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

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August 18, 2024

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Abstract

This paper investigates the relationship between the inter-generational transmission of educational achievement ("test-score transmission") and the inter-generational transmission of higher earnings ("income transmission"). We use administrative data from Israel to track the evolution of education and earnings gaps between "second-generation" (SG) students, whose parents have some tertiary education, and "first-generation" (FG) students, whose parents have none. We find that SG students achieve much better results on the screening tests that regulate access to selective tertiary education than FG students with similar eighth-grade test scores. Consequently, they enjoy greater access to the most selective tertiary degree programs, crowding out FG students with higher eighth-grade achievement. Yet this advantage does not manifest itself in earnings differentials at age 29, similarly conditioned on eighth-grade achievement, which are not statistically significant, and we find no evidence that these patterns are driven by SG students choosing study fields with steeper earnings curves. We find evidence of two mechanisms that mediate the relationship between achievement gains and earnings: FG students compensate for fewer options in tertiary education by accumulating more labor market experience; and SG students are more likely to forgo higher earnings for non-pecuniary benefits in employment, particularly by choosing public-sector employment.

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

JEL Classification Numbers: I24 , I26 , J24 , J62

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1 Introduction

Universal public education goes only so far in equalizing educational opportunity as reflected in the prevalence of “test-score transmission”, children with more educated parents achieving significantly better educational outcomes than children with less educated parents (Rothstein, 2019; Blanden et al., 2023). One important channel through which test-score transmission works is high stakes testing, which even the most egalitarian education systems use regulate admission to the selective academic programs that open doors to prestigious, well-paid professions. They provide better educated, well informed, more affluent parents an opportunity to invest substantial resources in improving their children’s achievement on these tests and thus expand their future educational and occupational options.[1] However, the extent to which test-score transmission is in fact an important mechanism in determining inter-generational income mobility—"income transmission"—remains an open question. The mostly indirect evidence suggests a limited impact, at best. Thus, Rothstein (2019) finds that the substantial geographical variation in test-score transmission across the United States is only weakly correlated with observed variation in income transmission, and Blanden et al. (2023), analyzing international PISA data, find only a weak link between income inequality and inequality in educational achievement across countries.

We extend this line of research using longitudinal administrative data to estimate socioeconomic gaps in high-stakes screening test scores and labor market earnings, in Israel. Israel’s education system is a particularly apt setting for this purpose, as tertiary education is dominated by public-sector institutions charging heavily subsidized tuition fees. Consequently, high-stakes tests play a greater role than financial constraints in regulating access to educational opportunities, compared to countries where tuition fees play a large role in constraining the educational options of less advantaged students (Hardy and Marcotte, 2020). We follow two half-cohorts of students in Hebrew-language schools from eighth grade to age 29, comparing the evolution educational

[1] This is often referred to as "shadow education". On the extent of shadow education and its relation to high-stakes testing around the world, see, among others, Buchmann et al. (2010) and Zwier et al. (2020). In the appendix, Table A1 shows that in Israel private spending on education increases markedly with parents’ education and family income, and is more than twice as large in secondary school as in primary school.

achievement and earnings between two groups of students: "first generation" (FG) students, neither of whose parents has more than 12 years of schooling; and "second generation" (SG) students, at least one of whose parents has some tertiary education, and with a family income in the top two quintiles of the income distribution. Our emphasis on parental education as the primary factor defining parents' socioeconomic advantage accords with the lesser role of financial constraints in limiting access to educational opportunity in Israel, and with recent research highlighting the importance of parental education, and its direct impact on educational outcomes, beyond the ability to purchase supplementary education services (Sikhova, 2023; Adamecz-Völgyi et al., 2022; Edwards et al., 2022).[2]

We begin tracking students in the eighth grade (aged 13-14), when they participate in a nationwide standardized testing scheme, Growth and Effectiveness Measures for Schools (GEMS), and use their ranks in eighth-grade GEMS mathematics as our baseline measure of academic ability.[3] These scores capture socioeconomic differences in endowments and early childhood investments reflected in the substantial rank advantage that SG students already have at this stage (Mogstad and Torsvik, 2023). However, with matriculation still several years down the road, these tests predate most if not all targeted investments in test preparation aimed at improving performance on the screening tests that regulate the transition from secondary to tertiary education, on which we focus here. We then quantify test-score transmission by estimating SG-FG gaps in rankings on two main components of these screening tests, the high-school matriculation exam in mathematics and the quantitative section of the Psychometric Entrance Test (PET), conditioned on eighth-grade achievement ranks. We find large conditional gaps in both, indicating a substantial widening of socioeconomic advantage in the transition from secondary to tertiary education. Comparing SG and FG students with the same eighth-grade GEMS mathematics rank, we find that SG students

[2] A broader view of mobility as movement between social strata, defined not only by income and education, but also as class (Hauser and Warren, 1997; Bukodi and Goldthorpe, 2018), is less relevant for the population we study, a relatively young society of immigrants without an entrenched class structure, where education is arguably the most salient class marker.

[3] We use rankings rather than actual scores throughout. This allows us to consistently compare gaps across very different sets of outcomes (Jacob and Rothstein, 2016; Bond and Lang, 2013), and accords with the ordinal use of screening tests scores to determine admission to selective programs.

out-perform FG students by 12.7 percentiles in matriculation mathematics rankings and by 19.5 percentiles in quantitative PET rankings, on average. These test score gaps then lead, as they must, to large, similarly conditioned, socioeconomic gaps in admissions to the most selective tertiary degree programs. Again comparing SG and FG students with the same eighth-grade GEMS mathematics rank, we find that, on average, SG students are 23 percentage points more likely to enter tertiary education, twice as likely to study in a university (the more selective type of institution), and three times more likely to enter the most selective tertiary degree programs.[4]

We then estimate similarly conditioned SG-FG gaps in the rankings of labor market earnings at age 29, and find no significant difference in labor market earnings at age 29 between SG and FG students with the same eighth-grade GEMS mathematics rankings, for men as for women.[5] These are, of course, only early-stage earnings, and we cannot rule out the possibility that SG students gain an advantage in lifetime earnings that is not yet apparent at age 29, if the occupations they choose exhibit steeper earnings trajectories (Leighton and Speer, 2023). We test for this indirectly by using external data to characterize the ten-year earnings trajectories of different study fields in our sample, and do not find that FG students are over-represented in study fields characterized by high initial earnings or under-represented in study fields with steep earnings growth in the first ten years after graduation. These findings accord with earlier evidence on the weak link between test score transmission and income transmission (Rothstein, 2019; Blanden et al., 2023; Chetty et al., 2023).

These patterns raise two related questions, which we address in the second part of the paper. Why do these substantial conditional gaps in screening test scores and enhanced access to the most selective tertiary programs not translate into substantial conditional gaps in earnings, and why do students and parents invest time, effort and material resources in improving screening test scores if they have no impact on earnings? The tentative answers we offer are not mutually exclusive. One possible answer is that "returns to selectivity" are modest at best, as Dale and Krueger (2002,

[4] We characterize selectivity *ex post* by the actual distribution of matriculation and PET rankings in each degree program. This is described in detail in Section 4.

[5] The unconditioned SG-FG gap is also modest: 3.6 percentiles, corresponding to 6.9% higher wages, on average.

2014) and Ge et al. (2022) found for the United States. This is consistent with the hypothesis that test-score gains after eighth grade reflect increases in test-taking skills that contribute little to labor-market productivity; with less-selective degree programs preparing their students for the labor market as well (or better) than their more selective, more academic counterparts; and with employers readily able to discover the actual productivity of their new hires, as Hansen et al. (2024) recently found to be the case in Denmark. A second, related hypothesis is that because FG students are more financially constrained they acquire more labor market experience before and during their studies, which may offset some (or all) of the educational advantages of SG students, and indeed the FG students we observe have nearly a full year of additional work experience compared to SG students. This is especially relevant for Israel, where students from Hebrew-language schools enter tertiary education 3-6 years after high school completion and have ample time to gain various kinds of labor market and military experience during this time. This experience can directly add to their productivity, as well as generating informative signals for future employers, which our findings suggest are reflected more reliably by their baseline human capital measured in eighth grade than by high-stakes screening tests This suggests that within similarly selective tertiary degree programs, FG students should exhibit higher earnings at age 29 than SG students with the same eighth grade rankings, and that the difference is mediated by their greater labor market experience, as we do indeed find.

As for our second question, why do SG students and their parents invest resources in improving screening test scores if this has no impact on earnings, we note first that even if facilitating access to higher education in general, and to the most selective degree programs in particular, does not lead to pecuniary gains in the labor market, it does expand SG students' choice set, which educated parents may appreciate in itself and wish to pass on to their children. SG students enjoying greater financial security may then use this advantage in admissions to pursue non-pecuniary goals in employment such as job satisfaction, social prestige, political influence, job security, or amenable working conditions. This is consistent with the findings of Hérault and Kalb (2013) on the inter-generational persistence of job security in Australia, and more generally with the extensive work of Bukodi and

Goldthorpe (2018) and others on the inter-generational persistence of class in Britain. We find indirect support for this hypothesis in the Israeli context. SG students are substantially more likely to choose public sector jobs, generally associated with lower earnings but better amenities; and when we cluster study fields by earnings rather than selectivity, the conditional SG-FG gap in admission to the most selective programs shrinks from 6.5 percentage points to 1.6 percentage points.

Understanding what screening tests do, and specifically the extent to which they reliably reflect human capital accumulation, is crucial for designing policies that foster social mobility. To the extent that screening test scores are reliable measures of human capital, socioeconomic gaps in test scores reflect productivity differences (Barrios Fernández et al., 2023; Markussen and Røed, 2023), indicating 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, manipulable screening devices that motivate socially advantaged parents to invest unproductively in their children's test-taking skills, this indicates a need to re-examine the screening systems that regulate access to higher education (Fang and Noe, 2022; Lee and Suen, 2023; Posso et al., 2023). "Leveling the playing field" is not only equitable but also offers efficiency benefits, if lower-ability students with a more advantaged background are crowding out less-advantaged, higher-ability students from the competitive degree programs that potentially lead to jobs for which they are better suited. (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 data and outlines our empirical strategy. Section 3 presents estimates of raw and conditional gaps in test scores and earnings between FG and SG students, from eighth grade to age 29. Section 4 shows how the gaps in test scores shape admissions to selective tertiary degree programs. Section 5 discusses possible interpretations of our findings and offers suggestive evidence in their support. Section 6 concludes.

2 Data and empirical strategy

To track the evolution of socioeconomic gaps in educational outcomes and earnings from eighth grade to age 29, we form a synthatic cohort of 76,054 eighth grade students (aged 13-14), comprising two half-cohorts of students in Israel's non-ultra-orthodox Hebrew language schools participating in the GEMS eighth-grade testing scheme, one half in 2002 and the other half in 2003.[6] We follow these students from eighth grade through the educational pipeline and in the labor market to age 29 using administrative data compiled by Israel's Central Bureau of Statistics (ICBS) from 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. Column (1) of Table 1 presents descriptive statistics on these 76,054 students

2.1 Main variables and descriptive statistics

Our baseline measure of student achievement is drawn from the GEMS testing scheme, which 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). We choose students' ranks on the GEMS mathematics test as our measure of their baseline human capital, as matriculation and PET tests also include required mathematics/quantitative sections; mathematics scores show 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

[6] In 2002, the year of its inception, GEMS split all schools in Israel with an eighth grade into two balanced samples of equal size, with half the schools participating in GEMS tests in spring 2002 and the other half in spring 2003. Middle schools in Israel are all publicly funded and almost all are publicly administered. We exclude from this analysis students in Arabic language schools, because the Arab minority in Israel is predominantly first generation and we want to avoid confounding FG and minority status effects (see also Friedman-Sokuler and Justman (2020).) Ultra-orthodox schools were not included in the GEMS as they do not follow the national curriculum and generally do not prepare their students for tertiary education.

on the other scores and on all available background characteristics for students with all scores. Descriptive statistics for the 65,222 students with at least two GEMS scores are presented in column (2) of Table 1. Comparing them to those of 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.[7] 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.

We use two indicators to characterize students' socioeconomic status: their parents' self-reported years of education and their family income quintile, calculated from tax records when the student was in eighth grade. We are able to calculate income quintiles for all students in our sample, but drop 5 percent of students for whom we do not have information on either parent's years of schooling. Column (3) of Table 1 presents descriptive statistics on the 61,926 students for whom we have at least two GEMS scores and years of schooling for at least one parent. We define parents' education as the greater of the parents' reported years of schooling. The distribution of family income is identical, at the two-digit level, to column (2), suggesting that missing information on both parents' schooling levels is uncorrelated with socioeconomic status.

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. This leaves us with 53,489 students, described in column (4), which again is very similar to column (3). 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 student's GEMS score percentile and appearing in the tax records. These findings

[7] 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.

indicate that individuals not appearing in earnings records are not necessarily unemployed. They are more likely to be absent for other reasons: moving abroad, continuing full-time studies, or disability. We therefore drop from the sample individuals who do not appear in the tax registry in either of these years rather than including them with zero earnings.

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 data on parental education and family income are FG. The other half are students with at least one parent with more than 12 years of schooling. Our intended focus is on comparing families with and without the experience of a college education, but as we only observe parents' years of schooling, not the nature of their post-secondary education, we sharpen the comparison by defining our comparison group of "second-generation" (SG) students, as students 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.[8] This leaves us with a final sample of 44,316. The right-hand panel of Table 1 compares the 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 (Autor et al., 2019). 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 one 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; and where all SG students come from families in the top two income quintiles (by definition), only 36 percent of FG students come from families in the top two income quintiles.

[8]Appendix Figure A1 replicates the main non-parametric analysis in the paper, including the group of low-income SG students. As expected, they consistently fall between our FG and SG group. None of our results are sensitive to the choice to exclude them, as shown in appendix Table A4.

Column (6), (7) and (8) of Table 1 compare raw (unconditioned) SG and FG outcomes at various points of the education-earnings pipeline. The initial gap in "baseline human capital" measured in eighth grade is 18 percentile points between the mean ranks of FG and SG students on the eighth-grade 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, after military service. Matriculation is a precondition for most tertiary programs, a passing score in mathematics is required for matriculation, and PET is required for all the more selective programs, with matriculation and PET scores serving to rank applicants to programs with excess demand. In our empirical analysis, we focus on mathematics matriculation exams and the quantitative section of 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. Columns (6) and (7) of Table 1 shows that 83 percent of FG students and 95 percent of SG students sit for the mathematics matriculation test, a gap of 12 percentage points, with a much larger gap, of 35 percentage points, in PET participation rates. These gaps have direct implications for participation in tertiary education. While SG students are only slightly more likely (6 percentage points) 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 at age 29 are 10.5 percent higher at the median and 17.4 percent higher at the mean than FG students' earnings. Figure 1 compares the cumulative distribution functions of FG and SG student *ranks* for our main variables of interest: the mathematics GEMS test, matriculation mathematics, the quantitative section of PET, and earnings at age 29. It highlights the initial SG advantage on GEMS, the yet greater advantage in matriculation and PET, and the much smaller advantage in earnings at age 29.

2.2 Empirical strategy

Our empirical approach is descriptive rather than causal. We follow the evolution of SG-FG gaps in test outcomes and earnings from eighth grade to age 29. To allow a consistent comparison of these gaps despite inherent differences in content matter and scales, we convert all test scores and earnings to percentile ranks within the distribution of our eighth-grade population.[9] All students in our population have GEMS scores and earnings, by construction, but many do not have matriculation or PET scores. Students without a matriculation or PET score are assigned a score of 0, which places them at the bottom of the matriculation or PET distribution, as they would be ranked for admission purposes.

Equation 1 estimates the average raw test-score gaps, shown graphically in Figure 1. Student i's percentile rank on test t is denoted by $R(S_i^t)$, where t is either the matriculation mathematics test or the PET quantitative section; SG_i is an indicator variable; X_i is a vector of fixed individual characteristics, including sex, relative age in cohort and whether the student is an immigrant, which we include to account for compositional differences; and α_1^t is our estimate of raw test-score transmission on these tests, the difference in average test score ranks between SG and FG students controlling only for fixed individual characteristics. Equation 2 does the same for earnings ranks at age 29, denoted by $R(w_i)$, where α_1^w estimates the raw difference in earnings ranks between SG and FG students. To the extent that these estimated gaps, α_1^t and α_1^w, represent underlying differences in human capital, we expect them to be of the same sign and of comparable magnitude.

$$R(S_i^t) = \alpha_0^t + \alpha_1^t SG_i + X_i'\theta^t + \epsilon_i^t \tag{1}$$

$$R(w_i) = \alpha_0^w + +\alpha_1^w SG_i + X_i'\theta^w + \epsilon_i^w \tag{2}$$

To focus our analysis on the role of "test-score transmission" in screening tests, regulating the transition from secondary to tertiary education, we estimate SG-FG gaps conditioned on no-stakes eighth-grade GEMS mathematics ranks, to net out earlier differences in innate abilities and accumulated human capital.[10] Thus we include $f(R(S_i^G))$, a second-degree polynomial of student

[9] *Cf.* 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] GEMS tests are no-stakes in the sense that achievement on these tests had no direct impact on student evaluation or progression. The stated goal of GEMS was to evaluate schools and not individual students, and so in the early years of its inception, the years we observe here, neither students nor schools were informed of individual GEMS scores.

i's rank on the eighth-grade mathematics GEMS test, as a baseline measure of human capital, on the right-hand side of Equations 3 and 4, and β_1^t and β_1^w are our estimates of the conditional gaps. The coefficients β_1^t capture, in reduced form, the change in the SG-FG gap in test score ranks from middle school to the transition from secondary to tertiary education, and β_1^w does the same for earnings at age 29.[11] Comparing these three coefficients allows us to map the evolution of gap from eighth grade to age 29, which we do in the following section.

$$R(S_i^t) = \beta_0^t + \beta_1^t SG_i + X_i'\theta^t + f(R(S_i^G)) + \epsilon_i^t \tag{3}$$

$$R(w_i) = \beta_0^w + +\beta_1^w SG_i + X_i'\theta^w + f(R(S_i^G)) + \epsilon_i^w \tag{4}$$

3 The evolution of FG-SG gaps in test scores and earnings

Figure 2 presents a non-parametric, graphical analysis of the evolution of conditional gaps 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. In the three left-hand graphs, each black (gray) dot represents the *mean* rank of FG (SG) students in matriculation mathematics, quantitative PET, and earnings at age 29 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.[12] In the three right-hand graphs, each black (gray) dot represents the *median* rank of FG (SG) students within each GEMS percentile. The four topmost graphs in Figure 2 illustrate the substantial increase of the SG advantage in the transition from secondary to tertiary education throughout the distribution of eighth-grade GEMS ranks. It is greatest at the GEMS median, and larger for PET than for matriculation. The difference at the GEMS median between the median FG and SG

[11] Angrist and Pischke (2009, p.68) discuss the use, in causal inference, of control variables that are themselves outcomes, distinguishing between "bad controls", which should be avoided, and the occasional need to use "proxy controls". Noting the importance of skills in shaping education and labor market outcomes, they suggest that it is often preferable to include test scores as proxies for skills, though they are outcomes.

[12] Note that, by construction, all students in our sample have eighth grade GEMS scores and observed earnings at age 29.

matriculation ranks is 16 percentile points and the difference between their mean ranks is 14.3 percentile points. The difference at the GEMS median between the median FG and SG PET ranks is 69.7 percentile points (!) and the difference between their mean ranks is 23.1 percentile points. The huge difference in conditional PET medians reflects the fact that a majority of FG students at the GEMS median did not take the PET. By any measure, SG students achieve, on average, much higher matriculation and PET outcomes than FG students with the same eighth-grade rank. This illustrates the substantial reinforcement of test-score transmission in the transition from high school to tertiary education in Israel.

The left-hand panel of Table 2 presents estimates of the raw and conditional SG-FG 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. Columns (1) report estimates of average raw gaps, corresponding to Equation 1 and Figure 1; and columns (2) report estimates of average conditional gaps, adding a second-order polynomial in eighth-grade mathematics ranks to the regression, corresponding to equation 3 and Figure 2. The average raw (unconditioned) SG-FG gaps are 22.9 percentile points on the matriculation mathematics test and 30.8 percentile points on the PET quantitative section. The regressions reported in columns (2) add a second-order polynomial in eighth-grade mathematics ranks to estimate conditional SG-FG gaps (with the same controls), quantifying the average growth in the SG-FG gaps after eighth grade. Overall, GEMS ranks are highly predictive of future achievement ranks, substantially increasing the explanatory power of the matriculation and PET regressions, while reducing the SG-FG gap in matriculation ranks by less than half and the gap in PET ranks by over a third.[13] The gaps remain large—12.7 percentile points in matriculation ranks, 19.5 in PET ranks—giving SG students a substantial advantage in access to selective tertiary education programs, compared to FG students with the same eighth-grade achievement, as we show explicitly in section 4. Note that the SG-FG gaps are larger for PET ranks, where test preparation is

[13]These gaps reflect differences in direct parental investment and in access to better schools and neighborhoods, In appendix Table A5 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 variation between schools.

entirely private, than for matriculation ranks, preparation for which is an important part of the high school curriculum; and that they are much greater than either the gender gaps or the gap between immigrants and natives.

In contrast to the large, highly significant gaps in achievement, the unconditional SG advantage in earnings ranks at age 29 is much smaller, and the conditional earnings gaps are not statistically significant. This is shown graphically in the bottom panel of Figure 2. The gap between SG and FG students in median earnings percentiles within each GEMS percentile is again largest at the GEMS median, where it equals 2.3 percentile points; and the largest gap in mean earnings percentiles, also at the GEMS median, is 1.4 percentile points. The regression results reported in columns (1) and (2) of the right-hand panel of Table 2 estimate average gaps. Column (1) presents our estimate of the raw SG-FG gaps in earnings ranks at age 29 conditioned only on cohort, gender, immigration and relative age within cohort, corresponding to Equation 2 and Figure 1. It equals 3.6 percentiles, much smaller than the raw test score gaps and equal to about a third of the gender gap in earnings ranks. The rightmost columns report logarithmic regression of earnings, indicating that the average raw gap equals 6.7 percent of earnings, compared to a raw gender gap of 24.5 percent. Column (2) shows that the gap in earnings ranks conditioned on students' GEMS mathematics ranks, is statistically insignificant, equal to 0.12 of a percentile. This stands in contrast to the estimated gender and immigration gaps which remain unchanged when conditioning on early achievement.

3.1 Heterogeneity by 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. Socioeconomic disadvantage adversely affects the educational achievement of young men more than it affects 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 achievement, they have 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 3 presents SG-FG percentile gaps in mean matriculation, PET and earnings ranks, conditioned on eighth-grade GEMS mathematics percentiles, separately by gender. It shows that the broad patterns are similar though not identical. For both men and women, the conditioned SG advantage on screening tests, represented by the darker lines, is substantial, and much larger than any SG advantage in earnings at age 29. However, the SG advantage on screening tests is slightly larger for men than for women, and while we see no SG advantage in earnings among men, and at some points in the distribution even a slight FG advantage, there is a small SG advantage of 2 to 3 percentile points in earnings ranks among women, conditioned on GEMS percentiles. This SG advantage in earnings disappears at the very top of the GEMS distribution.

3.2 Steeper earnings slopes

One possible explanation for why the 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 is that while SG students choose occupations that are associated with higher lifetime earnings, these occupations also exhibit steeper age-earnings trajectories, which hide this advantage when we observe them at age 29. This explanation is supported in other contexts by the work of Trejo (2016) and Leighton and Speer (2023), who highlight the importance of parental education in determining students' choice of a college major, and show that it leads FG students to favor majors with strong early-career returns. To get a sense of whether this is likely, we ask whether FG students in Israel choose study fields that lead to occupations with flatter earnings trajectories, using information on the evolution of average earnings by study field from Israel Ministry of Labor's "Avodata" database.[14] These can be thought of as approximating the future earnings that the students in our study anticipate in choosing their study fields.

In Figure4, panel (a) illustrates the relationship between the share of FG students in a study field, on the horizontal axis and the percentile rank of average earnings in study field 1-2 years after graduation, and panel (b) illustrates the relationship between the share of FG students in a study field and the percentage growth in average earnings of its graduates from the first two years after graduation to years 9 and 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 higher initial earnings or 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 2, 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) 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.

4 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 and generally widening their options. In this section, we show just how successful these efforts are. Tertiary academic programs in Israel vary in selectivity by

[14]Israel Ministry of Labor's "Avodata" database 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 different type of tertiary institutions. For full documentation of the Avodata dataset 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.

both study field and type of institution—"university" or "college"—with cutoff matriculation and PET scores largely determined ex-post by supply and demand.[16] 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,[17] and a sixth comprises individuals without tertiary education. The list of programs in each category is presented in Table A6 in the appendix.

Table 3 presents descriptive statistics. The most selective cluster comprises only university programs while the two least selective clusters are almost all 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-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 cluster 6, 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 than clusters 3, 4 and 5. Work experience declines with cluster selectivity, which may explain the similar average earnings of clusters 3, 4

[16]There is a clear distinction in Israel between universities, which are research-oriented, receiving extensive funding for research, and are accredited to confer all levels of academic degrees; and colleges ("mikhlalot" in Hebrew) that are teaching-oriented, receive minimal research funding, and are not accredited to confer doctoral degrees.

[17]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.

and 5, despite the large differences in selectivity between them. Students in cluster 3 have 13 months more work experience at age 29 than students in cluster 5.

The success of SG parents in boosting their children's access to tertiary programs is illustrated graphically in Figure 6, which shows the conditional share of FG and SG students in each of our six tertiary education clusters, by GEMS mathematics percentiles. The difference between SG and FG students' enrollment shares, conditioned on eighth-grade achievement, is striking. Thus, nearly 70 percent of SG students at the 25th 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 the most selective cluster of tertiary programs, 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, illustrating the effectiveness of raising matriculation and PET scores as a means of gaining greater access to selective academic programs.

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-hand panel. Regressions include study sample, first generation (FG) and second generation (SG) students, $N = 44,316$. Math8 is the GEMS mathematics percentile, centered at the median and immigrants are all students born outside of Israel. All regressions also include a cohort fixed-effect, and relative age within cohort. Standard errors in parentheses are clustered at the school level for matriculation scores and are robust standard errors for PET and earnings.

5 Mechanisms mediating test-score and income transmission

In this section we address two related questions: why do SG students' clear advantage on the screening tests that regulate admissions to higher education and improved access to the most selective tertiary degree programs, conditioned on eighth-grade achievement, not translate into an advantage in earnings at age 29, similarly conditioned? And this being the case, why do SG parents and children invest time, effort and material resources in improving their performance on these tests? We consider several explanations that are consistent with our findings. One explanation, explored in section 3.2, above, is that earnings at age 29 do not yet capture the earnings advantage of SG students who choose occupations with steeper earnings slopes. The indirect evidence we examined does not support this hypothesis, though we cannot rule it out altogether. A second possible explanation is that wider access to selective programs has an option value in its own right. We find evidence, in section 5.1, that a disproportionate share of SG students—more financially secure, less constrained than FG students—choose to take advantage of their improved access to tertiary education for non-pecuniary aims. Yet another possible explanation, which we examine in section 5.2, is that parents exaggerate the labor-market value of selective degree programs: labor markets place limited value on the enhanced signals that test-score transmission produces. These very different explanations are not mutually exclusive: each may be valid for different segments of our population.

5.1 Non-pecuniary benefits

As SG parents are generally able and often willing to provide their children with more of a financial safety net than FG parents, this affords their children greater freedom to trade off higher lifetime earnings for non-pecuniary benefits such as social status, job satisfaction, or better working conditions. This is consistent with research on the determinants of study field choices reviewed by Zafar et al. (2021), which highlights the importance of job amenities and family domains in determining college major choice. To obtain some indication of whether this might hold in some measure for our population, 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.[18] The two middle columns of Table 5 show estimates of the raw and conditioned SG-FG gaps in the share of students studying in programs associated with highest earnings at age 29. Comparing them to the two left-hand columns (which replicate the two rightmost columns of Table 4), we find that while we still see a slight SG advantage in the conditional gaps—SG students are 1.6 percentage points more likely to enroll in programs in the highest earnings clusters conditioned on eighth-grade ranks—it is much smaller than the 6.5 percentage point conditional SG-FG gap in enrolling in the most selective academic cluster. This is consistent with SG students being more inclined than FG students to trade off higher earnings for non-pecuniary benefits.

Further indication of a similar effect is shown in the right-hand panel of Table 5, which 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, offer shorter hours, greater job security, 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 to this gap. Again, this is consistent with FG students being less inclined to trade off higher earnings for non-pecuniary benefits.

5.2 Labor markets place limited value on advantages gained through test-score transmission

It is also possible that SG parents exaggerate the value of screening test scores that produce inflated signals of labor market productivity. In the Appendix we outline a simple formal model in which SG parents invest private resources in their children's test-taking skills, skills that improve students' scores on the screening tests that regulate entry to selective degree programs but

[18] See list of programs by earnings clusters in Table A7

add little to their labor market productivity, which the market discovers. This implies that if we compare an SG student and an FG student with the same eight grade test scores, admitted to the same selective degree program, the FG student should be more productive, as the similar success of the SG student in gaining access to the program should be attributed in part to superior test-taking skills, which are unproductive. Table 6 presents regression results that estimate the SG-FG earnings gap within each selectivity cluster, conditioned on GEMS percentiles, corresponding to the similarly conditioned enrollment regressions reported in columns (2) of Table 4. The results show 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.

Furthermore, FG students may be able to overcome their relative educational disadvantages due to test-score transmission, by accumulating labor market experience, which can both add to their human capital and generate signals of their labor market productivity. Financially constrained FG students are more likely to work at an earlier age and during their studies than SG students. We find that this is indeed the case. We measure work experience as number of months of employment between age 18 and 29 with earnings equal or greater to full time employment at the minimum wage. The first two columns in Table 7 show that by age 29 FG student accumulate nearly a year more experience than SG students; and when we add months worked to the wage regression in column (3), we find an SG conditional advantage of 5.5 percentiles.[19]

[19]Similar patterns hold when we define experience as full years of employment, rather than months which may be more sporadic, and when we measure only experience after graduation, among those attending tertiary education.

6 Conclusion

Using longitudinal administrative data to follow Israeli students in Hebrew-language, non-ultra-orthodox 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 in its education system. 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 standardized test scores, and do indeed gain greater access to these programs compared to FG students with similar eighth-grade scores. Yet this advantage does not manifest itself in earnings differentials at age 29, similarly conditioned on eighth-grade achievement, which are statistically insignificant. We do not find evidence that this is driven by FG students choosing occupations with higher initial earnings and flatter earnings trajectories.

We examine several explanations for this gap between test score transmission and earnings. One is that achievement gains in screening tests are driven by investment in test taking skills that have limited value in the labor market, 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, may not result in meritocratic selection. Indeed, we find that when comparing SG and FG students admitted to the same selective degree programs, and with the same eighth-grade test scores, the earnings of FG students are higher, despite their lower screening test achievement. Additionally we find that FG students compensate for poorer access to tertiary education by accumulating more experience in the labor market, allowing them to acquire additional skills and generate signals of their value in the labor market independently from tertiary achievement.

Other factors that may erode the SG advantage in the labor market are the importance of non-academic qualities—willingness to work hard, working well with others, integrity, dependability, emotional intelligence—which FG students may acquire in overcoming the greater obstacles they face (Edwards et al., 2022). In addition, it is possible that in some cases, the less selective, less prestigious tertiary programs in which FG students find themselves are more practically oriented to the needs of the labor market than the more academic programs from which FG students are excluded, employers observe this directly and adjust earnings accordingly, thus eroding the gains from selectivity. Our findings are consistent with such an explanation, as they are with the other possible explanations offered above, each of which may apply to different segments of the population.

Our basic finding of test score transmission expanding socioeconomically advantaged students' education options, is not a uniquely Israeli phenomenon, and can be observed in many countries. It is less clear, whether our finding that these advantages are not observed in conditional earnings at age 29, apply similarly in other countries as sharply as we found here. One feature of the Israeli setting that seems conducive to the ability of FG students to compensate for test score transmission is compulsory military service which creates a hiatus of several years (beyond the years of service themselves) after secondary education before tertiary education and labor market entry, with alternative pathways to success.

A very different explanation for which we find indirect support is that SG students take advantage of the expanded choice set that test-score transmission affords them to pursue non-pecuniary goals in employment such as job satisfaction, social prestige, political influence, job security, amenable working conditions, rather than higher pay. In support of this, we find that SG students are more heavily over-represented in academically selective study fields than in fields associated with higher earnings, and are more likely to choose public-sector employment than FG students. 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, which figures prominently in the sociological literature (e.g., Bukodi and Goldthorpe (2018)).

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 encourage unproductive investment in producing signals that impede social mobility and potentially distort the efficient allocation of talent and skills to the uses for which they are best suited.

The authors have no competing interests to declare that are relevant to the content of this article. 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. We gratefully acknowledge the financial support of Yad HaNadiv Foundation and the Maurice Falk Institute for Economic Research in Israel. The authors thank the referees and editor of this Journal for their detailed, constructive comments and suggestions. Thanks also for their helpful comments to Rebbeca Dizon-Ross and participants at AEA Annual meeting, 2023; Ben-Gurion University; WITS University; IWEEA, 2023; SOLE, 2024 and Yoav Goldstein and participants in the IEA annual meetings, 2024.

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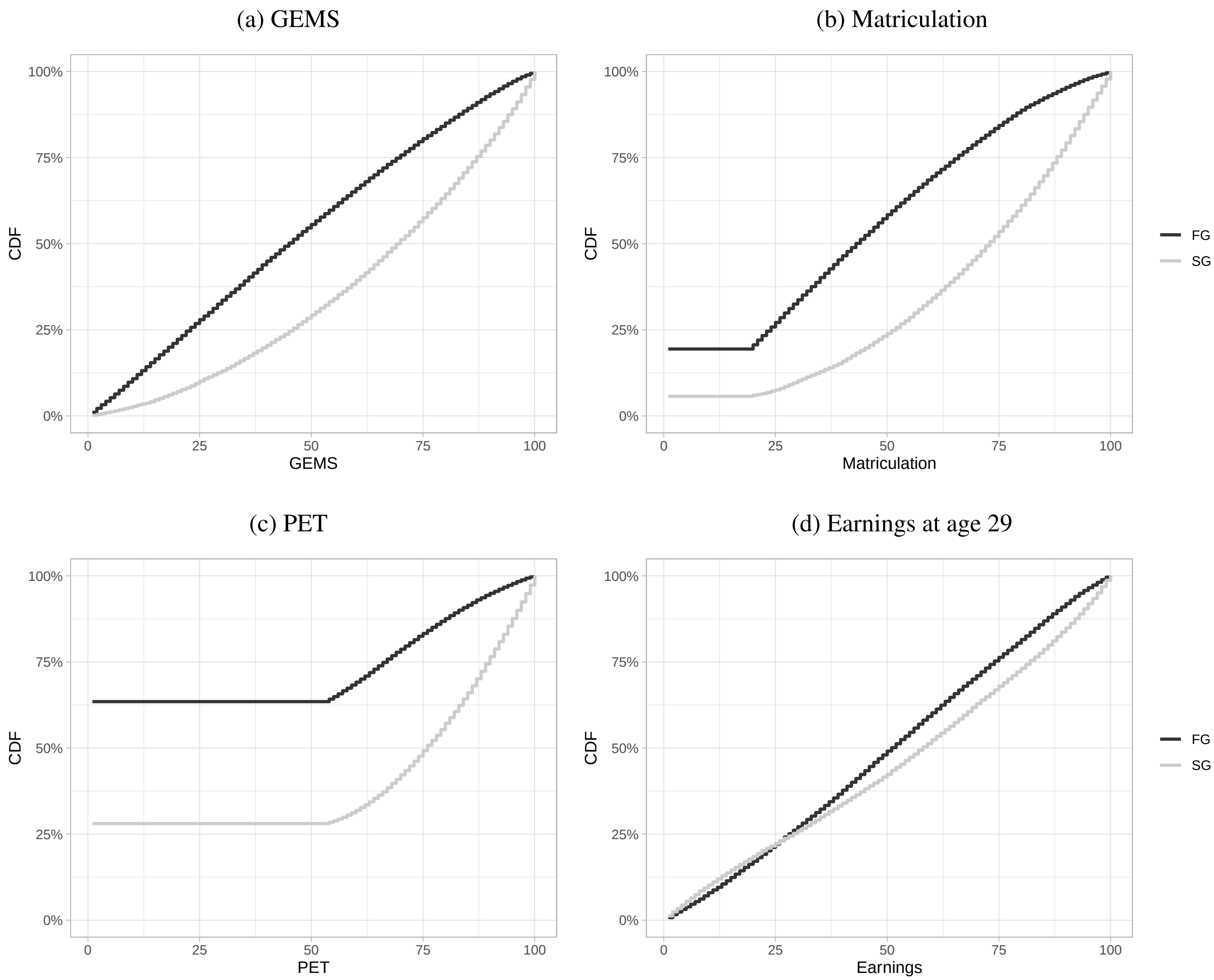
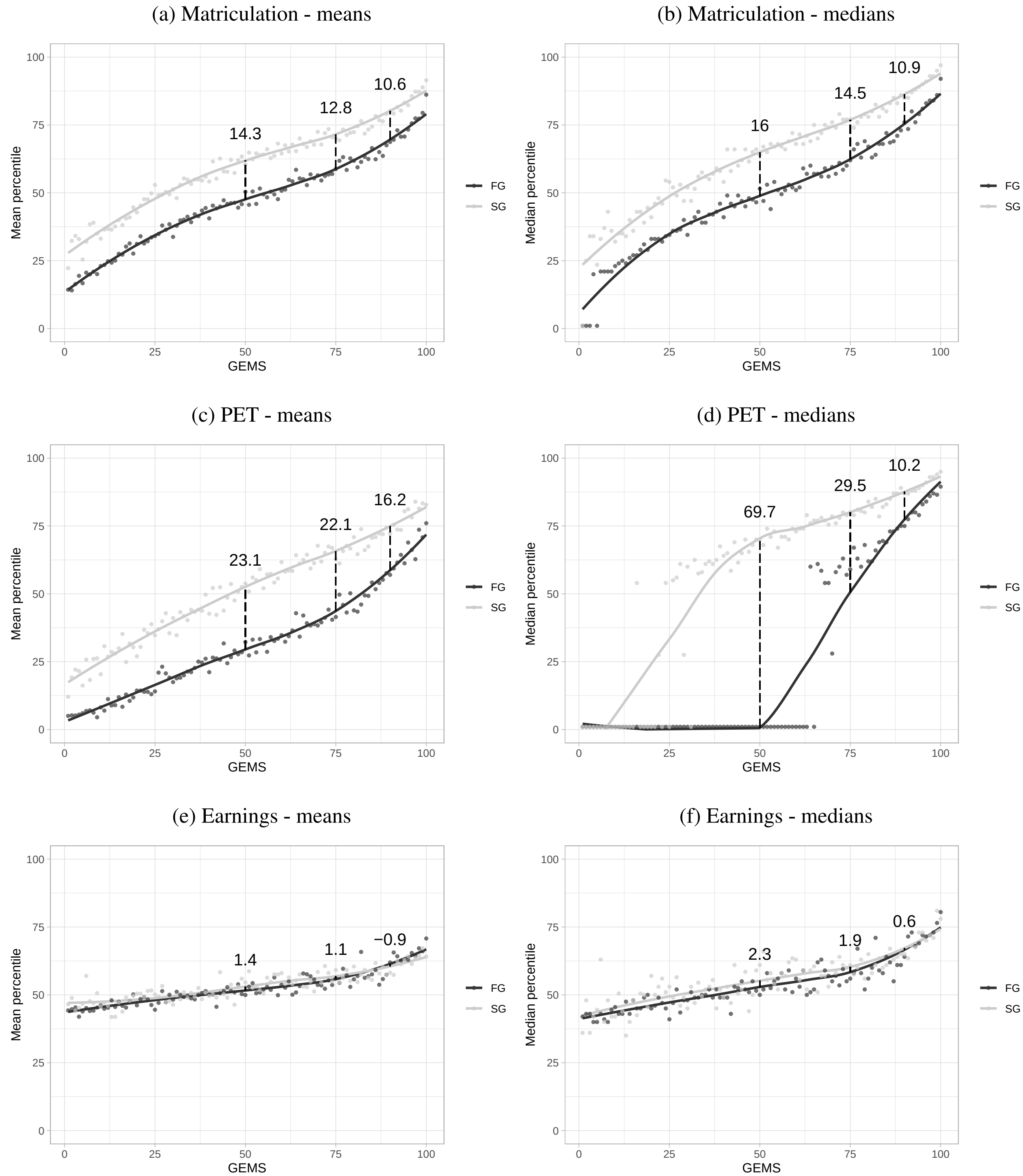
Figure 1: CDF of Percentile ranks for test-scores and earnings, FG and SG students



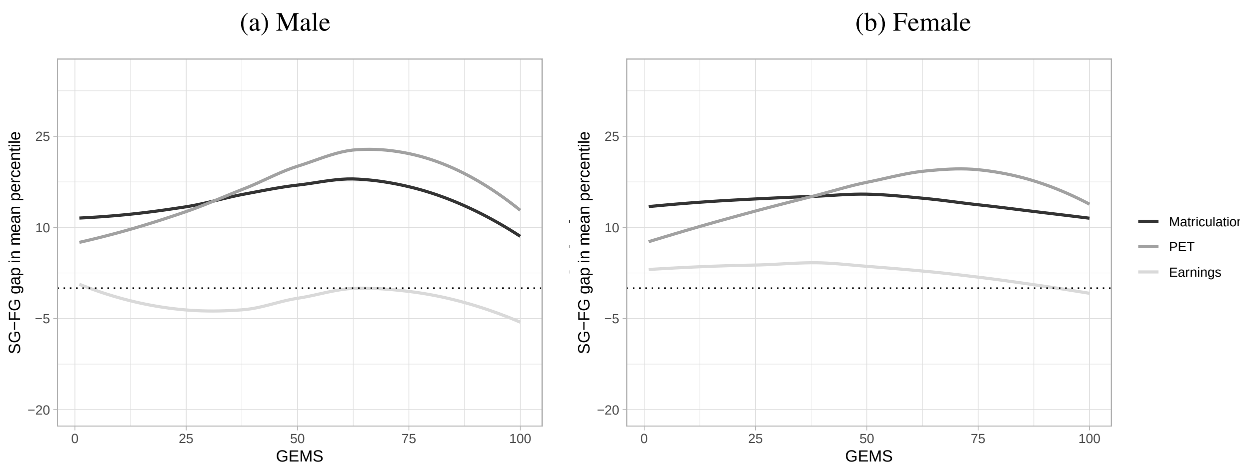
Notes: $N = 44,316$. Figures include study sample, first generation (FG) and second generation (SG) students. Each figure represents the cumulative density function of achievement/earnings percentiles, separately for FG and SG. Achievement percentiles are defined over the entire student population in the two GEMS cohorts. Non-test-takers in matriculation and PET are included in the lowest respective percentile.

Figure 2: Achievement percentiles conditional on GEMS percentiles, FG and SG students



Notes: $N = 44,316$. Figures include study sample, FG and SG students. 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. Non-test-takers in matriculation and PET are included in the lowest respective percentile. Numbers indicate SG advantage in percentile points at the 50th, 75th and 90th GEMS percentiles. Solid lines generated by locally weighted smoothing.

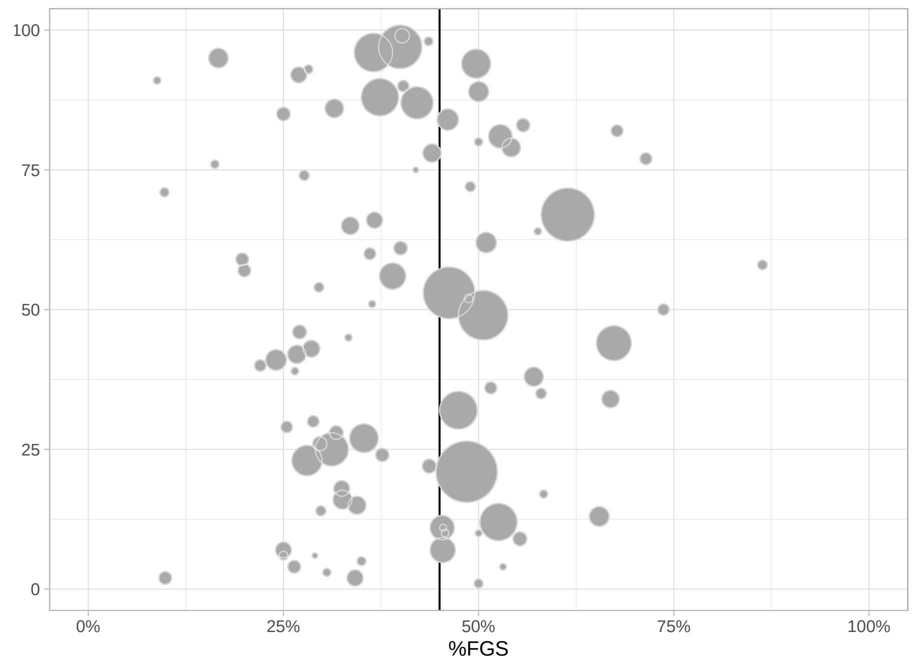
Figure 3: SG-FG gaps in matriculation, PET, and earnings percentiles, by gender



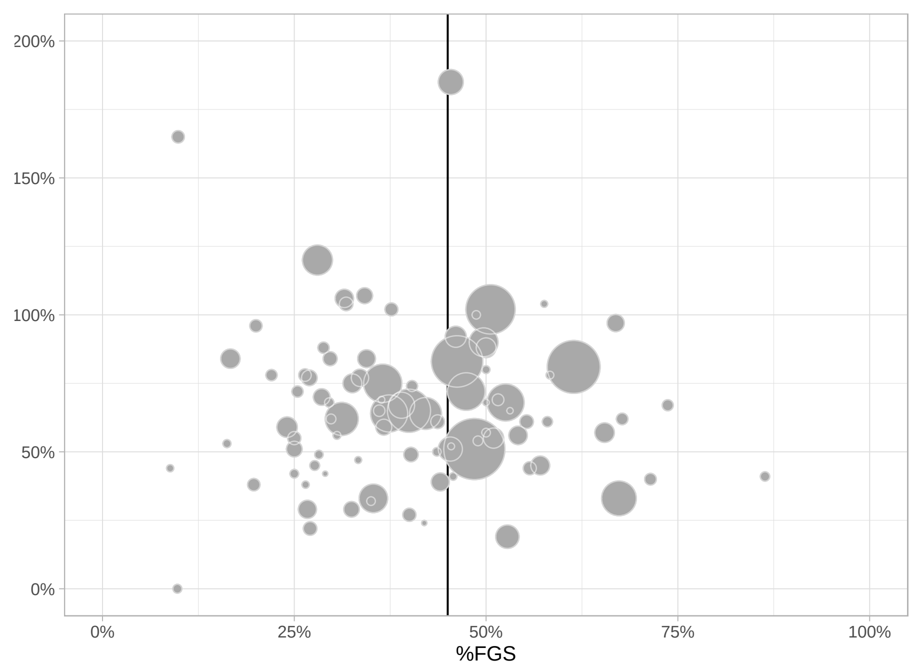
Notes: $N = 44,316$. Figures include study sample, first generation (FG) and second generation (SG) students. Solid lines generated by locally weighted smoothing of SG-FG gaps in average achievement percentiles within one-percent bins of ranks on eighth-grade standardized mathematics tests (GEMS), separately for male and female students.

Figure 4: FG share, and expected starting-level earnings and 10 year earnings growth, by study field

(a) Expected earnings percentile, 1-2 years post graduation

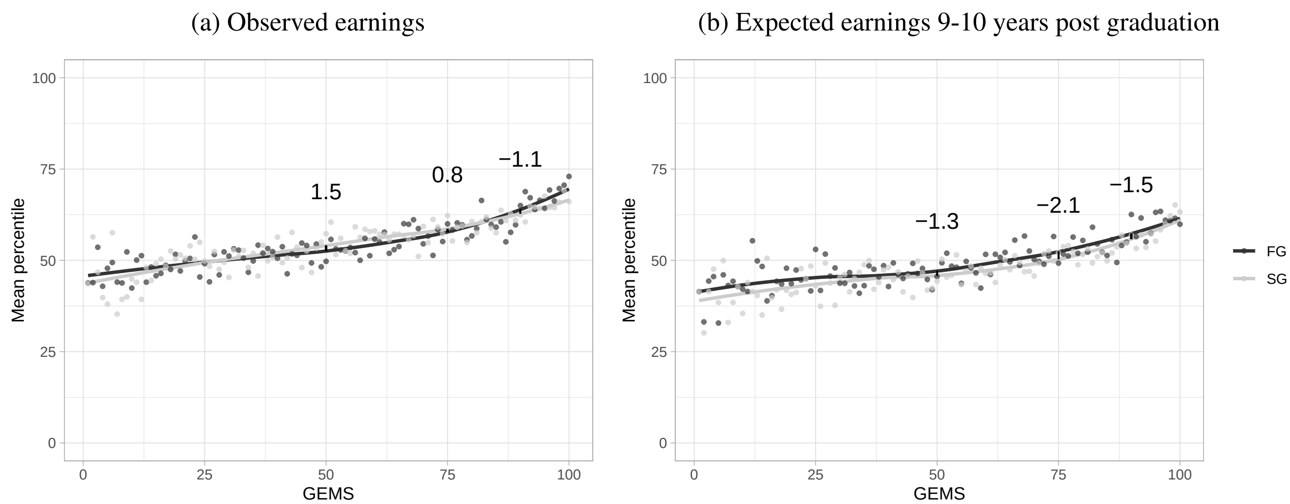


(b) Expected earnings percentile growth



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, in panel (a), the percentile rank of average earnings in study field 1-2 years after graduation; and in panel (b) 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.

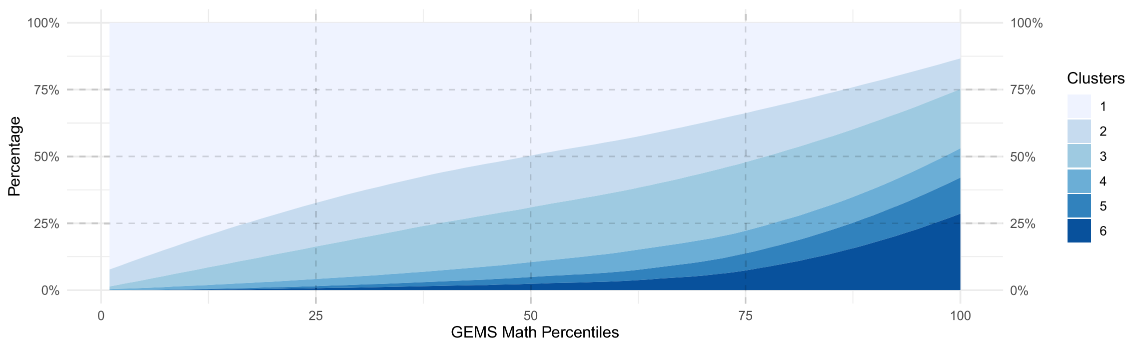
Figure 5: Expected earnings 10 years after graduation, by study field



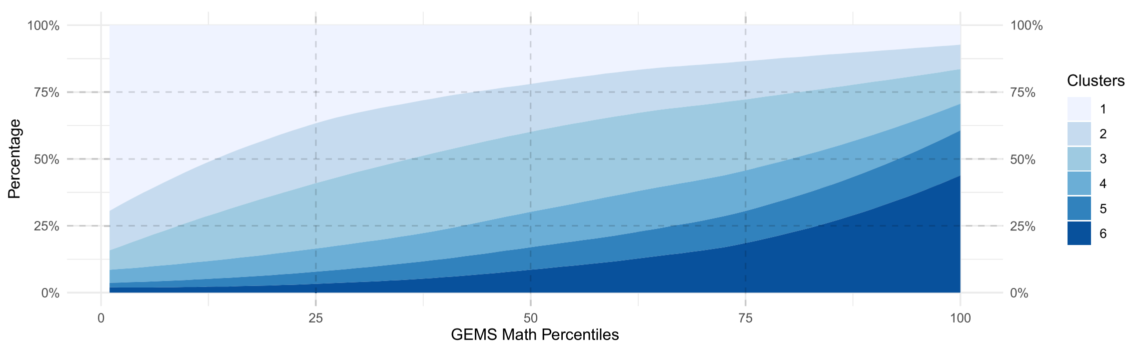
Notes: $N = 23,037$. Figures include students in study sample enrolled in tertiary education, less 1,897 students who chose study fields too small to be included in the "Avodata" database. Panel (a) replicates the lower left hand panel of Figure 2 for this sub-sample, showing mean earnings percentiles 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.

Figure 6: Share of FG and SG students in selectivity clusters by GEMS percentiles

(a) FGS



(b) SGS



Notes: $N = 44,316$. Figures include study sample, first generation (FG) and second generation (SG) students. Clusters 3-6 are tertiary academic programs clustered into 4 groups by selectivity on matriculation and PET 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; and cluster 1 comprises students with no tertiary education. Shares calculated for each GEMS percentile, and smoothed using a locally weighted regression.

Table 1: Sample construction

	GEMS schools	GEMS test takers			Study sample			
		All	SES	& wage	All	SG	FG	SG-FG
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female share	0.49	0.50	0.50	0.52	0.52	0.50	0.53	-0.03
Immigrant share	0.21	0.19	0.19	0.19	0.15	0.13	0.16	-0.03
Parents' years of schooling	13.7	13.8	13.8	13.8	13.42	16.50	11.36	5.14
Family income quintile								
Lowest		0.12	0.12	0.11	0.10	—	0.16	
2nd		0.17	0.17	0.17	0.14	—	0.23	
3rd		0.21	0.21	0.21	0.15	—	0.25	
4th		0.24	0.24	0.25	0.30	0.39	0.24	
Highest		0.26	0.26	0.26	0.32	0.61	0.12	
GEMS mathematics percentiles		54.3	54.5	54.6	53.94	64.87	46.71	18.16
Attrition - appears in:								
Twelfth grade	0.90	0.93	0.93	0.94	0.94	0.98	0.92	0.06
Matriculation mathematics	0.81	0.86	0.87	0.88	0.88	0.95	0.83	0.12
PET quantitative		0.49	0.49	0.52	0.51	0.72	0.37	0.35
Studied in tertiary education		0.53	0.54	0.57	0.56	0.78	0.42	0.36
Studied in university		0.22	0.23	0.23	0.23	0.38	0.13	0.25
Tax authority records		0.86	0.86	1.00	1.00	1.00	1.00	
Median wage, age 29				7,947	7,963	8,487	7,678	809
Mean wage, age 29				9,341	9,345	10,263	8,743	1,519
Share of population	1.000	0.858	0.814	0.703	0.583	0.231	0.352	
Share of full data				1.000	0.829	0.328	0.500	
Observations	76,054	65,222	61,926	53,489	44,316	17,555	26,761	

Notes: Full population in column (1) comprises all students attending eighth grade in Hebrew-language schools in the year a school participated in GEMS (2002 or 2003). 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 sample in each column, 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	22.917	12.687	30.801	19.536	3.598	0.123	0.069	-0.008
	(0.262)	(0.239)	(0.366)	(0.367)	(0.282)	(0.292)	(0.007)	(0.007)
Female	6.229	5.303	5.619	4.781	-11.254	-11.506	-0.245	-0.250
	(0.258)	(0.217)	(0.351)	(0.316)	(0.269)	(0.265)	(0.007)	(0.007)
Immigrant	-3.325	-3.192	-0.01	0.036	0.301	0.311	0.017	0.017
	(0.371)	(0.314)	(0.477)	(0.420)	(0.375)	(0.365)	(0.009)	(0.009)
Math8		0.559		0.601		0.185		0.004
		(0.004)		(0.006)		(0.005)		(0.000)
Math8^2		0.0002		0.002		0.001		0.00003
		(0.0001)		(0.0002)		(0.0002)		(0.0000)
Constant	39.614	39.694	25.349	23.454	57.569	56.901	9.018	8.993
	(0.266)	(0.260)	(0.352)	(0.375)	(0.273)	(0.318)	(0.007)	(0.008)
Adjusted R2	0.185	0.429	0.167	0.329	0.045	0.075	0.034	0.059

Notes: $N = 44,316$. Regressions include study sample, first generation (FG) and second generation (SG) students. 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-hand panel. Math8 is the GEMS mathematics percentile, centered at the median and immigrants are all students born outside of Israel. Immigrants are students born outside of Israel. All regressions also include a cohort fixed-effect, and relative age within cohort. Standard errors in parentheses are clustered at the school level for matriculation scores and are robust standard errors for PET and earnings.

Table 3: Descriptive statistics by selectivity cluster

	Most selective Cluster 6	Cluster 5	Cluster 4	Cluster 3	Least selective Cluster 2	No tertiary Cluster 1
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: $N = 44,316$. Table includes study sample, first generation (FG) and second generation (SG) students. Clusters 3-6 are tertiary academic programs clustered into 4 groups by selectivity on matriculation and PET 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; and cluster 1 comprises students with no tertiary education. 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	0.352	0.234	0.246	0.159	0.110	0.065
	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
Female	0.130	0.118	0.028	0.026	-0.023	-0.022
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Immigrant	-0.073	-0.071	0.006	0.004	(0.001)	(0.003)
	(0.006)	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)
Math8		0.007		0.004		0.002
		(0.000)		(0.000)		(0.000)
Math8^2		-0.00002		0.0001		0.0001
		(0.00000)		(0.0000)		(0.0000)
Constant	0.366	0.386	0.115	0.053	0.042	-0.010
	(0.004)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Adjusted R	0.162	0.283	0.093	0.191	0.049	0.126

Note: $N = 44,316$. Coefficients estimated using LPM regressions over the entire study sample, first generation (FG) and second generation (SG) students. Dependent variables are binary indicators for enrollment in any tertiary program in the left-hand panel; enrollment in university programs (selective institutions) in the middle panel; and enrollment in highly selective tertiary programs in the right-hand panel. Math8 is the GEMS mathematics percentile, centered at the median and immigrants are all students born outside of Israel. All regressions also include cohort indicators, and relative age within cohort. Robust standard errors in parentheses. The most selective programs are the cluster 6 programs listed in Table A6 in the appendix

Table 5: 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	0.110	0.065	0.049	0.016	0.076	0.074
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Female	-0.023	-0.022	-0.079	-0.080	0.210	0.209
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
Immigrant	(0.001)	(0.003)	0.014	0.013	-0.035	-0.034
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Math8		0.002		0.002		0.0002
		(0.000)		(0.000)		(0.000)
Math8^2		0.0001		0.00003		-0.00001
		0.000		0.000		0.000
Constant	0.042	-0.010	0.084	0.059	0.108	0.112
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Adjusted R	0.049	0.126	0.039	0.081	0.068	0.068

Note: $N = 44,316$. Coefficients estimated using LPM regressions over the entire study sample, first generation (FG) and second generation (SG) students. Dependent variables are binary indicators for enrollment in highly selective tertiary programs in the left-hand panel; enrollment in tertiary programs associated with highest earnings at age 29 in the middle panel; and public sector employment at age 29 in the right-hand panel. The most selective programs are the cluster 6 programs listed in Table A6 and the programs associated with highest earnings are the cluster 6 programs listed in Table A7 in the appendix. Math8 is the GEMS mathematics percentile, centered at the median and immigrants are all students born outside of Israel. All regressions also include cohort indicators, and relative age within cohort. Robust standard errors in parentheses.

Table 6: Earnings regressions estimated within tertiary selectivity clusters

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

Notes: $N = 44,316$. Regressions include study sample, first generation (FG) and second generation (SG) students, separated according to tertiary selectivity cluster. Clusters 3-6 are tertiary academic programs clustered into 4 groups by selectivity on matriculation and PET 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 is non-selective tertiary programs; and cluster 1 comprises students with no tertiary education. Dependent variables are earnings percentiles at age 29 in the top panel; and log earnings at age 29 in the bottom panel. 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 7: Accumulated work experience and earnings at age 29

	Work experience (months)	Earnings at age 29			
		Percentiles		Ln(wage)	
	(1)	(2)	(3)	(4)	(5)
SG	-11.046	0.123	5.493	-0.008	0.119
	(0.303)	(0.292)	(0.252)	(0.007)	(0.006)
Female	-4.442	-11.506	-9.346	-0.25	-0.199
	(0.286)	(0.265)	(0.229)	(0.007)	(0.006)
Immigrant	2.77	0.311	-1.036	0.017	-0.015
	(0.411)	(0.365)	(0.317)	(0.009)	(0.008)
Math8	-0.049	0.185	0.209	0.004	0.005
	(0.006)	(0.005)	(0.004)	(0.0001)	(0.0001)
Work experience (months)			0.486		0.01
			(0.003)		(0.0001)
Constant	56.135	56.901	29.607	8.993	8.349
	(0.341)	(0.318)	(0.346)	(0.008)	(0.009)
Adjusted R2	0.051	0.075	0.33	0.059	0.295

Notes: Dependent variables are work experience—accumulates months of employment between age 18-29—in the left-hand panel; and earnings percentiles at age 29 and the log of earnings at age 29 in the right panel. Regressions include study sample, first generation (FG) and second generation (SG) students, $N = 44,316$. Month of employement is defined as amonth where earnings are equivalent to or higher than full time minimum wage monthly earnings. Math8 is the GEMS mathematics percentile, centered at the median and immigrants are all students born outside of Israel. 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	FG only
			Eighth grade		
Test takers					
Mathematics	0.86	0.88	0.88	0.88	0.88
Literacy	0.90	0.92	0.92	0.92	0.92
English	0.87	0.89	0.89	0.90	0.89
Science & tech	0.85	0.87	0.87	0.87	0.88
Average score					
Mathematics	52.36	52.61	52.76	52.86	46.16
Reading	63.55	63.92	64.04	64.31	59.37
English	78.30	78.61	78.72	78.80	72.52
Science & tech	64.24	64.42	64.53	64.60	60.11
			End of secondary education		
Test takers					
Matriculation, mathematics	0.84	0.86	0.87	0.88	0.83
PET, quantitative		0.49	0.49	0.52	0.37
Average score					
Matriculation, mathematics	68.31	70.83	71.14	72.27	60.71
PET, quantitative		56.33	56.59	59.16	39.54
2002 cohort	0.49	0.49	0.49	0.48	0.50
N	67,905	65,222	61,926	53,489	26,761

Notes: Population in column (1) comprises all students who have a score in at leat one GEMS test. Parental education is the years of schooling of the parent with the most education. FG are first generation students—neither parent has more than 12 years of schooling. Test-taking shares are calculated with respect to the entire sample in each column, including non-test-takers. Average GEMS scores are calculated among test takers in each subject. Matriculation and PET average scores are calculated for the entire sample, assigning non-test takers a score of 0. Mathematics matriculation scores are weighting according to level of difficulty.

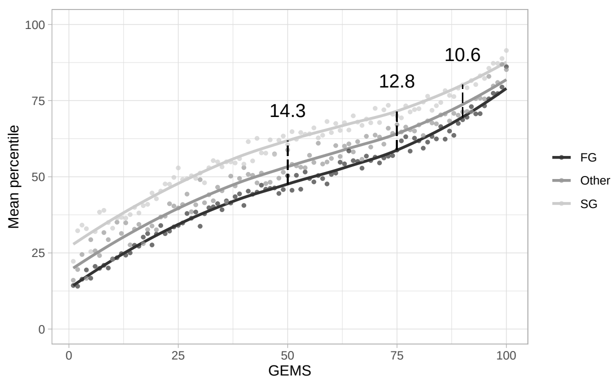
Table A3: Probability of appearing in tax records in 2017 or 2018

	Appears in tax records in 2017/18		
	(1)	(2)	(3)
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)
Math8			-0.0001
			(0.0001)
Constant	0.845	0.756	0.758
	(0.003)	(0.006)	(0.007)
Adjusted R	0.008	0.008	0.013

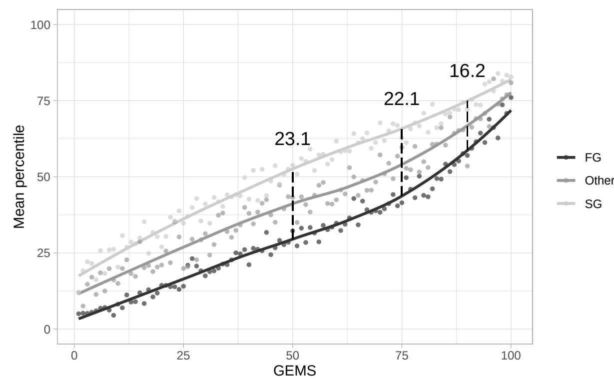
Notes: $N = 51,036$ LPM regression estimating the relationship between observed characteristics and the probility of appearing in the national income tax records in either 2017 or 2018. Sample includes all individuals in the 2002 and 2003 cohorts for whom we observe at least two GEMS scores and at least one parent's years of schooling.

Figure A1: Replication of main figures including students who are neither FG nor SG

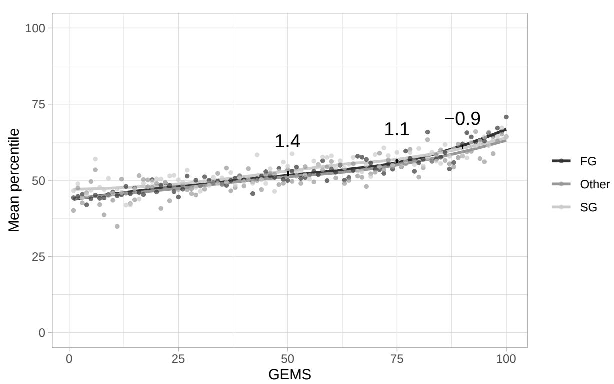
(a) GEMS-Matriculation



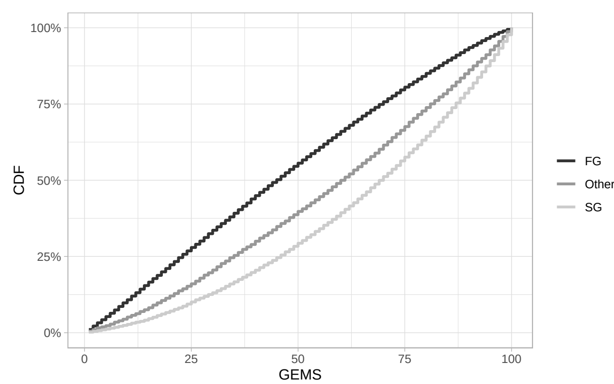
(b) GEMS-PET



(c) GEMS-Earnings at age 29



(d) GEMS



Notes: $N = 53,489$. Figures include study sample, FG and SG students, and 'other' students—whose parents have some tertiary education and income in the lowest three quintiles, and are therefore neither FG nor SG students in our study sample. 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, SG and other students. Non-test-takers in matriculation and PET are included in the lowest respective percentile. Numbers indicate SG-FG advantage in percentile points at the 50th, 75th and 90th GEMS percentiles. Solid lines generated by locally weighted smoothing.

Table A4: Estimated SG-FG gaps in all outcomes, SG defined solely by parental schooling

	Achievement		Labor market			Tertiary education			
	Matriculation percentiles	PET percentiles	Earnings percentiles	Earnings Ln(earnings)	Public sector employment	Any	University	Selective programs	High earnings programs
SG (all income)	10.486	16.245	-0.39	-0.019	0.064	0.197	0.130	0.050	0.013
	(0.214)	(0.319)	(0.251)	(0.006)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Female	5.159	4.703	-11.307	-0.247	0.211	0.120	0.026	-0.024	-0.082
	(0.2)	(0.293)	(0.243)	(0.006)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)
Immigrant	-4.995	-2.486	1.210	0.039	-0.053	-0.105	-0.020	-0.015	0.014
	(0.268)	(0.368)	(0.31)	(0.008)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)
Math8	0.566	0.613	0.184	0.004	0.0002	0.007	0.004	0.002	0.002
	(0.004)	(0.005)		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00004)	(0.00004)
Constant	39.885	23.744	56.668	8.989	0.115	0.387	0.056	-0.007	0.060
	(0.246)	(0.355)	(0.297)	(0.007)	(0.004)	(0.005)	(0.004)	(0.002)	(0.002)
Adjusted R2	0.406	0.304	0.072	0.057	0.069	0.26	0.175	0.116	0.08

Notes: $N = 53,489$. Regressions include first generation (FG) students for whom neither parent has more than 12 years of schooling and second generation (SG) students for whom at least one parent has more than 12 years of schooling, irrespective of income. Dependent variables vary by column. The most selective programs are the cluster 6 programs listed in Table A6 and the programs associated with highest earnings are the cluster 6 programs listed in Table A7 in the appendix. All coefficients are estimated using linear models, LPM for binary outcomes. Math8 is the GEMS mathematics percentile, centered at the median and immigrants are all students born outside of Israel. Immigrants are students born outside of Israel. All regressions also include a cohort fixed-effect, and relative age within cohort. Standard errors in parentheses are clustered at the school level for matriculation scores and are robust standard errors for all other outcomes.

Table A5: Estimated SG-FG gaps in all outcomes with eighth grade school fixed-effects

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

Notes: $N = 44,316$. Regressions include study sample, first generation (FG) and second generation (SG) students. Dependent variables vary by column.The most selective programs are the cluster 6 programs listed in Table A6 and the programs associated with highest earnings are the cluster 6 programs listed in Table A7 in the appendix. All coefficients are estimated using linear models, LPM for binary outcomes. Math8 is the GEMS mathematics percentile, centered at the median and immigrants are all students born outside of Israel. All regressions also include fixed effect for schools attendedd in eighth grade as well as a cohort fixed-effect, and relative age within cohort. Standard errors in parentheses are clustered at the school level for matriculation scores and are robust standard errors for all other outcomes.

Table A6: Tertiary programs by selectivity cluster

Cluster 6 - most selective	**Cluster 5**	**Cluster 4**	**Cluster 3 - least selective**	**Cluster 2 - 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)		

Table A7: Tertiary programs by earnings at age 29 cluster

Cluster 6 - highest earnings (age 29)	**Cluster 5**	**Cluster 4**	**Cluster 3**	**Cluster 2 lowest earnings (age 29)**
3096	**2405**	**9792**	**10113**	**1402**
Computer Science	Administrative Information Systems	Accounting	BA Social Science	Animal Science
Computer Science and Engineering	Aerospace and Space Engineering	Arab Nation History	Behavioral science	Archaeology
Electrical Computer Engineering	Bio-Medical Engineering	Arabic Language and Literature	Bible Studies	Architecture and Urban Construction
Electrical Engineering	Civil Engineering	Banking	Biology	Art (Specific)
Information Systems Engineering	Economics and Business Management	Biotechnological Engineering	Biotechnology	Art and Culture Studies
Mathematics	Engineering Science	Brain Science	Chemistry	Art History
	Industrial engineering	Business Management	Criminology	Botany
	Information System	Chemical Engineering	Dietetics	Dance
	Information System - Administration	Communication	East Asian Studies	Dental Medicine
	Insurance	Economics	Education	Ecology
	International Relations	Electronics Engineering	Education Theory and Research	Engineering and Water Resource Management
	Learning Management System	Environmental Economics	Emergency Medical Services	Geography , Geology and Meteorology
	Mathematics-Computer Science	Food Engineering & Biotechnology	English Language and Literature	Geology
	Nursing	General Administration and public administration	Environmental Engineering	History and General History
	Pharmacy	Hotel Management	Fashion Design	Industrial design
	Physics	Human Services	Film and Visual Studies	Jewelry Design
	Sustainability	Hydrotechny	Food Science	Literature
	Telecommunications engineering	Industry Management	Food Sciences	Medical Sciences
		Islam History and Culture	Forensic medical Science	Multi-Discipline Humanities
		Law	General Studies	Music
		logistics	Geography	Philosophy
		Marketing Management	Health Systems Management	Photography
		Materials science	Hebrew Language	Plant Protection
		Mechanical Engineering	Hebrew Literature	Textile Design
		Optometry	History of Judaic Thought	Theatre History
		Pharmaceutical Engineering	Human Service Management	
		Political Science	Humanities	
		PPE (Philosophy,politics,economics)	Interior Building	
		Second Major Social Science	Interior Design	
		Service Management	Israel Region Studies	
		Statistics	Israeli History	
		Structural Engineering	Latin languages Studies	
		Teacher Math and Science Certificate	Linguistics	
			Medicine	
			Multi-Discipline Judaism Studies	
			Occupational Therapy	
			Physiotherapy	
			Psychology	
			Public Administration	
			Social Work	
			Sociology and Anthropology	
			Soil and Water Sciences	
			Special-Needs Education	
			Speech-language Therapy	
			Teacher Education Certificate	
			Visual Communication	

A1 Investment in unproductive test-taking skills - a simple model

In this appendix we set out a simple conceptual framework that illustrates the relationships between ability, socioeconomic background, human capital, test scores, and earnings on the assumption that parents are able to make unproductive investments in their children's test-taking skills to boost their performance on screening tests.

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 θ 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 having more education and 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 (we assume uniformity for convenience; our results hold equally if SG schools are better than FG schools); and parents' private investment in their children's basic education, p_{g1}, which we assume is higher for SG parents, $p_{f1} < p_{s1}$. To fix ideas, we write, for the human capital of child i in group g at the end of stage 1:

$$h_{ig1} = a_i + c_1 + p_{g1} \tag{5}$$

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_{ig1}, are an increasing function of a child's human capital stock, h_{ig1}, and of factors affecting test scores that are orthogonal to the child's' human capital, ϵ_{i1}:

$$R_{ig1} = f_1(h_{ig1}, \epsilon_{i1}) \tag{6}$$

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, ϕ<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 ϕ 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_{g2}, and investment in their test-taking skills, m_g. We assume again that private investment is uniform within student type, with SG parents investing more than FG parents, $p_{s2} > p_{f2}$ and $m_s > m_f$. Students' end of period human capital is then:

$$h_{ig2} = h_{ig1} + c_2 + p_{g2} \tag{7}$$

Their ranking on the screening tests that determines entry to tertiary education is a function of their human capital, h_{ig2}, of their test-taking skills, m_g, and of test-specific measurement error ϵ_{i2}:

$$R_{ig2} = f_2(h_{ig2}, m_g, \epsilon_{i2}) \tag{8}$$

In the third stage, the top ϕ 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 $j (j = 0, 1)$.[A1] 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 degree, while those without a degree work in non-academic occupations that pay less.[A2] 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_{ig2}, further occupation-specific human capital obtained in tertiary education, k_j, where $k_1 > 0 = k_0$, and a stochastic error term ϵ_{ij}^{w}:

$$w_{igj} = h_{ig2} + k_j + \epsilon_{ij}^{w} \tag{9}$$

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. $\delta_2 > \delta_w$

[A1] Our conceptual 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.

[A2] 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.

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_{ig1}:

Hypothesis 3. $E(w_{isj}|R_{is1} = R, k_j = 1) < E(w_{ifj}|R_{if1} = R, k_j = 1)$