators, to rank students applying to selective tertiary programs. ${ }^{10}$ We therefore convert all test scores and earnings to percentile ranks within the distribution of our eighth-grade population, assigning students without matriculation or PET scores a score of 0 , which places them at the bottom of our matriculation or PET distribution, as they are regarded for actual admission purposes. Figure A1 in the appendix compares the cumulative distribution functions of FG and SG student ranks' with regard to our main variables of interest-the mathematics component of GEMS, matriculation and PET, and earnings at age 29-highlighting the SG advantage at each stage. In the following section we compare the conditional gaps.

## 4 The evolution of FG-SG gaps in achievement and earnings

Figure 1 presents a non-parametric graphical analysis of the evolution of the gap between first and second generation students from the end of high school to the labor market at age 29, conditioned on eighth grade achievement ranks. Each dot represents the mean or median outcome percentile-in matriculation mathematics, PET mathematics, and earnings-within each GEMS mathematics percentile, with students without a matriculation or PET score assigned a score of zero and ranked at the bottom of the distribution. The top panel of Figure 1 shows that the SG advantage in achievement substantially increases during high school, throughout the distribution of early achievement. The SG advantage in matriculation is greatest at the GEMS median. The difference at the GEMS median between the median FG and SG matriculation ranks is 16 per-

[^9]centile points and the difference in their means is 14.3 percentile points. The middle panel of Figure 1 presents the same analysis for PET numeracy rankings, and shows a yet greater SG advantage. The difference at the GEMS median between the median FG and SG PET ranks is 69.7 percentile points and the difference in their means is 23.1 percentile points. The much larger difference in conditional PET medians at the GEMS median is a result of a majority of FG students at the GEMS median not taking the PET. These findings strongly support our Hypothesis 1, that SG students achieve stochastically higher scores on matriculation and PET tests than FG students with similar eighth grade scores.

Columns (1) in the left panel of Table 2 present estimates of the raw and conditional SGFG gaps in screening test ranks, obtained from regressions of individual matriculation and PET percentiles on an SG indicator and controls for cohort, gender, immigrant status and relative age within cohort, with and without a second-order polynomial in eighth-grade mathematics ranks. On average, SG students rank 22.9 percentile points above FG students on matriculation mathematics tests and 30.8 percentile points above them on PET numeracy tests. Strikingly, The FG-SG gaps are much greater than either the gender gap or the gap between immigrants and natives; and it is larger for PET numeracy than for matriculation mathematics while the other gaps are significantly smaller. Columns (2) estimate the conditional SG-FG gaps on these high-stakes tests, conditioned on eighth grade mathematics GEMS ranks, quantifying the average growth in the SG-FG gaps shown in Figure 1. Overall, GEMS ranks are highly predictive of future achievement ranks, but differences in early achievement account for less than half of the SG-FG gap in matriculation ranks and just over a third of the gap in PET ranks. ${ }^{11}$ The remaining gaps- 12.7 percentile points in matriculation, 19.5 in PET—give SG students a substantial advantage in access to selective tertiary education programs, which we discuss in section 5 .

In contrast to the large, highly significant gaps in achievement, the SG advantage in earnings ranks at age 29 is much smaller, and the conditional earnings gaps are not statistically significant.

[^10]The bottom panel of Figure 1 shows that the relative gains of SG students on the matriculation and PET screening tests do not translate into significantly higher earnings at age 29, within eighthgrade GEMS mathematics percentiles. The gap between SG and FG students in median earnings percentiles at the GEMS median, where it is largest, is 2.3 percentile points; and the largest gap in mean earnings percentiles, also at the GEMS median, is 1.4 percentile points. This is further supported by the regressions reported in the right-hand panel of Table 2 where we estimate SGFG gaps in earnings percentiles and log earnings. Columns (1) present estimates of raw SG-FG earnings gaps at age 29 conditioned only on cohort, gender, immigration and relative age within cohort; columns (2) show the conditional gaps, conditioned on students' GEMS mathematics percentiles. In raw gaps, there is a moderate SG advantage of 3.6 percentile points, much smaller than the raw gaps in matriculation and PET rankings, which corresponds to a 6.9 percent advantage in relative earnings. Moreover, when we control for eighth-grade GEMS mathematics percentiles, in columns (2) of the right-hand panel, we find that the conditional gaps are not significantly different from zero-indicating that socioeconomic difference in earnings are largely explained by differences in human capital accumulated early in life. This stands in contrast to the estimated gender and immigration gaps which remain unchanged when conditioning on early achievement. This is consistent with our Hypothesis 2, that the gains in the SG advantage on the screening tests that regulate admissions to higher education reflect investment in skills that improve test outcomes but have little impact on labor market earnings at age 29.

## SG-FG gaps and gender

While the SG-FG gaps in matriculation and PET ranks are much larger than the corresponding gender gaps, the gender gaps in earnings, shown in Table 2 are three times larger than the corresponding SG-FG gaps. This is consistent with well-established findings on both points. Young men suffer more from socio-economic disadvantage, in terms of educational achievement, than young women (DiPrete and Jennings, 2012; Friedman-Sokuler and Justman, 2016; Autor et al., 2019; Sikhova, 2023); and though women have surpassed men in many aspects of education achieve-
ment, this has not closed the gender earnings gap, and many high-paying occupations, both white and blue collar, remained largely segregated by gender (Goldin et al., 2006; Blau and Kahn, 2017). This leads us to ask whether there are gender differences in the general patterns of test-score transmission described above.

Figure 2 shows the FG-SG percentile gaps in mean matriculation, PET and earnings ranks, conditioned on eighth-grade GEMS mathematics percentile, separately by gender. In line with Figure 1, the conditioned SG advantage on screening tests, represented by the darker lines, is large for both men and women, much larger than any SG advantage in earnings percentiles at age 29 . However, while we see no SG advantage in earnings among men, and at some points even a slight FG advantage, there is a small but persistent SG advantage in earnings ranks of 2 to 3 percentile points among women, conditioned on GEMS percentiles, despite the smaller disadvantage of FG women in matriculation and PET rankings. This FG disadvantage in earnings disappears at the very top of the GEMS distribution.

## 5 Why does test-score transmission not translate into higher earnings?

In this section we explore several possible explanations for why SG students' clear advantage in the screening tests that regulate admissions to higher education, conditioned on eighth-grade achievement, do not translate into an advantage in earnings at age 29 , similarly conditioned. They are not mutually exclusive. Our preferred explanation, corresponding to Hypotheses 2 and 3 of our conceptual model, is that SG students' enhanced performance on screening tests might get them through the door, but when employers discover the true abilities of their employees, they adjust their pay accordingly. One alternative explanation, which we explore below, is that SG students can better afford to choose study fields with a more lucrative but steeper earnings curve, forgoing some current earnings in favor of greater future gains. Another possible explanation that we consider is that SG students are more likely to trade off some lifetime earnings for non-pecuniary advantages
such as social status, more interesting or satisfying work, or less demanding working conditions. To explore these explanations in greater detail, we take a closer look at how test score transmission actually affects access to different types of tertiary academic programs.

### 5.1 The impact of test-score transmission on access to selective tertiary academic programs

Parents' private investment in improving their children's performance on PET and matriculation tests are aimed directly at improving their chances of gaining admission to selective tertiary programs that lead to better paying jobs. We show just how successful these efforts are. Tertiary academic programs in Israel vary in selectivity by both study field and type of institution-"university" or "college"-with cutoff matriculation and PET scores determined ex-post by supply and demand. ${ }^{12}$ To characterize program selectivity ex post, we use the universe of all students from the two cohorts who enrolled in tertiary education to generate four clusters of tertiary programs, characterized by study field and type of institution, using a k-means procedure to minimize distance in students' matriculation and PET ranks within clusters and maximize the distance between clusters. A fifth cluster comprises tertiary programs that do not require a PET score, ${ }^{13}$ and a sixth comprises individuals without tertiary education. The list of programs in each category is presented in Table A5 in the appendix.

Table 3 presents descriptive statistics. The most selective cluster comprises only university programs while the two least selective clusters are overwhelmingly college programs. FG students are under-represented in all tertiary clusters, their share decreasing as cluster selectivity increases. Thus, while the share of FG students in the full sample is 60 percent, their share in the most selective cluster is only 20 percent. Women are over-represented in the middle clusters and under-

[^11]represented in the most selective cluster and in the cluster with no tertiary education. The level of selectivity is positively correlated with eighth-grade GEMS mathematics achievement; and by construction, with matriculation and PET achievement. We find positive SG-FG achievement gaps within each cluster, with a larger SG advantage in matriculation and PET ranks than in GEMS.

The relationship between the selectivity of the academic program and earnings at age 29 is uneven. Students in the most selective cluster have 40 to 50 percent higher average and median earnings at age 29 than students in clusters 3, 4 and 5, which are similar to each other in earnings levels, while the two lowest-ranked clusters-non-selective programs and no tertiary education--have 13 to 17 percent lower earnings. Work experience declines with cluster selectivity, which may explain the similar average earnings of clusters 3 and 5, despite the large difference in selectivity between them: students in cluster 3 have an extra 13 months of work experience at age 29.

The success of SG parents in boosting their children's access to tertiary programs is illustrated graphically in Figure 3, which shows the conditional share of FG and SG students in each of our six tertiary education clusters, by GEMS mathematics percentiles. The differences between SG and FG students in enrollment shares, conditioned on eighth-grade achievement, are striking. Thus, nearly 70 percent of SG students at the 25 th GEMS percentile, enroll in some tertiary program while FG students reach the same enrolment share only at the 75th GEMS percentile; and where 40 percent of SG students in the top GEMS decile enroll in a highly selective cluster 6 tertiary program, only a quarter of FG students in the top GEMS decile enroll in a cluster 6 program.

Table 4 presents estimates of two regressions for each of three levels of access to tertiary education: enrolment in any tertiary program, enrolment in a university program, and enrolment in a university program in the most selective cluster. The regressions follow the same specifications as our previous estimations. Columns (1) show the large unconditional gaps favoring SG students, corresponding to the SG and FG tertiary and university shares in Table 1 and the top cluster share in Table 3. SG students are almost twice as likely as FG students to enroll in tertiary education, and four times as likely to gain admission to the most selective cluster. Adding eighth-grade GEMS
ranks in columns (2) reduces the unconditional gaps by about half but the SG advantage remains very large and highly significant in all three cases, highlighting the effectiveness of improving performance on the matriculation and PET screening tests in gaining better access to academic programs.

Table 5 presents regression results on the earnings difference between FG and SG students within each selectivity cluster, conditioned on GEMS percentiles, corresponding to the similarly conditioned enrollment regressions reported in columns (2) of Table 4. The results are consistent with our Hypothesis 3, that FG students have higher earnings than SG students within each selectivity cluster, conditioned on eighth grade achievement ranks. Thus, the earnings of FG students in cluster 6 , the most selective cluster of academic programs, are 8.1 percent higher, on average, than the earnings of SG students in cluster 6 , and rank 2.6 percentile points higher. This is consistent with matriculation and psychometric test scores overstating the difference in human capital between FG and SG students, and employers recognizing this and adjusting their employees' pay accordingly, as they learn more about their actual productivity.

### 5.2 Earnings slopes and non-pecuniary benefits

There are other possible explanations why this substantial SG advantage in access to selective higher education programs, conditioned on eighth-grade achievement, does not lead to a significant advantage in similarly conditioned earnings at age 29. One explanation follows from the work of Trejo (2016) and Leighton and Speer (2023), who show that parental education is an important factor in determining students' choice of a college major, and leads FG students to favor majors with strong early-career returns. This suggests that if we go back and look at these students' earnings when they are a few years older, we may see a significant SG advantage in conditional earnings. To sense how likely this may be, we use current data on the evolution of average earnings by study field to determine whether FG students in Israel choose study fields that lead to
occupations with flatter earnings trajectories. These can be thought of as approximating the future earnings that the students in our study anticipate in choosing their study fields ${ }^{14}$

In Figure 4 we examine the relationship between the share of FG students in a study field, on the horizontal axis; and, on the vertical axis, percentage growth in the average earnings of its graduates from the first two years after their graduation and years 9 to 10 . Each circle represents a study field, its size corresponding to the number of students in the field in our sample. We see no evidence that FG students are concentrated in study fields characterized by a slower growth rate in earnings.

Figure 5 compares the conditional average earnings of FG and SG students, shown in the lower left hand panel of Figure 1, and reproduced here in panel (a) for students who attended tertiary education, to a similarly conditioned graph, shown in panel (b), which replaces actual earnings observed at age 29 with the average earnings of of all graduates in the study field 9 to 10 years after graduation, drawn from the Avodata database. ${ }^{15}$ Comparing the two panels, we find the very small conditional SG advantage, in panel (a), actually reversed in panel (b). This, too, does not support the hypothesis that SG students in our sample chose study fields with a steeper earnings trajectory.

Another possible explanation is that FG students, having less financial support from their parents, are less inclined to trade off higher (lifetime) earnings for non-pecuniary benefits such as social status, job satisfaction, or better working conditions. To test this, we sort tertiary programs in our sample by earnings at age 29 (rather than by academic selectivity), again using a k-means algorithm, and focus on the top cluster. The two left-hand columns of Table 6 show estimates of the raw and conditioned SG-FG gaps in the share studying in programs associated with highest earnings at age 29. Comparing them to the two rightmost columns of Table 4, we find that while we still see an SG advantage in both unconditional and conditional gaps-SG students are more

[^12]likely to enroll in programs in the highest earnings clusters-these gaps are much smaller than the SG-FG gap in enrolling in the most selective academic cluster. This is consistent with FG students being less inclined than SG students to trade off higher earnings for non-pecuniary benefits.

The right-hand panel of Table 6 estimates raw and conditional SG-FG gaps in public sector employment at age 29. Public sector jobs in Israel as in many other countries are associated with lower pay but are often less stressful in terms of job security, offer shorter hours and more generous leave, as well as the satisfaction of public service, and possibly public exposure, influence and prestige. We find that SG students are over 7 percentage points more likely to be employed in the public sector than FG students. Interestingly, conditioning on eighth grade achievement makes no difference in this case. Again, this is consistent with FG students being less inclined to trade off higher earnings for non-pecuniary benefits.

## 6 Conclusion

Using longitudinal administrative data to follow Israeli students in Hebrew-language, non-ultraorthodox schools from eighth grade to age 29, we provide evidence that despite Israeli schools being publicly financed and tuition-free, test-score transmission is very much prevalent. Secondgeneration (SG) students with more educated and affluent parents do much better on the screening tests that regulate access to the most selective tertiary academic programs than first-generation (FG) students with similar eighth-grade standardized test scores, and this does indeed afford them better access to these programs. Yet this advantage does not manifest itself in earnings differentials at age 29, conditional on eighth-grade achievement, which are statistically insignificant or even reversed.

Testing hypotheses derived from our conceptual model supports our preferred explanation for these findings, that SG students' enhanced performance on these tests gets them into more selective tertiary programs compared to FG students, but any advantage they gain is short-lived. By age 29, their actual productivity is revealed and employers adjust their pay accordingly. Two features of the

Israeli setting seem to be conducive to the ability of FG students to "make up" for their initial lower signals: occupational choice is not strongly constrained by selectivity-most occupational study fields are offered by various intuitions with different levels of selectivity-and with the exception of the most selective programs, we do not observe in our data a strong association between study field average earnings and selectivity. Our empirical findings of a disconnect between achievement gains and earnings are consistent with recent theoretical analyses by Fang and Noe (2022) and Lee and Suen (2023), showing that in the presence of strategic contestants, seemingly meritocratic competitive mechanisms, such as selection determined by high-stakes screening tests, do not result in meritocratic selection. All of this highlights the need to re-examine the screening systems that regulate access to higher education, to ensure that educational institutions do not merely reproduce existing societal inequalities.

Finally, we note that our findings do not exclude the possibility of inter-generational test-score transmission conveying other kinds of benefits not captured by earnings. In their review of the research on the determinants of study field choices, Zafar et al. (2021) highlight the importance of job amenities and family domains in determining college major choice. We found some evidence that SG students are more likely to forgo earnings for non-pecuniary advantages-they are substantially over-represented in selective study fields but much less so in fields associated with higher earnings and are more likely to choose public-sector employment. In light of the growing importance of job amenities such as life-work balance, these findings highlight the importance of examining the non-income dimensions of inter-generational mobility as discussed by Bukodi and Goldthorpe (2018) in the sociological literature.

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Figure 1: Achievement percentiles conditional on GEMS percentiles, FG and SG students


Notes: Dots indicate mean or median matriculation, PET and earnings percentiles within one-percent bins of eighth grade scores on standardized (GEMS) mathematics tests, separately for FG and SG students. Numbers indicate SG advantage in percentile points at the 50th, 75 th and 90 th GEMS percentiles. Solid lines generated by locally weighted smoothing.

Figure 2: SG-FG gaps in matriculation, PET, and earnings percentiles, by gender


Notes: Solid lines generated by locally weighted smoothing of SG-FG average achievement percentiles within onepercent bins of eighth grade percentiles on standardized (GEMS) mathematics tests, separately for male and female students.

Figure 3: Share of FG and SG students in selectivity clusters by GEMS percentiles


Notes: Tertiary academic programs clustered by selectivity on matriculation and psychometric scores using ak-means procedure to minimizes distance in students' matriculation and psychometric scores within clusters and maximize the distance between clusters. Cluster 6 includes the most selective programs, cluster 2 the least selective, and cluster 1 those not enrolled in a tertiary academic program. Shares calculated for each GEMS percentile and smoothed using a locally weighted regression.

Figure 4: FG share and expected earnings growth, by study field


Notes: Circles indicate study fields. Their size is proportional to the number of students in the study-field in our sample. The horizontal axis shows the share of FG students in each study field. The vertical axis shows the percentage growth in average earnings of study-field graduates between the first two years and years 9 and 10 after graduation. The vertical line marks the share of FG students among all individuals attending tertiary programs in our sample. Earnings data by study-field drawn from the Avodata data base.

Figure 5: Expected earnings 10 years after graduation, by study field


Notes: $N=23,037$ comprising the 24,933 students in our sample who enrolled in tertiary education, less 1,897 students who chose study fields too small to be included in the "Avodata" database. Panel (a) replicates the lower left hand panel of Figure 1 for this sub-sample, showing mean earnings percentiles at age 29 within one-percent bins of eighth-grade GEMS mathematics scores, separately for FG and SG students. Panel (b) redraws the graph in panel (a), replacing actual earnings at age 29 with the average earnings of all study field graduates 9 to 10 years after graduation, retrieved from the "Avodata" database. Numbers indicate SG advantage in percentile points at the 50th, 75th and 90th GEMS percentiles (negative numbers indicate an SG disadvantage). Solid lines generated by locally weighted smoothing.

Table 1: Sample construction

|  | Population GEMS schools | GEMS test takers |  | Final sample with wage data |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | All | SES data | All | FG | SG |
| Female share | 0.49 | 0.50 | 0.50 | 0.52 | 0.53 | 0.50 |
| Immigrant share | 0.21 | 0.19 | 0.19 | 0.19 | 0.16 | 0.13 |
| Parents' years of schooling | 13.7 | 13.8 | 13.8 | 13.8 | 11.36 | 16.50 |
| Family income quintile |  |  |  |  |  |  |
| Lowest |  | 0.12 | 0.12 | 0.11 | 0.16 | - |
| 2nd |  | 0.17 | 0.17 | 0.17 | 0.23 | - |
| 3 rd |  | 0.21 | 0.21 | 0.21 | 0.25 | - |
| 4th |  | 0.24 | 0.24 | 0.25 | 0.24 | 0.39 |
| Highest |  | 0.26 | 0.26 | 0.26 | 0.12 | 0.61 |
| GEMS mathematics, percentiles | - | 54.3 | 54.5 | 54.6 | 46.71 | 64.87 |
| Attrition - appears in: |  |  |  |  |  |  |
| Twelfth grade registration (2006-7) | 0.90 | 0.93 | 0.93 | 0.94 | 0.92 | 0.98 |
| Matriculation mathematics, test takers | 0.81 | 0.86 | 0.87 | 0.88 | 0.83 | 0.95 |
| PET quantitative, test takers |  | 0.49 | 0.49 | 0.52 | 0.37 | 0.72 |
| Studied in tertiary education |  | 0.53 | 0.54 | 0.57 | 0.42 | 0.78 |
| Studied in university |  | 0.22 | 0.23 | 0.23 | 0.13 | 0.38 |
| Tax authority records (2017-18) | - | 0.86 | 0.86 | 1.00 | 1.00 | 1.00 |
| Median wage, age 29 |  |  |  | 7,947 | 7,678 | 8,487 |
| Mean wage, age 29 |  |  |  | 9,341 | 8,743 | 10,263 |
| Share of population | 1.000 | 0.858 | 0.814 | 0.703 | 0.352 | 0.231 |
| Observations | 76,054 | 65,222 | 61,926 | 53,489 | 26,761 | 17,555 |

Notes: Population comprises all students attending eighth grade in Hebrew-language schools in the year a school participated in GEMS (2001/2 or 2002/3). Parental education is the years of schooling of the parent with the most education. Family income quintiles are calculated using tax records of parents' income when students were in eighth grade. FG students are students neither of whose parents has more than 12 years of schooling; SG students are students with at least one parent with more than 12 years of schooling and whose family income is in the top two quintiles. Attainment shares and group mean test percentiles are calculated with respect to the entire study sample, including non-test takers.

Table 2: Regressions of matriculation, PET percentiles, and earnings on GEMS percentiles

|  | Mathematics percentiles |  |  |  | Earnings at age 29 |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Matriculation |  | PET |  | Percentiles |  | Ln(wage) |  |
|  | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| SG | $\begin{aligned} & 22.917 \\ & (0.262) \end{aligned}$ | $\begin{aligned} & 12.687 \\ & (0.239) \end{aligned}$ | $\begin{aligned} & 30.801 \\ & (0.366) \end{aligned}$ | $\begin{aligned} & 19.536 \\ & (0.367) \end{aligned}$ | $\begin{gathered} 3.598 \\ (0.282) \end{gathered}$ | $\begin{gathered} 0.123 \\ (0.292) \end{gathered}$ | $\begin{gathered} 0.069 \\ (0.007) \end{gathered}$ | $\begin{gathered} -0.008 \\ (0.007) \end{gathered}$ |
| Female | $\begin{gathered} 6.229 \\ (0.258) \end{gathered}$ | $\begin{gathered} 5.303 \\ (0.217) \end{gathered}$ | $\begin{gathered} 5.619 \\ (0.351) \end{gathered}$ | $\begin{gathered} 4.781 \\ (0.316) \end{gathered}$ | $\begin{aligned} & -11.254 \\ & (0.269) \end{aligned}$ | $\begin{gathered} -11.506 \\ (0.265) \end{gathered}$ | $\begin{aligned} & -0.245 \\ & (0.007) \end{aligned}$ | $\begin{gathered} -0.250 \\ (0.007) \end{gathered}$ |
| Immigrant | $\begin{aligned} & -3.325 \\ & (0.371) \end{aligned}$ | $\begin{aligned} & -3.192 \\ & (0.314) \end{aligned}$ | $\begin{gathered} -0.01 \\ (0.477) \end{gathered}$ | $\begin{gathered} 0.036 \\ (0.420) \end{gathered}$ | $\begin{gathered} 0.301 \\ (0.375) \end{gathered}$ | $\begin{gathered} 0.311 \\ (0.365) \end{gathered}$ | $\begin{gathered} 0.017 \\ (0.009) \end{gathered}$ | $\begin{gathered} 0.017 \\ (0.009) \end{gathered}$ |
| Math8 |  | $\begin{gathered} 0.559 \\ (0.004) \end{gathered}$ |  | $\begin{gathered} 0.601 \\ (0.006) \end{gathered}$ |  | $\begin{gathered} 0.185 \\ (0.005) \end{gathered}$ |  | $\begin{gathered} 0.004 \\ (0.000) \end{gathered}$ |
| Math $8^{2}$ |  | $\begin{gathered} 0.0002 \\ (0.0001) \end{gathered}$ |  | $\begin{gathered} 0.002 \\ (0.0002) \end{gathered}$ |  | $\begin{gathered} 0.001 \\ (0.0002) \end{gathered}$ |  | $\begin{aligned} & 0.00003 \\ & (0.0000) \end{aligned}$ |
| Constant | $\begin{gathered} 39.614 \\ (0.266) \end{gathered}$ | $\begin{gathered} 39.694 \\ (0.260) \end{gathered}$ | $\begin{aligned} & 25.349 \\ & (0.352) \end{aligned}$ | $\begin{aligned} & 23.454 \\ & (0.375) \end{aligned}$ | $\begin{aligned} & 57.569 \\ & (0.273) \end{aligned}$ | $\begin{aligned} & 56.901 \\ & (0.318) \end{aligned}$ | $\begin{gathered} 9.018 \\ (0.007) \end{gathered}$ | $\begin{gathered} 8.993 \\ (0.008) \end{gathered}$ |
| Adjusted R2 | 0.185 | 0.429 | 0.167 | 0.329 | 0.045 | 0.075 | 0.034 | 0.059 |

Notes: $N=44,316$. Dependent variables are matriculation mathematics and PET quantitative percentiles in the left-hand panel; and earnings percentiles at age 29 and the log of earnings at age 29 in the right panel. Math8 is the GEMS mathematics percentile, centered at the median. All regressions also include cohort indicators, relative age within cohort, and Math8 squared. Robust standard errors in parentheses.

Table 3: Descriptive statistics by selectivity cluster

|  | Most selective |  |  | Least selective |  | No tertiary Cluster 1 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Cluster 6 | Cluster 5 | Cluster 4 | Cluster 3 | Cluster 2 |  |
| Share FG | 0.20 | 0.25 | 0.30 | 0.45 | 0.45 | 0.67 |
| Share SG | 0.62 | 0.56 | 0.51 | 0.38 | 0.37 | 0.17 |
| Share university | 1.00 | 0.95 | 0.47 | 0.12 | 0.17 | 0.00 |
| Female share | 0.44 | 0.52 | 0.55 | 0.57 | 0.73 | 0.44 |
| Immigrant share | 0.15 | 0.18 | 0.15 | 0.17 | 0.13 | 0.23 |
| Mathematic percentiles |  |  |  |  |  |  |
| GEMS | 81.4 | 76.3 | 66.2 | 60.6 | 54.0 | 40.3 |
| Matriculation | 87.0 | 80.0 | 69.5 | 62.7 | 59.0 | 33.2 |
| PET | 90.7 | 85.7 | 66.5 | 54.8 | 45.2 | 12.1 |
| SG-FG percentile gaps |  |  |  |  |  |  |
| GEMS | 4.06 | 2.33 | 5.49 | 4.25 | 9.29 | 12.61 |
| Matriculation | 5.27 | 6.70 | 6.51 | 6.50 | 9.66 | 14.13 |
| PET | 4.28 | 3.91 | 5.71 | 11.44 | 11.98 | 12.08 |
| Labor market |  |  |  |  |  |  |
| Median monthly earnings at age 29 | 11,899 | 8,523 | 8,539 | 8,875 | 7,147 | 7,264 |
| Mean monthly earnings at age 29 | 14,345 | 9,918 | 10,305 | 9,972 | 7,521 | 8,360 |
| Months worked, 18-29* | 68 | 73 | 79 | 86 | 86 | 88 |
| Observations | 4,079 | 3,833 | 5,036 | 10,973 | 6,426 | 23,142 |

Note: Tertiary academic programs clustered by selectivity on matriculation and psychometric scores using a k-means procedure to minimizes distance in students' matriculation and psychometric scores within clusters and maximize the distance between clusters. Cluster 2 includes all programs that do not require PET scores for admissions. Months worked are drawn from tax records and sum over 11 years.

Table 4: Enrollment in tertiary education, in a university program and in the most selective programs

|  | Tertiary education |  | University |  | Selective programs |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (1) | (2) | (1) | (2) |
| SG | $\begin{aligned} & 0.352 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.234 \\ & (0.005) \end{aligned}$ | $\begin{aligned} & 0.246 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.159 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.110 \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.065 \\ & (0.003) \end{aligned}$ |
| Female | $\begin{aligned} & 0.130 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.118 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.028 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.026 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & -0.023 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.022 \\ & (0.002) \end{aligned}$ |
| Immigrant | $\begin{aligned} & -0.073 \\ & (0.006) \end{aligned}$ | $\begin{aligned} & -0.071 \\ & (0.006) \end{aligned}$ | $\begin{aligned} & 0.006 \\ & (0.005) \end{aligned}$ | $\begin{aligned} & 0.004 \\ & (0.005) \end{aligned}$ | $\begin{aligned} & (0.001) \\ & (0.003) \end{aligned}$ | $\begin{aligned} & (0.003) \\ & (0.003) \end{aligned}$ |
| Math8 |  | $\begin{aligned} & 0.007 \\ & (0.000) \end{aligned}$ |  | $\begin{aligned} & 0.004 \\ & (0.000) \end{aligned}$ |  | $\begin{aligned} & 0.002 \\ & (0.000) \end{aligned}$ |
| Math $8^{2}$ |  | $\begin{aligned} & -0.00002 \\ & (0.00000) \end{aligned}$ |  | $\begin{aligned} & 0.0001 \\ & (0.0000) \end{aligned}$ |  | $\begin{aligned} & 0.0001 \\ & (0.0000) \end{aligned}$ |
| Constant | $\begin{aligned} & 0.366 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.386 \\ & (0.005) \end{aligned}$ | $\begin{aligned} & 0.115 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.053 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.042 \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.010 \\ & (0.002) \end{aligned}$ |
| Adjusted R | 0.162 | 0.283 | 0.093 | 0.191 | 0.049 | 0.126 |

Note: $\mathrm{N}=44,316$. Math8 is the GEMS mathematics percentile, centered at the median. All regressions also include cohort indicators, relative age within cohort, and Math8 squared. Robust standard errors in parentheses.

Table 5: Earnings regressions estimated within tertiary selectivity clusters

|  | Most selective |  |  | Least selective |  | No tertiary Cluster 1 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Cluster 6 | Cluster 5 | Cluster 4 | Cluster 3 | Cluster 2 |  |
|  | Earnings percentiles, age 29 |  |  |  |  |  |
| SG | $\begin{gathered} -2.566 \\ (1.261) \end{gathered}$ | $\begin{array}{r} \hline-0.252 \\ (1.165) \end{array}$ | $\begin{aligned} & \hline-2.799 \\ & (0.982) \end{aligned}$ | $\begin{array}{r} 0.442 \\ (0.555) \end{array}$ | $\begin{gathered} -0.634 \\ (0.730) \end{gathered}$ | $\begin{array}{r} -1.775 \\ (0.523) \end{array}$ |
| Female | $\begin{aligned} & -7.236 \\ & (1.144) \end{aligned}$ | $\begin{aligned} & -4.130 \\ & (1.121) \end{aligned}$ | $\begin{aligned} & -5.883 \\ & (0.971) \end{aligned}$ | $\begin{array}{r} -6.406 \\ (0.565) \end{array}$ | $\begin{aligned} & -5.969 \\ & (0.882) \end{aligned}$ | $\begin{array}{r} -18.155 \\ (0.366) \end{array}$ |
|  |  |  | Log ea | nings, age 29 |  |  |
| SG | $\begin{aligned} & -0.081 \\ & (0.033) \end{aligned}$ | $\begin{gathered} -0.011 \\ (0.030) \end{gathered}$ | $\begin{aligned} & -0.066 \\ & (0.025) \end{aligned}$ | $\begin{gathered} 0.005 \\ (0.013) \end{gathered}$ | $\begin{aligned} & -0.030 \\ & (0.018) \end{aligned}$ | $\begin{aligned} & -0.052 \\ & (0.013) \end{aligned}$ |
| Female | $\begin{aligned} & -0.243 \\ & (0.031) \end{aligned}$ | $\begin{aligned} & -0.114 \\ & (0.029) \end{aligned}$ | $\begin{aligned} & -0.155 \\ & (0.025) \end{aligned}$ | $\begin{aligned} & -0.137 \\ & (0.013) \end{aligned}$ | $\begin{aligned} & -0.100 \\ & (0.022) \end{aligned}$ | $\begin{aligned} & -0.375 \\ & (0.009) \end{aligned}$ |
| Observations | 3,378 | 3,109 | 4,044 | 9,082 | 5,228 | 19,475 |

Notes: Tertiary academic programs clustered by selectivity on matriculation and psychometric scores using a k-means procedure to minimizes distance in students' matriculation and psychometric scores within clusters and maximize the distance between clusters. All regression also include a second degree polynomial in the eighth grade mathematics rank, centered at the median, indicators for immigrant status and cohort, and relative age within cohort. Robust standard errors in parentheses.

Table 6: SG-FG gaps in fields of study with highest earnings, and in public sector employment

|  | Selective programs |  | High earnings programs |  | Public sector |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (1) | (2) | (1) | (2) |
| SG | $\begin{aligned} & 0.110 * * * \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.065^{*} * * \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.049 * * * \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.016 * * * \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.076^{* * *} \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.074 * * * \\ & (0.004) \end{aligned}$ |
| Female | $\begin{aligned} & -0.023 * * * \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.022 * * * \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.079 * * * \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.080^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.210 * * * \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.209 * * * \\ & (0.004) \end{aligned}$ |
| Immigrant | $\begin{aligned} & (0.001) \\ & (0.003) \end{aligned}$ | $\begin{aligned} & (0.003) \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.014 * * * \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.013 * * * \\ & (0.003) \end{aligned}$ | $\begin{aligned} & -0.035^{* * *} \\ & (0.005) \end{aligned}$ | $\begin{aligned} & -0.034 * * * \\ & (0.005) \end{aligned}$ |
| Math8 |  | $\begin{aligned} & 0.002 * * * \\ & (0.000) \end{aligned}$ |  | $\begin{aligned} & 0.002 * * * \\ & (0.000) \end{aligned}$ |  | $\begin{aligned} & 0.0002 * * * \\ & (0.000) \end{aligned}$ |
| Math $8^{2}$ |  | $\begin{aligned} & 0.0001^{* * *} \\ & 0.000 \end{aligned}$ |  | $\begin{aligned} & 0.00003^{* * *} \\ & 0.000 \end{aligned}$ |  | $\begin{aligned} & -0.00001^{*} \\ & 0.000 \end{aligned}$ |
| Constant | $\begin{aligned} & 0.042 * * * \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.010^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.084 * * * \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.059 * * * \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.108 * * * \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.112 * * * \\ & (0.004) \end{aligned}$ |
| Adjusted R | 0.049 | 0.126 | 0.039 | 0.081 | 0.068 | 0.068 |

Note: $\mathrm{N}=44,316$. Tertiary academic programs clustered by earnings at age 29 using a k-means procedure to minimizes distance within clusters and maximize distance between clusters. Math8 is the GEMS mathematics percentile, centered at the median. All regressions also include cohort indicators, relative age within cohort, and Math8 squared. Robust standard errors in parentheses.

Table A1: Share of households using additional private educational resources

|  | Education level |  |
| :--- | :---: | :---: |
|  | Primary | Secondary |
| Full population | 23.5 | 37.3 |
| Hebrew speaking | 27.6 | 43.8 |
| Immigrants (1990's) | 33.0 | 43.1 |
| Parents' highest degree |  |  |
| None | 23.0 | 33.4 |
| Matriculation | 19.9 | 38.5 |
| Post secondary | 28.5 | 41.0 |
| Academic | 25.4 | 52.4 |
| Family income (per capita) |  |  |
| Low | 19.0 | 21.6 |
| Medium | 28.3 | 51.0 |
| High | 28.5 | 57.3 |

Source: Israeli Central Bureau for Statistics Social Survey (2007), Authors' calculations.

Table A2: Scores by sample

|  | All GEMS test takers | At least two GEMS |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  |  | With SES data |  |
|  |  |  | With wage |  |
| N | 67,905 | 65,222 | 61,926 | 53,489 |
| 2002 cohort | 0.49 | 0.49 | 0.49 | 0.48 |
| Share of students with score in GEMS test on: |  |  |  |  |
| Mathematics | 0.86 | 0.88 | 0.88 | 0.88 |
| Literacy | 0.90 | 0.92 | 0.92 | 0.92 |
| English | 0.87 | 0.89 | 0.89 | 0.90 |
| Science \& tech | 0.85 | 0.87 | 0.87 | 0.87 |
| Average score in: |  |  |  |  |
| Mathematics | 52.36 | 52.61 | 52.76 | 52.86 |
| Reading | 63.55 | 63.92 | 64.04 | 64.31 |
| English | 78.30 | 78.61 | 78.72 | 78.80 |
| Science \& tech | 64.24 | 64.42 | 64.53 | 64.60 |
| Share of test takers |  |  |  |  |
| Matriculation, mathematics | 0.84 | 0.86 | 0.87 | 0.88 |
| PET, quantitative |  | 0.49 | 0.49 | 0.52 |
| Average score in: |  |  |  |  |
| Matriculation, mathematics | 68.31 | 70.83 | 71.14 | 72.27 |
| PET, quantitative |  | 56.33 | 56.59 | 59.16 |

Notes:

Table A3: Probability of appearing in tax records in 2017 or 2018

|  | Appears in tax records in 2017 or 2018 |  |  |
| :--- | :--- | :--- | :--- |
| SG | 0.009 | 0.003 | 0.005 |
|  | $(0.003)$ | $(0.003)$ | $(0.003)$ |
| Female | 0.057 | 0.052 | 0.052 |
|  | $(0.003)$ | $(0.003)$ | $(0.003)$ |
| Immigrant | -0.029 | -0.023 | -0.023 |
|  | $(0.004)$ | $(0.004)$ | $(0.004)$ |
| Registered in 12th grade |  | 0.100 | 0.100 |
|  |  | $(0.006)$ | $(0.006)$ |
|  |  |  | -0.00005 |
| Math8 |  |  | $(0.0001)$ |
|  |  |  |  |
| Constant | 0.845 | 0.756 | 0.758 |
|  | $(0.003)$ | $(0.006)$ | $(0.007)$ |
| Adjusted R | 0.008 | 0.008 | 0.013 |

Notes: $N=51,036$ LPM regression estimating the relationship between observed characteristics and the probility of appearing in the national income tax records in either 2017 or 2018. Sample includes all individuals fro 2002 and 2003 cohort for whom we observe at least two GEMS scores and at least one parent's years of schooling.
Table A4: Estimated SG-FG gaps in all outcomes with eighth grade school fixed-effect

|  | Achievement |  | Labor market |  |  | Tertiary education |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Matriculation percentiles | PET percentiles | Earnings percentiles | Ln(earnings) | Public sector employment | Any | University | Selective programs | High earnings programs |
| SG | $\begin{gathered} 8.865 \\ (0.253) \end{gathered}$ | $\begin{aligned} & 14.639 \\ & (0.394) \end{aligned}$ | $\begin{gathered} 0.306 \\ (0.321) \end{gathered}$ | $\begin{gathered} -0.001 \\ (0.008) \end{gathered}$ | $\begin{aligned} & 0.047 \\ & (0.005) \end{aligned}$ | $\begin{aligned} & 0.173 \\ & (0.005) \end{aligned}$ | $\begin{aligned} & 0.124 \\ & (0.005) \end{aligned}$ | $\begin{aligned} & 0.048 \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.015 \\ & (0.003) \end{aligned}$ |
| Female | $\begin{gathered} 4.618 \\ (0.224) \end{gathered}$ | $\begin{gathered} 3.650 \\ (0.333) \end{gathered}$ | $\begin{aligned} & -11.882 \\ & (0.285) \end{aligned}$ | $\begin{gathered} -0.260 \\ (0.007) \end{gathered}$ | $\begin{aligned} & 0.193 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.113 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.020 \\ & (0.004) \end{aligned}$ | $\begin{aligned} & -0.023 \\ & (0.003) \end{aligned}$ | $\begin{aligned} & -0.083 \\ & (0.003) \end{aligned}$ |
| Immigrant | $\begin{aligned} & -1.452 \\ & (0.325) \end{aligned}$ | $\begin{gathered} 1.855 \\ (0.445) \end{gathered}$ | $\begin{gathered} 0.228 \\ (0.392) \end{gathered}$ | $\begin{gathered} 0.013 \\ (0.010) \end{gathered}$ | $\begin{aligned} & -0.024 \\ & (0.006) \end{aligned}$ | $\begin{aligned} & -0.041 \\ & (0.006) \end{aligned}$ | $\begin{aligned} & 0.015 \\ & (0.005) \end{aligned}$ | $\begin{aligned} & 0.001 \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.013 \\ & (0.003) \end{aligned}$ |
| Math8 | $\begin{gathered} 0.598 \\ (0.004) \end{gathered}$ | $\begin{gathered} 0.645 \\ (0.006) \end{gathered}$ | $\begin{gathered} 0.188 \\ (0.005) \end{gathered}$ | $\begin{gathered} 0.004 \\ (0.000) \end{gathered}$ | $\begin{aligned} & 0.0005 \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.007 \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.005 \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.002 \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.002 \\ & (0.000) \end{aligned}$ |
| Math $8^{2}$ | $\begin{gathered} 0.001 \\ (0.000) \end{gathered}$ | $\begin{gathered} 0.003 \\ (0.000) \end{gathered}$ | $\begin{gathered} 0.001 \\ (0.000) \end{gathered}$ | $\begin{gathered} 0.00003 \\ 0.000 \end{gathered}$ | $\begin{aligned} & 0 \\ & 0.000 \end{aligned}$ | $\begin{aligned} & -0.00001 \\ & 0.000 \end{aligned}$ | $\begin{aligned} & 0.0001 \\ & 0.000 \end{aligned}$ | $\begin{aligned} & 0.0001 \\ & 0.000 \end{aligned}$ | $\begin{aligned} & 0.00003 \\ & 0.000 \end{aligned}$ |
| Middle school FE Adjusted R2 | $\begin{gathered} \text { Yes } \\ 0.48 \end{gathered}$ | $\begin{gathered} \text { Yes } \\ 0.366 \end{gathered}$ | $\begin{aligned} & \text { Yes } \\ & 0.085 \end{aligned}$ | $\begin{gathered} \text { Yes } \\ 0.069 \end{gathered}$ | $\begin{aligned} & \text { Yes } \\ & 0.101 \end{aligned}$ | $\begin{aligned} & \text { Yes } \\ & 0.315 \end{aligned}$ | $\begin{aligned} & \text { Yes } \\ & 0.220 \end{aligned}$ | $\begin{aligned} & \text { Yes } \\ & 0.143 \end{aligned}$ | $\begin{aligned} & \text { Yes } \\ & 0.088 \end{aligned}$ |

Notes: $N=44,316$ Dependent variables are matriculation mathematics and PET quantitative percentiles on the left panel and earnings at age 29 in percentiles and natural logs on the right panel. Math8 is the GEMS mathematics percentile, centered at the median. All regressions also include cohort indicators and relative age within cohort. Robust standard errors in parentheses
Table A5: Tertiary programs by selectivity cluster

| Cluster 1 - most selective | Cluster 2 | Cluster 3 | Cluster 4 - least selective | Cluster 5 - not selective |
| :---: | :---: | :---: | :---: | :---: |
| Accounting (U) | Administrative Information Systems (U) | Arab Nation History (U) | Accounting (C) | Art and Culture Studies (C) |
| Aerospace and Space Engineering (U) | Animal Science (U) | Archaeology (U) | Arabic Language and Literature (U) | BA Social Science (C) |
| Bio-Medical Engineering (U) | Architecture and Urban Construction (U) | Architecture and Urban Construction (C) | Behavioral science (C) | BA Social Science (U) |
| Biotechnological Engineering (U) | Biology (U) | Art History (U) | Behavioral science (U) | Banking (C) |
| Brain Science (U) | Biotechnology (U) | Bio-Medical Engineering (C) | Biology (C) | Criminology (C) |
| Computer Science (U) | Chemical Engineering (U) | Botany (U) | Biotechnology (C) | Education (C) |
| Computer Science and Engineering (U) | Chemistry (U) | Civil Engineering (U) | Business Management (C) | General Studies (U) |
| Dental Medicine (U) | Communication (U) | Computer Science (C) | Chemical Engineering (C) | Health Systems Management (C) |
| Dietetics (U) | Economics (U) | Criminology (U) | Chemistry (C) | Hotel Management (C) |
| Electrical Computer Engineering (U) | Economics and Business Management (U) | Dietetics (C) | Civil Engineering (C) | Human Service Management (C) |
| Electrical Engineering (U) | Education Theory and Research (U) | East Asian Studies (U) | Communication (C) | Humanities (C) |
| Food Engineering \& Biotechnology (U) | Electro-Optics Engineering (C) | Ecology (C) | Computer Science and Engineering (C) | Industry Management (C) |
| Forensic medical Science (U) | Environmental Engineering (U) | Education (U) | Economics (C) | Insurance (C) |
| Industrial engineering (U) | Film and Visual Studies (U) | Emergency Medical Services (U) | Electrical Engineering (C) | Logistics (C) |
| International Relations (U) | Food Sciences (U) | Engineering Science (C) | Electronics Engineering (C) | Marketing Management (C) |
| Law (U) | Geography, Geology and Meteorology (U) | Engineering Science (U) | Food Engineering \& Biotechnology (C) | Public Administration (C) |
| Mathematics-Computer Science (U) | Geology (U) | English Language and Literature (U) | Food Science (C) | Service Management (C) |
| Mathematics (U) | History of Judaic Thought (U) | Environmental Economics (U) | Forensic medical Science (C) | Structural Engineering (C) |
| Medical Sciences (U) | Hydrotechny (U) | Film and Visual Studies (C) | Administration and public administration (U) | Teacher Education Certificate (C) |
| Medicine (U) | Information Systems Engineering (U) | Geography (U) | Health Systems Management (U) |  |
| Occupational Therapy (U) | Linguistics (U) | History and General History (U) | Hebrew Language (U) |  |
| Pharmacy (U) | Literature (U) | Hotel Management (U) | Hebrew Literature (U) |  |
| Physics (U) | Materials science (U) | Human Services (U) | Humanities (U) |  |
| Physiotherapy (U) | Mechanical Engineering (U) | Industrial design (C) | Information System - Administration (C) |  |
| PPE (Philosophy,politics,economics) (U) | Occupational Therapy (C) | Industrial engineering (C) | Information System (C) |  |
| Psychology (U) | Optometry (U) | Islam History and Culture (U) | Information Systems Engineering (C) |  |
| Speech-language Therapy (C) | Philosophy (U) | Israeli History (U) | Interior Building (C) |  |
| Speech-language Therapy (U) | Physiotherapy (C) | Latin languages Studies (U) | Law (C) |  |
|  | Structural Engineering (U) | Learning Management System (C) | Mechanical Engineering (C) |  |
|  | Teacher Math and Science Certificate (U) | Music (C) | Nursing (C) |  |
|  | Telecommunications engineering (U) | Music (U) | Nursing (U) |  |
|  |  | Pharmaceutical Engineering (C) | Optometry (C) |  |
|  |  | Plant Protection (U) | Political Science (C) |  |
|  |  | Political Science (U) | Second Major Social Science (U) |  |
|  |  | Psychology (C) | Social Work (C) |  |
|  |  | Social Work (U) | Teacher Education Certificate (TC) |  |
|  |  | Sociology and Anthropology (U) |  |  |
|  |  | Soil and Water Sciences (U) |  |  |
|  |  | Special-Needs Education (U) |  |  |
|  |  | Statistics (U) |  |  |
|  |  | Sustainability (C) |  |  |
|  |  | Theatre History (U) |  |  |
|  |  | Visual Communication (C) |  |  |

Figure A1: Percentile ranks distribution for achievement and earnings, FG and SG students


Notes: Achievement percentiles are defined over the entire student population. None test-takers in matriculation and PET are put in the lowest achievement percentiles.


[^0]:    Suggested Citation: Friedman-Sokuler, Naomi; Justman, Moshe (2024) : Family background, education, and earnings: The limited value of "test-score transmission", GLO Discussion Paper, No. 1388, Global Labor Organization (GLO), Essen

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[^2]:    *This research was generously supported by Yad HaNadiv foundation. This study was performed in the Israel Central Bureau of Statistics (ICBS) research room using de-identified microdata files prepared specifically for this project. Authors thank the staff at the Research Service Unit at ICBS for preparation of the data and support, with special thanks to Aviel Krenzler and Yifat Klopstock. Thanks to Anas Aesa who provided excellent research assistance.
    ${ }^{\dagger}$ Department of Economics, Bar Ilan University, Israel and GLO; friedmn6@biu.ac.il (corresponding author)
    ${ }^{\ddagger}$ Department of Economics, Ben Gurion University of the Negev, Israel; justman@bgu.ac.il

[^3]:    ${ }^{1}$ Admission processes vary greatly within and between countries, so the specific characteristics through which high-SES students gain advantage depends on the institutional setting of tertiary admissions.

[^4]:    ${ }^{2}$ In the economics literature parental income and levels of education are viewed as the defining features of socioeconomic status, and recent findings highlight the importance of parental education over income (Sikhova, 2023). In sociology, the question of mobility is broader, examining movement between social strata, defined not only by income and education, but also as class, referring to characteristics of employment relations and occupations (Hauser and Warren, 1997; Bukodi and Goldthorpe, 2018). Israel is an interesting case to study, because the dominant Jewish majority is a relatively young society of immigrants and while there are many ethnic and social divides, they are still evolving and do not constitute a well defined entrenched class structure, so that education is arguably the salient class marker.
    ${ }^{3}$ This allows us to examine the role of SES in generating achievement gaps, separately from the role of financial constraints and volatility in the transition from secondary to tertiary education identified by Hardy and Marcotte (2020)

[^5]:    ${ }^{4}$ This policy was changed in later years of the GEMS implementation

[^6]:    ${ }^{5}$ Our framework is easily extended to allow for a hierarchy of multiple tertiary programs with increasing selectivity, each leading to a different set of increasingly lucrative occupations, as in our data.
    ${ }^{6}$ See Gilboa and Justman (2005) for a more elaborate model that incorporates tuition and opportunity costs, allows for stochastic graduation conditioned on human capital, and endogenizes the decision to enrol, conditioned on acceptance.

[^7]:    ${ }^{7}$ Ultra-orthodox schools do not follow the national curriculum, do not participate in GEMS and generally do not prepare their students for tertiary education.

[^8]:    ${ }^{8}$ Students attending Arabic language schools participated in GEMS and are analyzed separately in FriedmanSokuler and Justman (2020). The Arab minority, is predominantly first generation. We do not include it in this analysis to avoid confounding FG and minority status effects.
    ${ }^{9}$ Non-participants include special education students and immigrants arriving in the year prior to the test who were exempt from GEMS, as well as students who were absent during all four test days. See Friedman-Sokuler and Justman (2016) for further discussion.

[^9]:    ${ }^{10} C f$. Jacob and Rothstein (2016), who argue that the observed increase in test score gaps with student age reflect a decline in measurement error with age; and Cunha et al. (2006) and Bond and Lang (2018) who use later life outcomes to anchor educational achievement and follow the evolution of gaps through the educational pipeline.

[^10]:    ${ }^{11}$ These gaps reflect differences in direct parental investment and in access to better schools and neighborhoods, In appendix Table A4 we add fixed effects for the school attended in eighth grade to these regressions and find that 4 percentile points of the conditional SG advantage in matriculation ranks and 4.4 percentile points of their conditional advantage on PET rankings are associated with access to better schools.

[^11]:    ${ }^{12}$ There is a clear distinction in Israel between universities, which are research-oriented, receiving extensive funding for research, and accredited to confer all levels of academic degrees, including doctoral degrees; and colleges ("mikhlalot" in Hebrew) that are teaching-oriented, receive minimal research funding, and are not accredited to confer doctoral degrees.
    ${ }^{13}$ There are two types of programs in this category: non-selective programs and programs in Arts and Design where selection is based on student portfolios, unobserved in our data and not necessarily correlated with scholastic achievement.

[^12]:    ${ }^{14}$ Earnings trajectories by study field drawn from the Israel Ministry of Labor's "Avodata" database, which uses administrative data on all tertiary education graduates from 2009/10 to construct average earnings by study field year by year. It does not distinguish between universities and colleges. For full documentation of the Avodata data set see here [in Hebrew]
    ${ }^{15}$ Of the 24,933 students in our sample who enrolled in tertiary education we drop 1,897 students who chose study fields too small to be included in the "Avodata" database.

