Learning Gains among Repeat Takers of the Turkish College Entrance Exam*

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Abstract

Using a unique dataset on the college entrance exam (ÖSS) in Turkey, we look at learning over multiple attempts. Using cross section data, we show how to use information on repeat takers (who make up more than two thirds of examinees) to estimate learning between the first and the n^{th} attempt, while controlling for selection into retaking in terms of observed and unobserved characteristics. Learning is important, and more so for less privileged and worse performing students, suggesting that repeat taking may reduce the effects of background inequalities on college admission.

Keywords: learning gains, higher education, factor analysis, selection
JEL Codes: C13, C38, I23

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1 Introduction

Every year about 1.5 million students take the ÖSS, the centralized university entrance exam (ÖSS) that regulates access to higher education in Turkey. Only a third of them get placed in an undergraduate program, including two and four year university programs as well as distance education programs.[1]. As competition for a seat in college is extremely fierce, taking the ÖSS is an immense source of stress and frustration for students who often have to take it multiple times before getting in.[2] The high demand for tertiary education in Turkey, paired with the extreme competition for access, has turned this exam into a social issue (Hatakenaka (2005)).

A current central theme in Turkey's political agenda is the expansion of the higher education system so as to meet the (supposedly) excessive demand. However, between 2000 and 2005, the ratio of high school ÖSS applicants to available seats was 1.1, suggesting that there may not be a shortage of seats but an excess of retakers who represent two thirds of the total pool of applicants each year. Although most repeat takers are students who fail to get placed, roughly a quarter had been previously placed, but decided either not to enroll or to enroll and reapply hoping for a better placement (YÖK (2006)).

In this paper, we look for evidence regarding catchup, or the lack thereof, among repeat takers in the Turkish system. While retaking imposes burdens both on students and the system, allowing it may give less prepared students a chance to catch up, as well as ensuring that all applicants achieve a minimum level of competence before going to college. If less privileged students learn more on retries, as our work seems to suggest, the Turkish approach may also have the benefit of leveling the playing field.

We use a unique dataset on a random sample of about 115,000 ÖSS applicants from three high school tracks (Science, Social Studies, Turkish/Math) in 2002 to estimate learning, in terms of *score improvement*, among repeat takers. Our goal, measuring *cumulative* learning between the first and the n^{th} attempt, is particularly challenging given the lack of panel data. However, by

[1]If we focus on four year college programs, the average placement rate between 2000 and 2005 is as low as 9.2% (Hatakenaka (2005))

[2]Only a third of those taking the exam are doing so for the first time.

making some plausible assumptions and relying on the availability of two performance measures for each student, high school GPA and exam score in the current attempt, we develop a creative estimation methodology that overcomes this limitation.

The key assumptions in our approach are i) students know their own (unobserved to the econometrician) ability, ii) learning is exogenous: it is a draw from a distribution that is allowed to vary with observables and/or unobservables, iii) performance is partly determinate (coming from observables, unobservables, and learning) and partly random, and iv) the system is in steady state.

As students know their own ability, their decision to retake will not be affected by the number of times they have taken the test unless the cost of retaking changes over attempts. Thus, to allow for attrition in retaking, we allow these costs to vary over attempts.[3] While we do not have a panel we can follow, only a cross section, we rely on the assumption of steady state to look at selection and learning. Under the steady state assumption, the sub-sample of first time takers is equivalent to a initial cohort of exam takers at any point in time and since almost all high school graduates in Turkey take the exam at least once, this sub-sample is free of selection. Moreover, since first time takers sit for the exam during their last high school year, their scores, by definition, do not contain any learning effects.

Although the student knows his ability, we do not: we only observe two noisy measures of ability, namely performance in high school (GPA) and in the college entrance exam (ÖSS score). Moreover, the student self selects into retaking: students who do better (worse) than they should, will not (will) retake. This selection needs to be accounted for when dealing with retakers. We estimate average cumulative learning gains while controlling for endogenous selection into retaking both in terms of observed and unobserved characteristics. We model GPA and ÖSS score as linear functions of observables and incorporate the effect of unobservables through factor structure that makes the correlation between error terms in both equations to be driven by students' types.

[3] Alternatively, exit can be generated in a context where students draw the cost of retaking as a shock that comes from a distribution that is fixed over attempts.

By jointly estimating the GPA and score equations in the sub-sample of first time takers, we obtain consistent estimates of the marginal effects of observed characteristics on both performance measures.[4] We can then use these estimates in each sub-sample of repeat takers to predict the portion of GPA and exam score explained by observed characteristics. Now, since the GPA equation does not contain any learning gains, its average residual in each sub-sample of repeat takers yields a noisy measure of the effect of unobservables on performance, conditional on the number of attempts. Using these estimates together with the estimates of the contribution of observables on scores we predict the scores that repeat takers would have gotten in their first attempt. Average cumulative learning gains are then obtained as the mean difference between observed performance in the n^{th} attempt and *predicted* performance in the first attempt, where the latter controls for endogenous selection into retaking.

Our study identifies important cumulative learning gains among repeat takers once selection into retaking is controlled for. We find, for example, that learning gains in the second attempt fluctuate between 8% and 18% of the predicted initial score. The gap between the score and the minimum cutoff required to be eligible for placement shrinks with attempts.[5] While we identify larger and increasing cumulative gains in the Social Studies and Turkish-Math tracks, repeat takers from the Science track see their learning gains dissipate as the number of attempts rises.

Most important, we identify larger gains among repeat takers from less advantaged backgrounds; in all tracks, students who come from worse schools, who spent less money on private tutoring centers (*dersanes* in Turkish), or who have less educated fathers, experience larger learning gains than more privileged students. These results suggest that setting high standards for passing the college entrance exam while allowing students to retake without penalties or monetary costs may help disadvantaged students reduce the academic gap before they go to college. Although we do not (and cannot) measure the net welfare impact of letting students retake the ÖSS in this paper, our results draw attention to the benefits that systems like the

[4]To estimate the system we make some parametric assumptions on the factors' distributions. An online Appendix that presents the non-parametric density estimates of the factors shows that these assumptions are appropriate.

[5]In the Science track, the average student is able to score above the cutoff only after retrying which may help explain the higher fraction of retakers in this track.

Turkish one, which is similar to that in much of continental Europe and Asia, may generate for repeat takers.

While we focus on the Turkish experience, the issues we study are far more general. Most countries rely on examinations of various kinds to place students. The extent to which they rely on an exam, and not the entire portfolio representing the student, varies considerably, as does the sort of exam used and the number of times the exam can be taken.[6] There is little or no work on the costs and benefits of the various approaches taken and a better understanding of the theory and evidence in this regard would be useful.

We proceed as follows. Section 2 discusses previous studies on catch up. In Section 3 we describe the Turkish higher education selection process while Section 4 describes the data. Our model is presented in Section 5 while Section 6 provides the econometric model we develop to estimate learning. Section 7 shows that the potential bias from our methodology is relatively small. Section 8 presents and discusses the results. Finally, Section 9 lays out some avenues for future research and concludes.

2 Relation to the Literature

Broadly speaking, our work is indirectly related to a large literature on the economics of education. It is more closely related to the literature on catchup and learning in various contexts as outlined below. Despite the importance that catch up should have in policy makers' agendas around the world, there are few empirical studies related to the topic. Moreover, previous evidence is, for the most part, limited to work on the US which we argue may not be the ideal

[6]In the US, for example, the SAT or ACT is widely used. But compared to the ÖSS, these exams test for much more basic skills being closer to an IQ test than a subject exam. Moreover, performance in these exams is only a small part of what colleges use in making their admissions decisions while in countries like India, China, Japan and Turkey performance in centralized exams (that test book learning at a high level) and/or high school performance are the unique criteria used to rank students. Other important differences relative to the exams used in a centralized system is that all previous SAT scores obtained by a student are observed and that the exam is offered frequently and taken while in school, so that the cost of retaking is low. In Turkey, only the most recent score is used and the exam is only offered once a year, raising the cost of retaking. In India, the number of times the Joint Entrance Examination (JEE) and the Indian Administrative Service (IAS) exams (that are taken by applicants for elite engineering schools and government service respectively) can be taken is limited to prevent serial retaking.

environment on which to focus.

2.1 Early Education and Catchup

It has been extensively documented that remediation of inadequate early investments in human capital is difficult and very costly as skills build on themselves generating cumulative effects. However, early investments by themselves are not sufficient if they are not matched by later investments (Cunha et al. (2006)).

A number of studies have looked at schooling as a way to ameliorate the effect of background disadvantages on human capital accumulation. After controlling for selection into schooling, Hansen et al. (2004) and Heckman et al. (2004) show that schooling does raise ability as measured by the AFQT achievement test but it does not eliminate gaps between children from different racial and economic groups.

2.2 Immigrant Performance

This strand of the literature compares the educational achievement of immigrants and/or immigrants' children born in the US to that of children whose parents are native born. Portes and Rumbaut (2001) found that children who arrive before age 13 and second generation children in Miami and San Diego tend to perform better than their native-born schoolmates in terms of grades, rates of school retention, and behavioral aspects (e.g., doing homework). However, those who arrive after age 13 tend to be outperformed by native-born students. Using the 1995-2002 Current Population Surveys (CPS), Card (2005) finds some evidence in favor of educational catch up among second generation migrants. While immigrants have about 1.2–1.4 fewer years of education than natives, second generation immigrants have 0.3–0.4 years more of schooling than people whose parents were born in the US.

2.3 Affirmative Action, Catchup and Mismatch

This strand of the literature evaluates the evolution of the academic performance of students admitted to college due to affirmative action (AA) preferences.

Rothstein and Yoon (2009, 2008)'s work suggests that there is moderate evidence of mismatch in law school, suggesting that catch up may be limited. They find a negative effect of school selectivity on black students both on graduation and bar passage rates in the US, but only among those in the lowest quintile of admission credentials.

Sander (2004) finds that the average performance gap between blacks and whites at selective law schools is large and, more importantly, tends to get *larger* as both groups progress through college. He also finds that black applicants in selective schools have a lower probability of graduation, mostly due to reduced grades.

The THEOP (Texas Higher Education Opportunity Project) run by Marta Tienda at Princeton also has implications for catchup. By law, the top 10% of graduating students from public high schools in Texas are automatically granted admission to the University of Texas, Austin. Alon and Tienda (2007) argue that students admitted under the 10% rule are more likely to graduate than those not admitted under this rule. Niu and Tienda (2010, Forthcoming.) claim that high school GPA better predicts college performance measured by GPA than performance in standardized tests. However, this work does not control for the difficulty of the courses taken. If those admitted under the 10% rule take easy courses they may be more likely to graduate and get better GPAs, which need not imply better performance or outcomes.

Work by Arcidiacono et al. (2011) in this regard has recently provoked a great deal of interest. It shows that although the GPA gap between white and black students at Duke University falls by half between the first and the ast year of college, this comes primarily from smaller variance in grading during later years and a higher proportion of black students switching into easier majors. Since a 4.0 GPA taking easy courses is not comparable with the same GPA taking harder courses, one might see what looks like catch up if weaker students choose easier courses and self-selection is ignored (see Loury and Garman (1993, 1995) as well on this subject). By having extremely good data on courses taken, Arcidiacono et al. (2011) are able to control for the selection that confounds much of the work done on the US.

Frisancho and Krishna (2012) use a remarkably detailed dataset on a single graduating class from an elite engineering institution (EEI) in India to evaluate the effects of AA on Indian minorities. They argue that the Indian higher education setting provides a fertile ground to evaluate AA policies due to its transparent admission criteria, extreme preferences in favor of minorities and a rigid course structure in college. They find that rather than catching up in college, minorities fall behind, and more so in more selective majors where, for institutional reasons, the gap between them and their non minority peers is greater.

2.4 SATs and Retaking

Although relatively scarce, there have been previous attempts to measure catch up in an environment similar to the Turkish one. Evidence presented by Nathan and Camara (1998) shows that 55% of the juniors taking the SAT in the US improved their scores as seniors while 35% of them experienced score reductions. Moreover, they find that the higher (lower) the student's initial SAT score as a junior, the lower (higher) is the score increase when retaking as a senior.

Vigdor and Clotfelter (2003) go a bit further. They use data on undergraduate applicants to three selective US research universities and look at the evolution of SAT scores over multiple attempts. They implement a two-stage Heckman sample-selection procedure and estimate that between 70% and 90% of the observed score increase can be accounted for by *learning*, either in terms of knowledge gains or exam taking skills improvements. A drawback of Vigdor and Clotfelter (2003)'s selection correction is that it does not impose any exclusion restrictions which implies that identification relies exclusively on parametric assumptions. Though they have a model they simulate to try and match to the data, the model is not dynamic and has a reduced form feel to it.

Although the contribution of this work is important, the drawback of using data on the SATs is twofold. First, as the SATs are far from the only basis of ranking students used in university admissions, students take them more lightly than the ÖSS and so there may be far more noise in the scores. Second, the level of difficulty of the SAT is far below that of the ÖSS, with the SAT being more of an IQ test than a skills test. This compromises its ability to distinguish between takers, especially at the high end. This is reflected in the fact that a non trivial number of students achieve perfect or near to perfect scores in the SATs.[7]

2.5 Summary

Although there is some evidence of catch up among immigrants' children, the rest of the evidence described above finds little or no evidence of catch up. Even in the cases in which some evidence of catch up is available, the issue of self-selection into courses in US universities creates problems in defining academic performance measures. When one thinks about it, the lack of evidence in favor of catch up among students admitted into college due affirmative action preferences is not surprising and may be because this is the wrong place to look for catchup. These students start college lagging behind those admitted under regular admission criteria. Consequently, the gap between them is likely to increase as both groups progress through college. Even by running as fast as they can, less advantaged students can hope, at best, to stay in the same place they started.

We argue that a better place to look for evidence of catch up should be one where the goal post is fixed and where the same academic standards are applied to evaluate student performance. We believe that the Turkish college entrance exam satisfies these two requirements and provides the ideal scenario to measure catch up among exam repeat takers. Since the exam is constant in terms of content and difficulty over time the goal post is fixed rather than constantly moving. As all students who want to access higher education have to take the same exam and this exam is at a high level,[8] performance can be accurately measured and compared across students and it is not influenced by individual choices as in the case of college GPAs. Finally, there are many retakers which lets us look at learning as the number of attempts increases.

Our study, we believe, contributes to the existing literature in a number of ways. First it implements an econometric methodology that controls for selection in observables and unobservables into retaking to measure learning. As discussed in more detail below, we have two

[7]In 2008, there were 294 students out of 1,518,176 who took the SAT with a score of 2400, a perfect score. Roughly 5683 students got a score of 2300 or more. As colleges take the maximum score over all attempts as the relevant score, this number or higher may be the relevant one.

[8]Since 2002, the only exceptions are vocational high school students who want to get into non-university entities providing two-year vocational or technical training.

measures of performance that allow us to use a factor structure approach to control for the effect of unobservables in the retaking decision. Second, the ÖSS is better than the SAT for our purposes, because it is more subject based[9] and harder, which allows it to better separate between students, especially at the high end. All of this makes the Turkish context a better setting in which to measure learning gains.[10] Third, our paper offers an empirical contribution by providing a novel methodology that allows us to do some of what can be done with a panel with only a cross section.

3 The Institutional Background

In Turkey, entrance to higher education institutions is regulated by the ÖSS (Student Selection Exam), a national examination administered by the Assessment, Selection and Placement Center (ÖSYM) on an annual basis. This exam is open and highly competitive. All high school seniors and graduates are eligible to take it and most seniors do in fact take it.[11]

The ÖSS evaluates students' performance in 5 subjects: Mathematics, Turkish, Sciences, Social Studies, and Foreign Languages, where the last portion is only mandatory for translation, tourism, and foreign literature programs, among others. Once the exam is administered, ÖSYM calculates raw scores in each subject. With these in hand, they calculate 4 additional scores (ÖSS-j) as weighted averages of different portions of the exam.[12] Students pass the exam and are eligible to submit preferences for two year schools or distance education programs if any of their ÖSS-j scores is at least 105. To be able to submit preferences for four year programs, a minimum score of 120 is required.

Students submit preferences for a particular program in a given school once they know their

[9]See section 3 for more details on the content of the ÖSS.

[10]However, a caveat is in order. In this paper we have little to say about the whether these gains are true knowledge gains or come from being better at taking exams. In the Turkish context, students are highly exposed to practice exams before their first attempt so we are going to claim that any learning effect identified should have a small component explained by exam-taking skills gains.

[11]See Türk Eğitim Derneği (TED or Turkish Educational Association) for more details on this exam.

[12]These are: ÖSS-j, for j={Verbal (SÖZ), Quantitative (SAY), Average (EA), and Foreign Language (DİL)}. In 2002, the cutoff percentage (percentile) for four year programs was equivalent to a score (*percentile*) of 68%, 59%, 66% , and 65% in terms of the ÖSS-Verbal, ÖSS-Quantitative, ÖSS-Average, and ÖSS-Foreign Language scores, respectively.

scores. Placement is merit based on the basis of one of four *aggregate* placement scores (Y-ÖSS-j) that are calculated for each student as the weighted average of each ÖSS-j score and a standardized measure of high school GPA.[13] Each program accepts applicants based on the relevant Y-ÖSS-j score.[14] Students are placed in their most preferred program among those they eligible for given their score.[15] Students may fail to be placed if, conditional on their score, competition to get into their preferred programs is too tough.

While in high school, most students choose between three broad fields of study or tracks: Sciences, Turkish-Mathematics, and Social Studies.[16] The college placement process is designed to encourage students to remain in the same field they chose in high school.[17] Since cutoff scores are relatively stable over time and are publicly available, one can think of students having complete information when providing their list of preferred programs and having no incentive to misrepresent their preferences.

Between 2000 and 2002, the number of ÖSS applicants fluctuated around 1.5 million with only a third of them being high school seniors taking the exam for the first time. Over 94% of the high school graduates took the ÖSS. While the number of secondary graduates is very close to the number of seats available for placement in each year, the placement rate is only about a third. Thus, though there are enough seats for each new cohort of high school graduates, the low placement rate comes in part from the large share of repeat takers among applicants. Table 4 in Appendix A shows these and some other basic statistics on the pool of applicants between 2000 and 2002.

[13]This standardization is implemented by the ÖSYM to make GPAs comparable. A detailed description of this process and the construction of the different placement scores is provided in Appendix B.

[14]For example, admission to a Radiotherapy program in Ankara University is rationed by Y-ÖSS-Quantitative scores while placement into law school in the same university relies on Y-ÖSS-Verbal scores.

[15]See Azevedo and Leshno (2011) for an elegant analysis on two-sided matching markets.

[16]A larger number of tracks is available for vocational school students.

[17]For example, the exam scores of a high school graduate from the Science track who chooses to change to the Social Studies field in college are penalized through the weight attached to her GPA in the construction of Y-ÖSS-j scores (see Figure 13 in Appendix B).

4 The Data

Our data covers a random sample of about 120,000 students who took the ÖSS in 2002. After cleaning the data and dealing with some minor inconsistencies, we lose 3.9% of the observations[18] so that our final cross section covers 114,800 applicants from the Science (38,771), Turkish-Math (38,571), and Social Studies tracks (37,458).[19]

Four sources of data are integrated in the ÖSYM data. First, applicants filled out application forms giving information on their high school track, name and type of school (Science, Anatolian, Private, Public, Other) from which they graduated[20], status of the student at the time the exam was taken (high school senior, repeat taker, graduated from another program, among other options), and gender. Applicants also filled out a survey that collected information on household monthly income, parents' education and occupation, family size, time and money spent on private tutoring during high school, number of previous attempts, and reasons to retake, among other variables. ÖSYM also obtained applicants' raw high school GPAs at graduation directly from each high school. Finally, ÖSYM institutional records provide us with raw exam scores, preference data, and ÖSS scores for each student, if and where the student is placed, and the type of score used for placement.

Survey data is of lower quality than the administrative data as there are no consequences for misreporting or lack of reporting. In particular, household monthly income data is problematic; income levels among ÖSS applicants seem to be much lower than the national average in

[18] Details available on request.

[19] Although we have information on the universe (37,340) of students who took he Foreign Language exam (YDS) in 2002, we exclude them from the analysis in this paper. We do so for two reasons. First, this sub-sample contains students from all high school tracks, although 57% of them come from the foreign language track. Consequently, these students are not comparable to the sub-samples of Science, Social Studies, or Turkish-Math, where track and college program tend to match. Second, since the YDS is an optional portion of the exam, some students in the Science, Social Studies, or Turkish-Math tracks might also be included in the Foreign Language dataset. Unfortunately, the data has no individual identifiers so including students who take the YDS in the analysis would lead to double counting.

[20] Science schools only offer the Science track. Admission to Science and Anatolian schools is based on a national competitive exam taken at the end of 8th grade.

Turkey.[21] One potential explanation for this tendency to misreport is that students see lower income levels as increasing their chances of qualifying for scholarships or government funded boarding options. For this reason, we rely less on this variable and more on other background characteristics that are likely to be correlated with income.

The ÖSYM data provides us with several raw and constructed scores. In this study, we focus on ÖSS-quantitative scores for Science track students, ÖSS-Average for Turkish-Math students, and ÖSS-Verbal for Social Studies students since these are the typical relevant scores for higher education programs related to each of these tracks. Since we want to measure high school performance across schools within our sample, we construct quality normalized GPAs to control for quality heterogeneity and grade inflation across high schools as described in Appendix C. This scaling allows us to compare high school GPAs of students from very different schools.

It is worth noting that, besides ours, the only papers that exploit the richness of the Turkish dataset are those by Tansel and Bircan (2005) who study the determinants of private tutoring in Turkey and its effects on performance, Saygin (2011) who looks at the gender gap in college, and Caner and Okten (2010) who look at career choice using data on preferences. Tansel and Bircan (2005) show that the most important predictor of private tutoring was the high school graduation rank of the student: the higher the rank, the more the tutoring. This suggest that tutoring is undertaken by the less prepared to catch up, but by better students to hone their competitive edge. Saygin (2011) tries to explain why despite performing better in school, women do not predominate at highly selective programs that lead to high-paying careers. A large part of this gender gap seems to come from female students being less ambitious in their preferences for university and less willing to retake the ÖSS exam if needed to attain their objectives. Caner and Okten (2010) find that, controlling for the ÖSS score and other socio-economic characteristics, students with richer parents are more likely to choose risky but rewarding careers like business, suggesting another channel through which inequality may persist.

[21] According to the Turkish Statistical Institute (TUIK, 2003), 27% of the population in Turkey lived under the national poverty line in 2002. However, poverty rates among ÖSS applicants in the same year are much higher and reach almost 50% in the Science track, 62% in the Social Studies track, and 52% in the Turkish-Math track.

4.1 Learning, Selection and Composition

It is worth thinking of three main effects that may be present in the data: learning, selection and composition. Students who retake can *learn*. This raises scores and shifts the score distribution of retakers to the right. Some students retake while others do not: this is *selection*. If worse students tend to retake, this effect will move their distribution of scores to the left. Thus, if retakers learn, and attrition is random, the distribution of scores should move to the right in later attempts. If bad students retake, and there is no learning, the opposite should occur. Finally, if learning and selection occur differently for the privileged and the less privileged we could have a *composition* effect if students with more advantaged backgrounds are differentially present across tracks. For example, learning may be greater for the less privileged as they are further away from their "frontier".[22] Privileged families are more likely to provide better conditions for their children to fully develop their potential so that students coming from such families will have smaller marginal improvements over attempts. In turn, poorer students and/or students coming from worse high schools may benefit greatly from another chance to take the exam.

Since almost all graduating students take the exam, there are no selection issues or learning among first time takers. However, for second time takers, selection and learning shape the distributions of ÖSS scores: some students do not retake and students who do retake may learn. Whether they learn how to take the exam or the material, we cannot say here.[23] In addition, learning and selection may differ by group creating a composition effect.

Below we take a look at the raw data to see if we can put together a simple story that can be formally evaluated later.

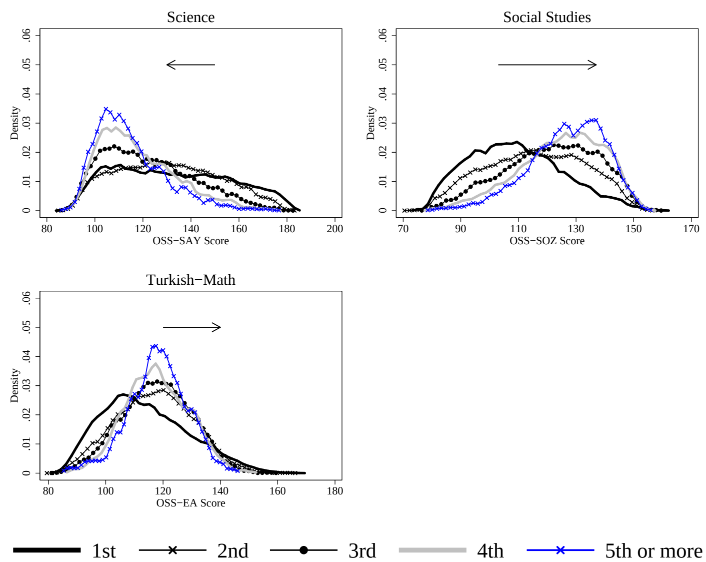
[22]This makes sense if one thinks of an individual's performance coming from a mix of privilege, potential, and randomness and there being limits to what each of them can do alone. As a result, the more privileged will learn less from retaking (as they have already learnt what they can) than the less privileged (who are farther from their frontier). Agents with the highest performance are also likely to be the most privileged.

[23]Of course, if both occur, we need a way to separate these two effects from each other. In ongoing work we are trying to cast some light on this by using information on number of wrong answers given, skipped questions, and correct answers and their changes over the number of attempts.

4.1.1 Scores, Tracks and Retakers

Figure 1 plots the empirical distributions of ÖSS scores by number of attempts and high school track. There is some evidence of compression in the distributions as the number of times the exam is taken increases. We see two distinct patterns. In the Science track the distribution of scores seems to move to the left, consistent with worse students selecting into retaking and limited, or even negative learning, while in Turkish-Math and Social Studies it moves to the right, which suggests less selection and more learning. This suggests that there may be more learning in some subjects than in others.

Figure 1: Distribution of ÖSS Scores by Track

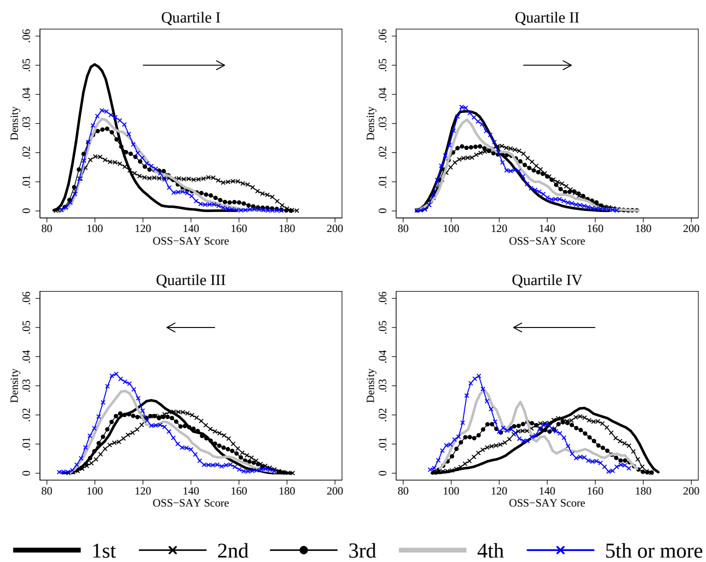


Source: ÖSYM data on 2002 ÖSS applicants.

A further look into the data identifies another pattern present in all tracks which suggests that there is a composition effect at work. Figures 2-4 present ÖSS score distributions by high school GPA quartiles and number of attempts. In *all* tracks, first time takers do worse than repeat takers in the lowest GPA quartiles but this pattern reverses as GPA increases. This effect is also present if we look at these distributions by school type (Figures 14-16 in Appendix D).

This is the same pattern shown in Vigdor and Clotfelter (2003) for SAT repeat takers in the US and it suggests that the best/most privileged students have the lowest learning. If these students are disproportionately found in the Science track, less so in Turkish-Math and the least in Social Studies, the pattern seen above could be due to a composition effect.

Figure 2: Distribution of ÖSS Score by GPA quartiles: Science Track

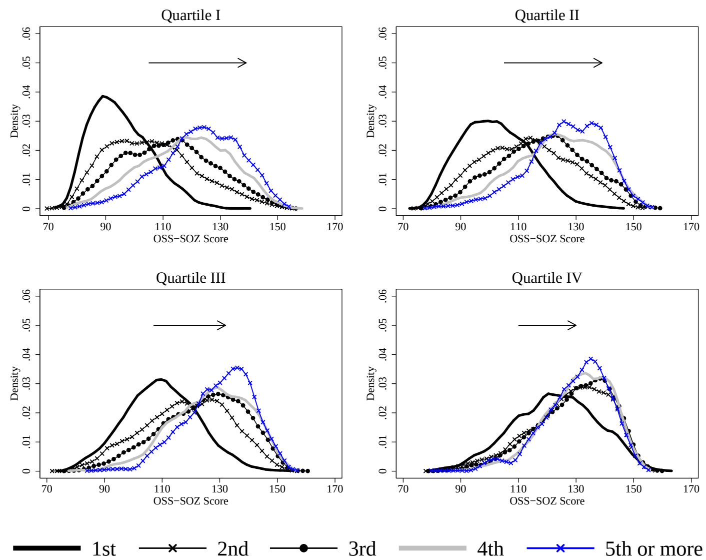


Source: ÖSYM data on 2002 ÖSS applicants.

From Tables 6-8 in Appendix D we see that this is exactly the case. Stronger students go to the Science track where the standardized HSGPA score is 51.68, less strong ones go to Turkish Math track where this score is 48.99, while the weakest are in Social Studies with an average score of 47.66. Moreover, less advantaged students are overrepresented in the Social Studies and Turkish-Math tracks. Compared to Science students, they have less educated parents and lower access to *dersanes* while in high school. They tend to be poorer, come from worse schools, and have less internet access at home.

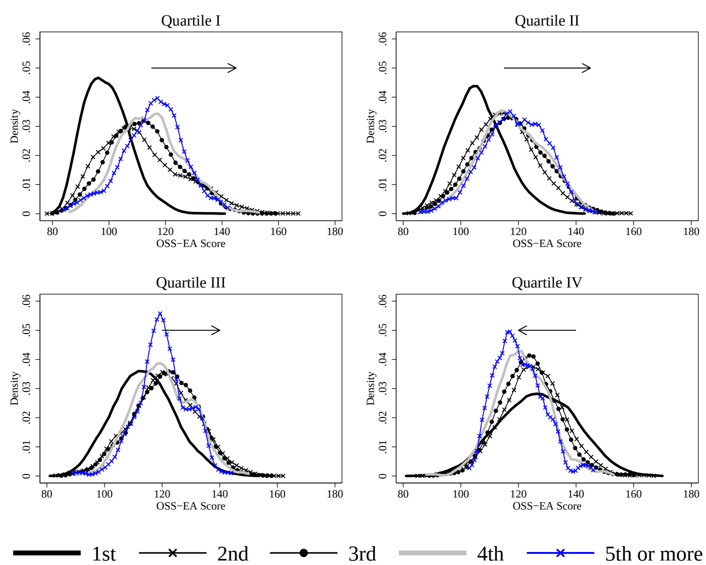
Table 9 casts some light on the selection patterns into retaking. The dependent variable is the fraction of second time takers to first time takers by number of attempts and background characteristics such as gender, expenditures in *dersanes*, high school type, parents' education,

Figure 3: Distribution of ÖSS Score by GPA quartiles: Social Studies Track



Source: ÖSYM data on 2002 ÖSS applicants.

Figure 4: Distribution of ÖSS Score by GPA quartiles: Turkish-Math Track



Source: ÖSYM data on 2002 ÖSS applicants.

and number of children in the household. It is clear that, irrespective of the track, this ratio decreases with the quality of the high school. Additionally, these exploratory results suggest that students with higher levels of prep school expenditures have a higher probability of retaking the ÖSS. Even though father's education does not seem to matter, mother's education appears to have a differential effect on the probability of retaking depending on the track. In the Social Studies track, the fraction of repeat takers is decreasing in mother's education while the opposite occurs in the Turkish-Math track. Surprisingly, gender does not seem to be an important determinant of the probability to retake. In general, the evidence is mixed and it suggests that the patterns of selection differ across tracks.

To summarize, the patterns in Figure 1 are consistent with worse students retaking (so that the selection effect is always negative), learning effects being positive for the most part, with learning effects being larger for worse/less privileged students than for better/more privileged ones. If this is the case, positive learning effects will dominate for the less privileged while negative selection effects will prevail for the more privileged, the latter being more prevalent in the Science and Turkish-Math tracks.

In this paper we focus on learning. Nevertheless, to do this correctly we need to understand and control for the biases that selection introduces. For this, a model is very useful and we turn to it next. In future work we hope to estimate a fully structural model and use it to run policy counterfactuals of interest.

5 The Model

To overcome the lack of longitudinal data on ÖSS applicants, we develop a simple dynamic model that inspires our methodology to measure learning.

Let student i's high school GPA be denoted as g_i while s_{in} stands for her ÖSS score in the n^{th} attempt. Moreover, let X_i denote observed individual and household characteristics of individual i while θ_i represents ability unobserved by the researcher. Let marginal learning for individual i in her n^{th} attempt be λ_{in}.

First, we assume that:

Assumption 5.1 *Students know their own θ_i.*

We argue that the assumption of known ability is reasonable in the Turkish context. Although the exam is taken in 12^{th} grade, students start preparing for this exam as early as in 9^{th} grade. This means that by the time they take the exam for the first time, they have already taken many practice exams and have a good idea of their average performance. Moreover, *before* the student submits her preferences, she is aware of her scores, her percentiles for each of her placement scores, the minimum placement scores for each program in the previous year, and the number of seats available in each program.[24]

The process through which academic performance measures are generated is assumed to be similar for high school GPAs and exam scores. In particular, we assume that:

Assumption 5.2 *Performance is a function of X_i, θ_i, λ_{in} (when applicable), and ϵ_{in} $\forall n \geq 0$, where ϵ_{in} is an iid random shock across individuals.*

High school GPA is then given by:

$$g_i = X_i\alpha_0 + \theta_i + \epsilon_{i0} \tag{1}$$

where ϵ_{i0} is a random shock. Similarly:

$$s_{in} = X_i\alpha_1 + \sum_{k=2}^{n} \lambda_{ik} + \theta_i + \epsilon_{in} \tag{2}$$

where $\sum_{k=2}^{n} \lambda_{ik}$ is the *cumulative* learning up to attempt n and ϵ_{in} is a random shock drawn from a density function common to all n and i. This shock captures unexpected and random events that may affect exam performance such as a sudden cold, a family loss, or just having a good or bad day. Notice that the summation in equation (2) starts from $k = 2$ since λ_{ik} represents learning after the student graduates from high school. As mentioned above, the ÖSS is first taken while still in the last year of high school so that the score in the first attempt should not contain any learning effects.

[24]Exit would not occur when the cost of retaking is fixed: once the student decides to take the exam, she will keep retaking until placed in her program of preference. Exit can occur if the cost of retaking rises over attempts or if the cost faced by each students is a random shock that comes from a distribution which is fixed over attempts.

Notice that the residuals, net of the effect of observables and learning, are modeled using a factor structure where "factor" θ_i can be thought of as the type of the individual. θ_i captures all possible unobservables affecting performance (e.g., unobserved ability and motivation) while factors ϵ_{i0} and ϵ_{i1} capture randomness in performance. This structure allows us to talk about a one-dimensional set of unobservables influencing performance in high school or any exam attempt.

In our setup, learning is defined as follows:

Assumption 5.3 *λ_{in} is a draw from a distribution that may differ according to X_i and/or θ_i.*

Marginal learning, λ_{in}, is assumed to be an exogenous shock drawn by individual i in her n^{th} attempt from a distribution that is allowed to vary by X_i and θ_i.

Assumption 5.4 *The system is in steady state.*

Although Assumption 5.4 is not specifically required for the development of the theoretical model, it will then be required to implement our estimation methodology.[25]

Let the system have a continuum of colleges so that there is also a continuum of college qualities. As explained in Section 3, ÖSYM imposes a 120 cut-off score to qualify for placement in two or four year university programs. We denote this exogenous cut-off as s_*, where $s_* > 0$. Although the scores obtained in the exam are critical, they are not the only determinant of placement (see Section 4). Once the student passes the exam, placement scores are finally obtained as a weighted average of the ÖSS score and high school GPA, g_i. Normalizing the weight on scores to 1, the instantaneous college utility is specified as follows:

$$u(s_{in}, g_i) = \begin{cases} 0 & \text{if } s_{in} < s_* \\ s_{in} + \upsilon g_i & \text{if } s_{in} \geq s_* \end{cases}$$

Students with a score below s_* (the cutoff for being eligible) choose between retaking and quitting, while those with a cutoff above s_*, choose between being placed, retaking and quitting.

[25] The steady state assumption seems reasonable in the Turkish setting. According to the evolution of the number of applicants and placements given in Table 4, 2002 appears to have a similar number of ÖSS candidates and placements when compared to previous years. In addition, no institutional shocks or changes in the exam itself that might bias our results were recorded during the period analyzed.

The utility of being placed is an increasing function of the placement score to reflect that a higher bid allows the student to get a better placement in line with her preferences.

Consider a student who has taken the exam for the n$^{\text{th}}$ time with a given background, cumulative learning, and unobservable $(X_i,\ \sum_{k=2}^{n}\lambda_{ik},\theta_i)$. The non random part of his score is $\bar{s}_{in} = X_i\alpha_1 + \sum_{k=2}^{n}\lambda_{ik} + \theta_i$. He takes the exam and obtains a score $s_{in} = \bar{s}_{in} + \epsilon_{in}$. What he chooses to do will depend on the shock ϵ_{in} and which case represents his situation.

Consider what happens to this student if he obtains a score just high enough to be offered a placement, i.e. a score of s_*.[26] This corresponds to the student obtaining a shock of $\epsilon'_{in} = s_* - \bar{s}_{in}$ in Figure 5. What would such an agent do?[27]

If quitting dominates retaking, i.e., if $V_Q > V_n$, then only students who obtain a high enough score will accept their placement and all others will quit. For example if $V_n \leq V_Q \leq u(s_*, g_i)$, then those not offered a seat quit as depicted in case (a). If $V_n \leq u(s_*, g_i) \leq V_Q$, then even some of those offered a place may not accept and quit. Note that, as long as $V_Q > V_n$, there is no retaking: the lucky get in, the unlucky quit. However, when quitting dominates both retaking and getting marginally placed, student i will not even take the exam for the first time and will be excluded from our sample to begin with. We ignore these agents from hereon.

Suppose that $V_n \geq V_Q$. Two scenarios are possible here, though the outcome is the same in both. If $V_n > u(s_*, g_i) \geq V_Q$ then even an agent with $\epsilon_{in} = \epsilon'_{in}$ will retake. Only those with a score high enough, i.e., those with $\epsilon_{in} \geq \epsilon''_{in}$ (where $\epsilon''_{in} = V_{in} - \bar{s}_{in} - \upsilon g_i$) accept while others retake as depicted in case (b). If $V_n > V_Q > u(s_*, g_i)$,, as depicted in case (c), the same outcome obtains.

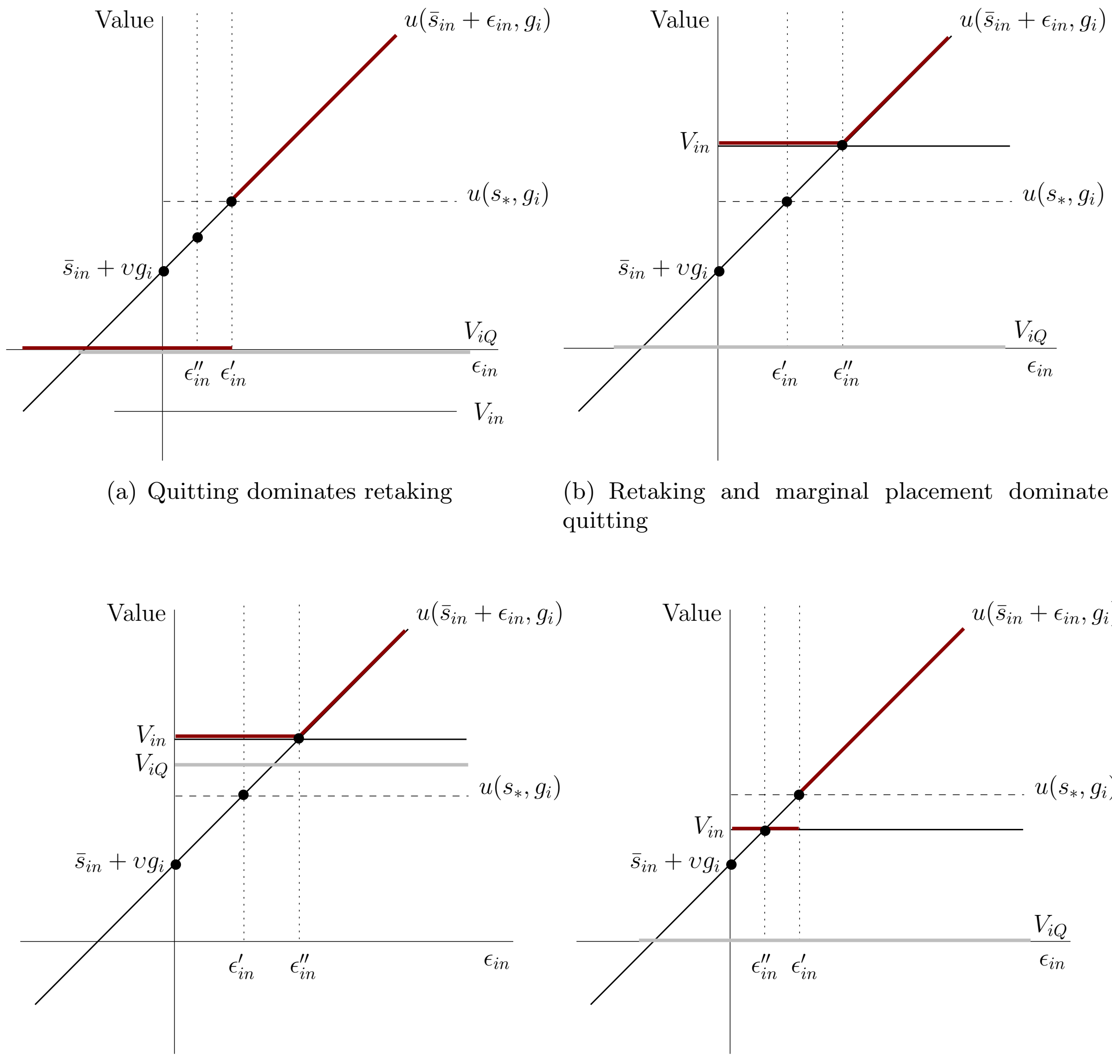
If $u(s_*, g_i) \geq V_n > V_Q$, then all those offered a placement accept. This is case (d). Thus, in real life, we are either in cases (b) or (c), where $\epsilon'_{in} < \epsilon''_{in}$ and those with shocks below ϵ''_{in} retake, or case (d), where $\epsilon''_{in} < \epsilon'_{in}$ and all those with shocks below ϵ'_{in} retake. Hence, define $\epsilon^*_{in} = \max[\epsilon'_{in}, \epsilon''_{in}]$ so that we can say that all those with shocks below ϵ^*_{in} retake.

There is a net cost of retaking ψ_n which changes over attempts but is fixed across individuals.

[26] Note that if this student accept his placement, so will all students with scores above his.

[27] The student's problem is similar to that faced by workers in the job search model (Mortensen (1984)).

Figure 5: Value Function



(a) Quitting dominates retaking

(b) Retaking and marginal placement dominate quitting

(c) Retaking dominates quitting but quitting dominates marginal placement

(d) Marginal placement dominates retaking

Let the discount factor be δ. After the n^{th} attempt, student i's value of retaking ("searching") next period is thus:

$$
\begin{aligned}
V_{in} &= -\psi_n + \delta \left\{ F(\epsilon^*_{i(n+1)}) \max[V_{i(n+1)}, V_Q] + \int_{\epsilon^*_{i(n+1)}}^{\infty} u(s_{i(n+1)}, g_i) f(\epsilon) d\epsilon \right\} \\
&= -\psi_n + \delta \left\{ F(\epsilon^*_{i(n+1)}) \max[V_{i(n+1)}, V_Q] + [1 - F(\epsilon^*_{i(n+1)})](\bar{s}_{i(n+1)} + \upsilon g_i) + \int_{\epsilon^*_{i(n+1)}}^{\infty} \epsilon_{i(n+1)} f(\epsilon) d\epsilon \right\}
\end{aligned} \tag{3}
$$

The second term inside the curly brackets has an integral in front of it to reflect that utility from future placement is uncertain. The random shock on the score is integrated out from $\epsilon^*_{i(n+1)}$ to infinity to reflect that enrollment occurs for values of the shock above $\epsilon^*_{i(n+1)}$.[28]

5.1 Selection

As shown above, a student retakes the exam for one of two reasons. She failed to be placed and chose to retake given her background characteristics and her ability, or she was placed but chose to retry anyway. In the former case, two conditions should hold among these repeat takers: $s_{in} < s_*$ (i.e., $\epsilon_{in} < \epsilon'_{in}$) and $V_{in} \geq V_Q$. In the latter case, $s_{in} \geq s_*$ (i.e. $\epsilon_{in} \in [\epsilon'_{in}, \epsilon''_{in}]$), and $V_{in} \geq u(s_{in}, g_i)$.

Recall that the distribution of learning draws is conditional on X_i and θ_i. But X_i and θ_i determine the pattern of selection and selection between attempts need to be taken into account to adequately estimate cumulative learning effects, $\sum_{k=2}^{n} \lambda_{ik}$. Although propensity score matching methods in effect would let us control for observables in selection, the inability to match individuals based on their unobservable characteristics will provide biased estimates.

To sum up, the model above provides us with the selection rules that determine retaking. Depending on the pattern of selection, n^{th} time takers scores may look better or worse than first time takers. The net effect of selection in score changes across rounds is thus an empirical issue. In the next section, we present a semi-structural approach that controls for selection into retaking on X_i and θ_i and obtains robust estimates of the learning gains among repeat takers.

[28] The shock for the GPA is realized at the end of high school so it is no longer uncertain for any $n > 0$. Once the GPA is "generated", it can be considered as a fixed exogenous variable.

6 Econometric Model

6.1 The Steady State Assumption

Our objective is to obtain an estimate of the cumulative learning gains between the first and the n^{th} attempt for ÖSS repeat takers taking into account that self-selection into retaking is *not* random as shown in the previous section. The complication arises from the lack of panel data since we cannot observe repeat takers' scores in previous attempts. However, we observe background characteristics and high school grades for *all* applicants. This information, together with assumptions 5.1-5.4, allows us to develop an econometric methodology that overcomes the lack of longitudinal data and estimates learning.

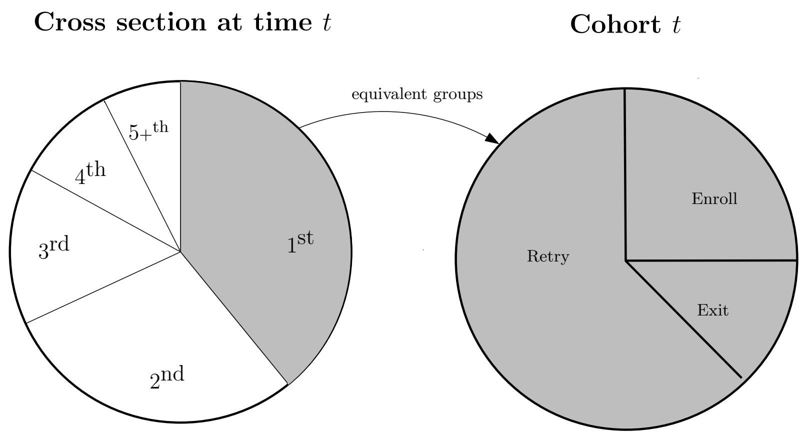
Consider an initial cohort of students, those graduating from high school and taking the ÖSS in year t. Some of these students are not placed in any college program and they decide either to quit or to try again the next year. Those who are placed in a university program (conditional on their preferences and exam score) also have the choice of retrying the following year.

When the system is in steady state, the set of students in the cross section who are taking the exam for the first time will be equivalent to the initial cohort from year t as depicted in panel (a) in Figure 6. Since almost all high school seniors in Turkey take the college entrance exam and selection into retaking has not yet occurred, we can assume that the distribution of s_{i1} in the sub-sample of first time takers is a selection-free measure of exam performance in the first attempt. Moreover, second time takers correspond to the people from cohort $(t-1)$ who were not placed at $(t-1)$ and did not exit, plus those who were placed at $(t-1)$ but decided to try again. In steady state, repeat takers from cohort $(t-1)$ are also equivalent to repeat takers from cohort t and that is why second time takers in our cross section are equivalent to repeat takers from cohort t as depicted in panel (b) in Figure 6. Similarly for sub-samples of higher order attempts.

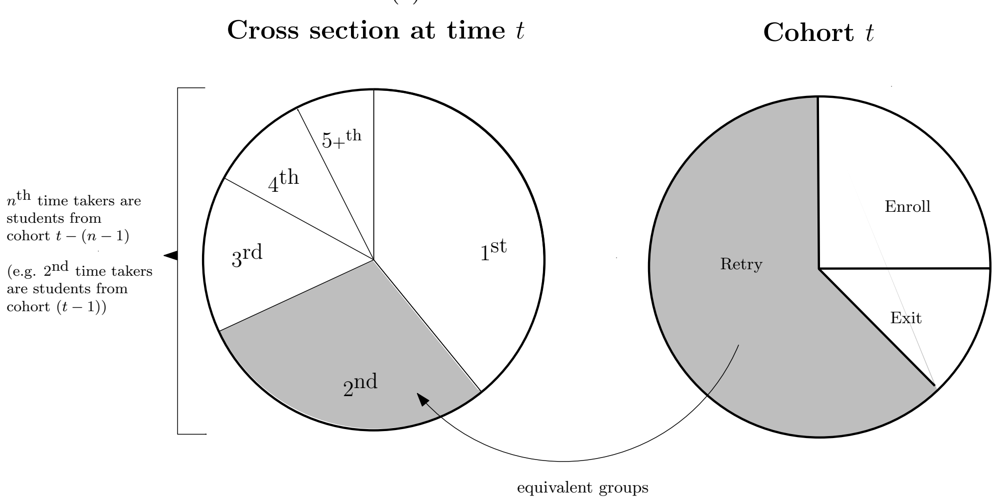
6.2 Estimation

Figure 7 summarizes our estimation strategy, starting on the box of first time takers on the left hand side of the diagram. As it will become more clear below, the availability of GPAs and

Figure 6: Relationship between cohort t and cross section at time t



(a) First time takers



(b) Second time takers

exam scores for all students as well as the steady state assumption are key for identification of the average cumulative learning gains.

First, remember that the sub-sample of first time takers is free of selection and it is thus

Figure 7: Estimation Strategy

1^{st} Time Takers

$$g_i = X_i\alpha_0 + \theta_i + \epsilon_{i0}$$
$$s_{i1} = X_i\alpha_1 + \theta_i + \epsilon_{i1}$$

n^{th} Time Takers

$$\begin{aligned} g_i &= X_i\alpha_0 + \theta_i + \epsilon_{i0} \\ s_{in} &= X_i\alpha_1 + \sum_{k=2}^{n} \lambda_{ik} + \theta_i + \epsilon_{in} \end{aligned}$$

STEP 1: $\hat{\alpha}_0,\ \hat{\alpha}_1$

STEP 2:

$$\begin{aligned} g_i - X_i\hat{\alpha}_0 &= \theta_i + \epsilon_{i0} \\ s_{in} - X_i\hat{\alpha}_1 &= \sum_{k=2}^{n} \lambda_{ik} + \theta_i + \epsilon_{in} \end{aligned}$$

STEP 3:

$$\begin{aligned} E(g_i - X_i\hat{\alpha}_0 | N_i = n) &= E(\theta_i | N_i = n) + E(\epsilon_{i0} | N_i = n) \\ &\approx E(\theta_i | N_i = n) \\ &= \hat{\theta}_n \end{aligned}$$

STEP 4:

$$\begin{aligned} E(s_{in} - X_i\hat{\alpha}_1 - \hat{\theta}_n | N_i = n) &= E\left(\sum_{k=2}^{n} \lambda_{ik} + \epsilon_{in} | N_i = n\right) \\ &= E\left(\sum_{k=2}^{n} \lambda_{ik} | N_i = n\right) \end{aligned}$$

comparable to any other initial cohort. In this sample, we can estimate the following system:[29]

$$g_i = X_i\alpha_0 + \theta_i + \epsilon_{i0} \tag{4}$$
$$s_{i1} = X_i\alpha_1 + \theta_i + \epsilon_{i1} \tag{5}$$

where equations (4) and (5) have zero learning due to the timing of the exam. Without learning in this sub-sample, the correlation between the error terms in both equations is driven by students' unobserved characteristics.

[29] We also normalized the weight of θ_i in one equation to one and identified the weight in the remaining equation. Results changed very little as the estimated weight was very close to one.

As standard in the factor analysis literature,[30] θ_i is defined as an iid shock across individuals while the random shocks are also iid across individuals and time. Moreover, we assume:

Assumption 6.1 $\theta_i \perp\!\!\!\perp X_i \quad \forall i.$

Assumption 6.2 $\theta_i \perp\!\!\!\perp \epsilon_{in} \quad \forall n.$

Assumption 6.3 $\epsilon_{in} \perp\!\!\!\perp X_i \quad \forall n.$

Assumption 6.4 $\epsilon_{in} \perp\!\!\!\perp \epsilon_{im} \quad \forall n \neq m.$

To estimate system (4)-(5), we rely on some parametric assumptions on the distribution of the factors. In particular:

$$\theta_i \sim N(0, \sigma_\theta^2) \tag{6}$$

$$\epsilon_{i0} \sim N(0, \sigma_0^2) \tag{7}$$

$$\epsilon_{i1} \sim N(0, \sigma_1^2) \tag{8}$$

We show in Appendix E that these parametric assumptions are appropriate by using a non parametric approach as a check. Applying a result due to Kotlarski (1967) it can be shown that the densities of each factor, f_θ, f_{ϵ_0}, and f_{ϵ_1}, can be identified from the knowledge of the joint density of (g, s_1). In the appendix, we briefly review Bonhomme and Robin (2010), who explicitly derive the identifying restrictions for these kind of problems when the factor loadings (coefficients on θ and ϵs) are known. We then implement a non-parametric estimator of the factors' densities and check it against our normality assumptions. In general, we find that our normality assumptions on the shocks seem to be introducing little bias in our estimates. The distributions of the shocks in most tracks seem to follow closely the normal distribution.

Estimates of α_0, α_1, σ_θ, σ_0, and σ_1 are obtained via Maximum Likelihood in the sample of first time takers (Step 1 in Figure 7).[31] Estimates of $\hat{\alpha_0}$ and $\hat{\alpha_1}$ can then be taken to the

[30] See Li and Vuong (1998). Recent applications can be found in Li et al. (2000) and Cooley et al. (2011).

[31] Full results are shown in Tables 10-12 in Appendix D. Standard errors are obtained from 300 bootstrap replications.

sub-samples of n^{th} time takers and combined with their X_i matrices to obtain $X_i\hat{\alpha_0}$ and $X_i\hat{\alpha_1}$, which takes into account selection into retaking through X_i. With these estimates in hand, residuals for both the GPA and exam score equations are obtained (Step 2 in Figure 7):

$$g_i - X_i\hat{\alpha_0} = \theta_i + \epsilon_{i0} \tag{9}$$

$$s_{in} - X_i\hat{\alpha_1} = \sum_{k=2}^{n} \lambda_{ik} + \theta_i + \epsilon_{i1} \tag{10}$$

In (9), the residual will only contain unobservables and randomness while in (10) the residual will include an additional component, learning.

Now, we also need to take into account the effect of selection through unobservables on performance (Step 3 in Figure 7). Let N_i denote the number of attempts of individual i. The expected value of (9), conditional on N_i being equal to a given number of attempts, n, is:

$$E(g_i - X_i\hat{\alpha}_0|N_i = n) = E(\theta_i|N_i = n) + E(\epsilon_{i0}|N_i = n) \tag{11}$$

However, there could be either positive or negative selection into retaking based on ϵ_{i0}. In other words, randomness in the GPA equation is a mean zero draw for the initial cohort of high school graduates but it stays with the student for all successive ÖSS attempts and $E(\epsilon_{i0}|N_i = n)$ may differ from zero depending on the pattern of selection into retaking. There is no a priori reason to believe that $E(\epsilon_{i0}|N_i = n)$ will necessarily go to zero so (11) provides us with a noisy measure of $E(\theta_i|N_i = n)$ for each sub-sample of repeat takers.

If we analyze the selection conditions derived in Subsection 5.1, there is no clear pattern of selection through the shock on GPAs. Intuitively, someone who was lucky in terms of how well he/she did in high school has no reason to be more or less likely to retake than someone who was unlucky in terms of how well he/she did in high school as your GPA follows you around. For fixed parameters, the model cannot predict if $E[\epsilon_{i0}|N_i = n]$ is either positive, negative, or close to zero. Simulations presented in Section 7 show that $E[\epsilon_{i0}|N_i = n]$ is close to zero in our data so that the bias in our estimates is likely to be very small. Therefore, $E(g_i - X_i\hat{\alpha}_0|N_i = n)$ is an approximation of $E(\theta_i|N_i = n)$ and is thus relabeled as $\hat{\theta_n}$ as shown in Step 3 in Figure 7.

Finally, we can go back to the score equation and get the expected value of (10), conditional on being in the n^{th} attempt (Step 4 in Figure 7). After slight manipulation, this yields an estimate of the mean cumulative learning effect between the first and the n^{th} attempt among n^{th} time takers:

$$\begin{aligned}
E\left(s_{in} - X_i\hat{\alpha_1}|N_i = n\right) &= E(\sum_{k=2}^{n} \lambda_{ik} + \theta_i + \epsilon_{in}|N_i = n) \\
E\left(s_{in} - X_i\hat{\alpha_1} - \hat{\theta_n}|N_i = n\right) &= E(\sum_{k=2}^{n} \lambda_{ik} + \epsilon_{in}|N_i = n) \\
E\left(s_{in} - X_i\hat{\alpha_1} - \hat{\theta_n}|N_i = n\right) &= E(\sum_{k=2}^{n} \lambda_{ik}|N_i = n)
\end{aligned}$$

where the second equality follows from $E[\epsilon_{in}|N_i = n] = 0 \ \ \forall n$.

Notice that the learning varies by observables and unobservables though there is noise in terms of the way it varies with unobservables.

Using the same procedure, and provided that we have allowed learning draws to come from distributions that may dependent on X_i or θ_i, we could also obtain average cumulative learning gains for different groups of students in the following way:

$$E\left(s_{in} - X_i\hat{\alpha_1} - \hat{\theta_n}|N_i = n, Z_i = z\right) = E(\sum_{k=2}^{n} \lambda_{ik}|N_i = n, Z_i = z)$$

where Z_i can denote any individual characteristic such as school type or *dersanes* expenditures.

Notice that our strategy acknowledges non-random selection into retaking without explicitly having to model it in the econometric framework. Since we are basically predicting mean exam scores for repeat takers in their *first* attempt, we do not need to model retaking; the parameter estimates we use to predict $E(s_{i1}|N_i = n)$ come from the sample of first time takers, which is free of selection.

A note of warning before proceeding to the results section. Cumulative learning gains are equal to the marginal learning gains obtained by second time takers. However, for higher order repeat takers, marginal learning gains cannot be obtained from our cumulative learning estimates. For example, since marginal learning gains vary across individuals and attempts, the mean λ_{i2} accrued by the sub-sample of second time takers may be quite different from the mean λ_{i2} obtained by third time takers between their first and second attempt. Therefore, the difference between third time takers' and second time takers' cumulative learning in our estimates should *not* be interpreted as marginal learning.

7 Simulations

Our estimates of the learning effect will rely on the presumption that the bias introduced by $E[\epsilon_{i0}|N_i = n]$ is negligible. This section shows how large the bias can be using the model described in Section 5 as a basis for simulations.

First, since the variable that indicates the number of attempts in our data is censored at 5, we assume that there is no more learning after the fifth attempt so that the problem becomes stationary at that point. Since the problem is assumed to be stationary after the fifth attempt, the value of ψ_n is fixed for $n \geq 5$.

Fixing some of the parameters of the model as showed in Table 13 (see Appendix D), and for given draws of θ_i, ϵ_{i0}, ϵ_{in} for $n \in [1, 5]$, and λ_{in} for $n \in [2, 5]$, we can use vector X_i on *first time takers* as well as $\hat{\alpha}_1$ and $\hat{\alpha}_0$ to construct a simulated database. We choose S as the number of simulated datasets generated for each track. Within each simulated dataset, we estimate the net opportunity cost of taking the exam, ψ_n, to match certain moments generated for the original data on repeat takers (e.g., the average score by number of attempts). Notice that each iteration in the process of solving for ψ_n implies solving for V_{i5} for each i. With the value function in the stationary problem in hand, V_{in} for $n \in [1, 4]$ can then be easily obtained for each i.[32]

Once we obtain $\hat{\psi}_n$ for each simulated dataset, we use this vector as well as the shocks that generated the simulated data to find the sets of second, third, fourth and fifth (and up) time takers. For each S, we can then obtain the true cumulative learning effect for each group of repeat takers and compare it to the estimated learning effect that we obtain with the methodology

[32] To estimate the value functions, we assume that students use the mean value of cumulative learning gains to predict their value from retaking in their next attempts. For example, we assume that student i uses $E\left(\sum_{k=2}^{4} \lambda_{ik}\right)$ to get V_{i3}.

described in Section 6. Table 1 below shows the average bias across the S simulated samples for each track, where the bias is defined as the distance between the estimated and the true learning effect as a percentage of the true effect. In general, the preliminary evidence from our simulations shows that there is a relatively small downward bias in our estimates which tends to *underestimate* the learning effects captured by our methodology. In the Social Studies track, our methodology underestimates the learning effect by about 0.2% among second time takers and the bias increases up to 2% among fifth time takers. In the Turkish-Math track, the bias is between 2% and 3.5% between second and fifth time takers. The Science track is the one with the largest bias, which can move between 4% and 23%. In all tracks, the bias tends to be smaller and insignificant for early tries. However, the bias increases and becomes significant for a higher number of attempts.

Table 1: Simulation Results: Bias as a Percentage of the True Learning Effect ($S = 50$)

Number of Attempts	Science	Social Studies	Turkish-Math
2^{nd}	-4.123	-0.246	-2.008
	(3.814)	(0.715)	(2.589)
3^{rd}	-7.579	-1.537	-2.911
	(5.918)	(0.722)	(3.429)
$4th^{th}$	-14.498	-1.997	-3.414
	(2.766)	(0.636)	(2.646)
5^{th}	-22.915	-1.983	-3.474
	(4.075)	(0.562)	(1.790)

Source: ÖSYM data on 2002 ÖSS applicants.

Note: Standard deviation in parenthesis.

8 Results

Table 2 below presents the estimated average cumulative learning gains for repeat takers in terms of their absolute improvement in points (100 scale). In general, students from Social Studies and Turkish-Math tracks tend to exhibit the greatest cumulative learning gains across attempts. Although Science track students tend to have the largest learning gains in early retries, especially between the first and the second attempt, these decrease as the number of attempts rises.

Figure 8 presents the main results in a different way that gives us a better idea of the meaning of this score improvement. The round markers represent the expected value of the current score conditional on being an n^{th} time taker while the squared markers are the (predicted) average initial score conditional on being an n^{th} time taker. The difference between both markers at a given number of attempts is equivalent to the learning gains presented in Table 2.

Table 2: Mean Cumulative Learning Effects (Points in the 100 Scale) by Track and Number of Attempts

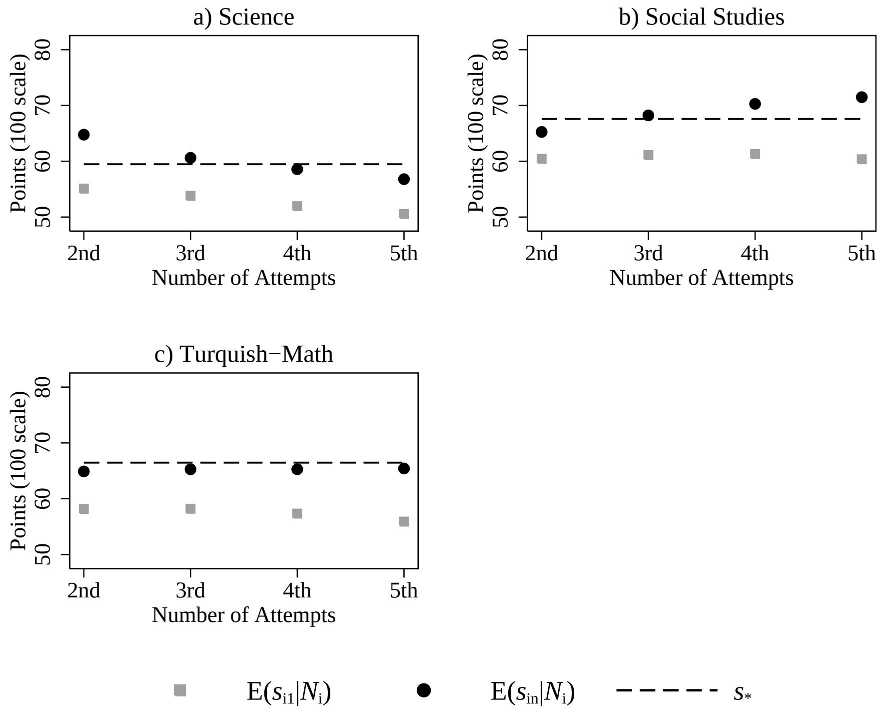
	Attempts			
Track	2^{nd}	3^{rd}	4^{th}	5^{th}+
Science	9.7	6.8	6.6	6.2
	(0.09)	(0.11)	(0.13)	(0.14)
Social Studies	4.8	7.1	9.0	11.1
	(0.10)	(0.10)	(0.12)	(0.14)
Turkish-Math	6.7	7.1	7.9	9.5
	(0.06)	(0.09)	(0.15)	(0.23)

Source: ÖSYM data on 2002 ÖSS applicants.
Note: Standard error of the mean in parenthesis.

In general, Figure 8 shows that an average repeat taker, irrespective of her track or number of attempts, is always able to close the gap between his initial score and the exogenous cutoff, s_*. However, different patterns emerge depending on the track and the number of attempts. In the Science track,retrying seems to be helping students pass the exam (which makes them eligible to submit preferences) only after two or three attempts. Students in higher order attempts are not able to improve as much so as to pass the exam. In the Social Studies track, cumulative learning gains are increasing and only students in their third or higher order attempt are able to close the gap with respect to s_*. An average second time taker from this track has positive learning gains but still fails the exam in a retry. Finally, Turkish-Math students have important and fairly constant cumulative gains over attempts. But irrespective of the number of attempts, an average retaker from this track is never able to close the gap with respect to s_*.

These heterogenous patterns in the evolution and distribution of the learning gains over

Figure 8: Results: Improvement in Gap from s_*



Source: ÖSYM data on 2002 ÖSS applicants.

attempts may be related to differences in the patterns of selection into retaking relative to the the initial pool of applicants. Table 3 decomposes the average gross change in the observed scores of repeat takers with respect to first time takers into the contribution of observables, unobservables, and learning to get a better idea of how severe is selection.

In the Science track, the gross change reflects the patterns initially found in Figure 2: without taking into account the role of observables, repeat takers seem to be doing worse than first time takers. Even though they learn over attempts, a strong negative selection, both in terms of X_i and θ_i, explains the movement of the score distribution and mean to the left over attempts. Although negative selection among second time takers is mostly explained by differences in unobservables, negative selection in terms of X_i becomes more important for higher order attempts.

Table 3: Decomposition of Change in Mean Scores Between n^{th} and 1^{st} Time Takers

	Attempts			
	2^{nd}	3^{rd}	4^{th}	$5^{\text{th}}+$
Science				
Gross Δ in score between n^{th} and 1^{st} time takers	*-0.9*	*-5.0*	*-7.1*	*-8.9*
Δ due to X_i	-3.6	-6.4	-8.0	-9.0
Δ due to θ	-6.9	-5.5	-5.7	-6.1
Δ due to $\sum_{k=2}^{n} \lambda_{ik}$	9.7	6.8	6.6	6.2
Social Studies				
Gross Δ in score between n^{th} and 1^{st} time takers	*3.7*	*6.7*	*8.7*	*9.9*
Δ due to X_i	-0.3	0.3	0.5	0.2
Δ due to θ	-0.8	-0.7	-0.8	-1.5
Δ due to $\sum_{k=2}^{n} \lambda_{ik}$	4.8	7.1	9.0	11.1
Turkish-Math				
Gross Δ in score between n^{th} and 1^{st} time takers	*1.7*	*2.1*	*2.1*	*2.2*
Δ due to X_i	-1.5	-2.0	-2.6	-3.1
Δ due to θ	-3.6	-3.0	-3.2	-4.1
Δ due to $\sum_{k=2}^{n} \lambda_{ik}$	6.7	7.1	7.9	9.5

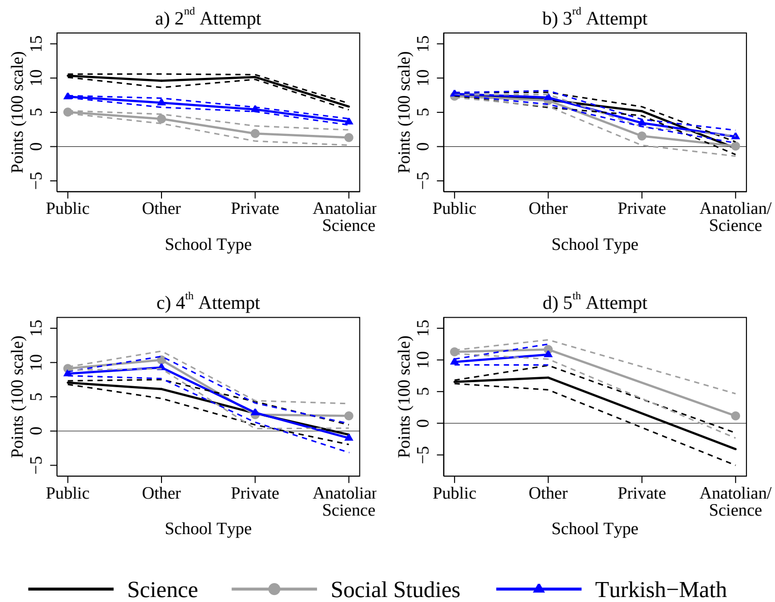
Source: ÖSYM data on 2002 ÖSS applicants.

Among Social Studies students, the change in gross scores suggests that scores of repeat takers improve relative to the sub-sample of first time takers. However, most of the improvement is in fact explained by the learning gains that repeat takers accrue. On average, selection in terms of θ_i or X_i seems to have a small effect on the scores of repeat takers. The Turkish-Math track also exhibits an improvement of the distribution and mean of scores over attempts, but the effect is smaller compared to Social Studies students. Although the learning gains are comparable in both tracks, negative selection into retaking in terms of X_i and θ_i is stronger among Turkish-Math students.

Note that Table 3 offers clear support to the argument that it is critical to allow for unobservables as we do here. Had we not done so, our results would have been biased. Since $E[\widehat{\theta_i|N_i = n}] < 0 \ \forall n > 1$, irrespective of the track, correcting for selection into retaking only on X_i would have underestimated the learning gains; without taking θ_i into account results in a higher predicted initial scores among repeat takers.

The aggregate patterns in Table 2 and Figure 8 could be hiding compositional differences across tracks. Although in the Science track lower learning gains seem to be related to more

Figure 9: Cumulative Learning b/w first and n^{th} Attempt, by School Type



Source: ÖSYM data on 2002 ÖSS applicants.
Note: Dashed lines depict 95% confidence interval.

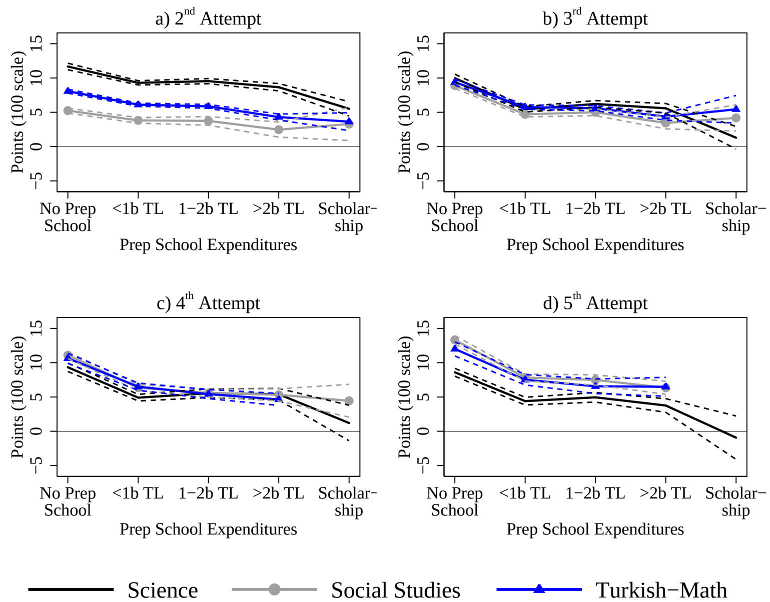
severe negative selection on X_i, this relationship does not hold for the other tracks. We will now look at the differential learning gains by students' background in each track to find out if there is a common explanation for the learning patterns identified so far.

Figure 9 reports the estimated learning gains by school type. Here, and in the graphs that follow, we have just kept combinations of individual characteristics (such as school type) and number of attempts that had at least 30 observations. In the horizontal axis, we have ordered schools from the worst to the best ones.[33] In general, we observe that students who come from less advantaged schools such as regular public schools are the ones who benefit the most from

[33] In Turkey, students' socioeconomic background is correlated with high school type. The secondary education system can be broadly classified into general high schools and vocational and technical high schools. Within the group of general high schools, there are regular public, Anatolian, science, private, and other specialized schools (military and police, for example). Anatolian and science select students based on a national placement test at the end of 8^{th} grade and are thus considered the best schools in the country. Since private schools charge tuition, they tend to have students with better socioeconomic backgrounds who can afford the cost. Regular public high schools are populated with students who are, on average, less advantaged than students from other schools.

retaking the exam, irrespective of the number of attempts or the track. Students from private, Anatolian, and science schools almost always exhibit negligible gains. In particular, science students from more privileged schools have negative catch up effects.

Figure 10: Cumulative Learning b/w first and n^{th} Attempt, by Expenditures on *Dersanes*



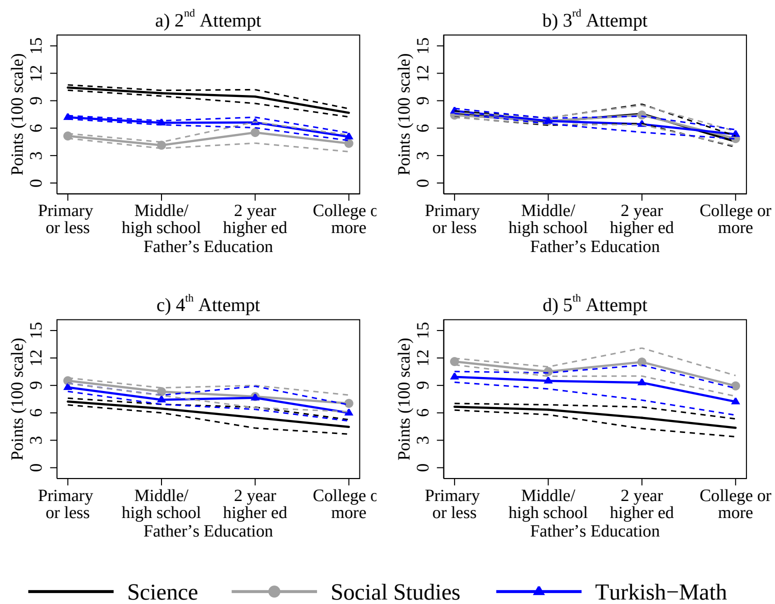
Source: ÖSYM data on 2002 ÖSS applicants.
Note: Dashed lines depict 95% confidence interval.

The same pattern is present if we analyze cumulative learning gains by expenditures on *dersanes* while in high school. Figure 10 shows that, in all tracks, students who had no prep school at all are the ones who have the highest learning gains relative to their initial attempt and these decrease as the student' coaching expenditures increase. Finally, if we look at the pattern of learning according to the father's education as depicted in Figure 11, we also find that students who learn the most when they retake are those with less educated fathers.[34]

In sum, we identify large learning effects and these are particularly prevalent among repeat takers with less advantaged background. But, what are these students learning? That remains

[34]We also checked if these patters hold once we look at learning gains relative to the initial (predicted) score of repeat takers. See Figures 17-19 in Appendix D.

Figure 11: Cumulative Learning b/w first and n^{th} Attempt, by Father's Education Level



Source: ÖSYM data on 2002 ÖSS applicants.
Note: Dashed lines depict 95% confidence interval.

the question. As Vigdor and Clotfelter (2003) point out, score changes over attempts can be explained by greater knowledge on the subjects being tested or by better exam taking skills specific to the admission exam, once selection is taken into account. Although we cannot separate learning about the material (true learning) from learning how to write the exam, we have good reasons to believe that most of the score improvement among Turkish repeat takers' is explained by true learning. Many students start preparing for the ÖSS as early as 9^{th} grade even though the exam is only taken in 12^{th} grade, the last high school year. Early and continuous exposure to practice while in high school is very common so we can expect that most of the gains in terms of exam taking skills occur before they graduate from high school.

If this is the case, as we believe, our study shows that although performance may be negatively affected by adverse background conditions, less advantaged students have greater learning gains. Under the right conditions, the greater potential for learning among less privileged students can be translated into improved access to higher education. Moreover, if retaking generates a window of opportunity for less prepared students to get better prepared *before* they go to college, allowing students to take the entrance exam as many times as they want could also be effective in reducing the effect of background inequalities on future college performance.

If repeat takers are mostly learning *how* to take the exam, our results still imply that allowing retaking can be helpful for some groups. The results above show that the important score improvements can help students who did not get into college in their first attempts obtain a placement in college. If this is the case, learning has an effect on college admissions but not on college performance.

9 Conclusions and Proposed Agenda

Using the ÖSYM 2002 dataset, we test if the Turkish centralized college admissions system is conducive to learning over multiple attempts. In particular, we develop an econometric methodology that controls for selection into retaking and estimates the cumulative learning gains (in terms of score improvement) between the first and the n^{th} attempt.

We find that negative selection on observables and unobservables is more severe in the Science track. We also show that worse types are more likely to retake the exam in all tracks which suggests that ignoring selection on unobservables would have underestimated learning estimates.

After controlling for selection, we identify important learning gains for all sub-samples of repeat takers. An average repeat taker is able to reduce the gap from s_* and, in some cases, she is even able to close it. Our study also presents interesting relations between a student's background and her potential for learning. We found that less advantaged students (whether they are defined by the high schools they attend, coaching expenditures, or father's education) improve their performance as they keep retaking the ÖSS while students from more advantageous backgrounds do not. This implies that by simply allowing students to take the university entrance exam as many times as they want the effects of background inequalities on college admission can be reduced. Moreover, if students are truly learning about the subjects tested, the option of retaking may also level the playing field for students with adverse background characteristics by allowing them to get better prepared *before* they go college.

Although the option to retake seems to work as a window of opportunity for less advantaged students in Turkey, the reduction of the effect of background inequalities on access to and performance in college should envisage earlier alternatives to deal with theses inequalities. In this sense, providing government-financed early remedial tutoring for disadvantaged students should be a top priority in the Turkish education agenda.

A recent article (see The Economist (2010)) argues that the French system has led to discouragement among French high school students by setting consistently high standards for passing from one grade to the next; by age 15, the percentage of students who have repeated at least one grade is 38% in France and only 11% in the US. Moreover, by not giving in to grade inflation (which makes it easier to judge performance at the high end), the article argues that the system has put French students at a disadvantage worldwide where grade inflation is the norm. Our work suggests that there may be a benefit to this approach: by not promoting students until they are ready, the French system, and systems like the one used by ÖSYM in Turkey, may evade the problem caused by putting students in the "Red Queen's race"[35] where they have to run as fast as they can to stay at least in the same place.

Relying on a cross section of data, we are able to develop a creative methodology that allows us to overcome the lack of panel data to measure learning. We believe that this is a valuable contribution that can be replicated in other settings with the similar data limitations. Our work is also relevant because it is able to overcome the limitations of previous studies on catch up, mostly available for the US. We believe that the Turkish system provides the right setting to measure learning gains by having a fixed goal post defined by the ÖSS and by providing objective performance measures comparable across students and time.

One of the limitations of our paper is the known ability assumption. Our research agenda includes the development of a model in which students learn about the subjects tested as well as about their own ability over time. Although excluded from this paper, the Foreign Language data has information on the preference lists submitted by each students, offering a nice setting to test the unknown ability model.

[35]As in Lewis Carroll's Alice in Wonderland.

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A Basic Statistics on the ÖSS, 2000-2002

Table 4: ÖSS over the years, 2000-2002

		2000	2001	2002
A.	No. of ÖSS Applicants	1,414,223	1,471,197	1,817,590
	A1. Applicants who took ÖSS	1,414,223	1,471,197	1,534,913
	A2. Applicant for exam-less placement	0	0	282,677
B.	No. of applicants who are HS seniors	499,220	504,620	547,094
C.	No. of applicants who are repeat takers	915,003	966,577	1,270,496
	C1. Not placed before		697,974	894,257
	C2. Previously placed		217,802	302,512
	C3. College graduate		50,802	73,727
D.	Placement in undergraduate programs	440,028	471,371	614,125
	D1. 4+ year	160,247	166,963	169,835
	D2. 2 year	117,873	129,462	158,895
	D3. Open University 4+ year	98,764	110,779	107,754
	D4. Open University 2 year	63,144	64,167	177,641
E.	No. of secondary graduates	532,952	507,363	530,259
B/E	HS senior applicants/HS graduates	94%	99%	103%
B/A	% applicants in HS	35%	34%	30%
C1/A	% applicants retaking not placed before		47%	49%
C2/A	% applicants previously placed		15%	17%
C3/A	% applicants who are college graduates		3%	4%
E/D	Secondary graduates/Placement	121%	108%	86%
D/A	Placement rate	31%	32%	34%
	Placement rate, HS Graduates			30[a/]
	Placement rate, repeat takers			34[a/]

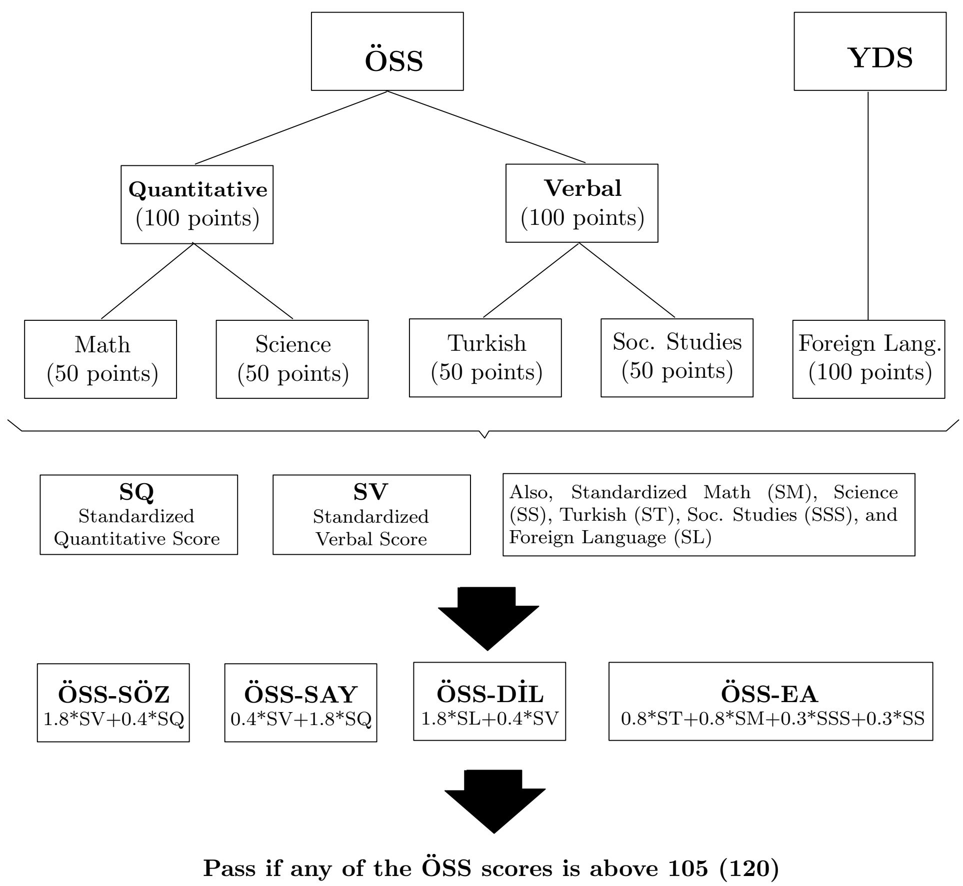
[a/] Own estimates from ÖSS 2002 database.
Source: ÖSYM website, press releases, Hatakenaka (2006).
To take the exam, students have to be in their last year of high school but the exam is only valid if the student graduates from secondary school. This explains why there are 530,259 high school graduates but 547,094 senior applicants in 2002.

In 2002, over 1.2 million applicants were repeat takers. Although most of them retake the ÖSS after failing to be placed in previous attempts, there is an non negligible share of repeat takers who keep trying even after getting into college. In 2002, 17% of the total pool of applicants were repeat takers who had been placed in the past (row C2/A in Table 4), suggesting that an important proportion of students placed through the ÖSS are unhappy with their college placement. In other words, some students are not just trying to get into college; they are after a specific program and/or university and they keep retrying until they get the seat they aim for.

B ÖSYM and the Higher Education Placement Process

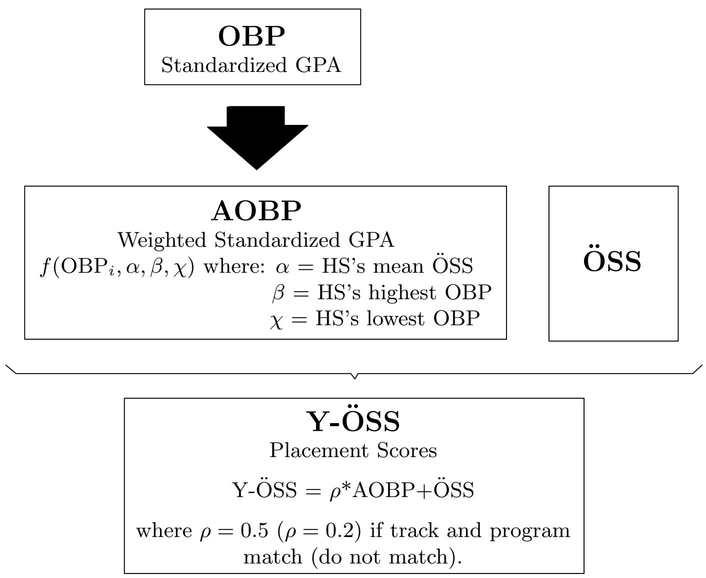
Figure 12 shows how ÖSYM handles raw scores in Math, Science, Turkish, Social Studies, and Foreign Language to construct standardized performance measures. Using the mean and the standard deviation of raw scores in each portion of the exam, a standardized verbal (SV) and quantitative score (SQ) are constructed. In addition, five more standardized scores are obtained: math (SM), science (SS), Turkish (ST), social sciences (SSS), and foreign language (SL). From these standardized scores, three ÖSS scores (four if the student takes the foreign language exam, YDS) are obtained. A student is eligible for placement in a regular 2 or 4-year program (distance education and some 2-year programs) if *any* of the ÖSS scores is at least 120 (105) points.

Figure 12: Passing the ÖSS



After the exam is cleared, placement is determined by the placement scores, Y-ÖSS, and the capacity constraints of the programs preferred by the student. A maximum of four Y-ÖSS scores are constructed from a weighted average of the standardized high school GPAs (OBP) and each of the four ÖSS scores.[36] Figure 13 presents the details of Y-ÖSS scores' construction. From the OBPs, ÖSYM obtains weighted standardized GPAs (AOBP), which are just OBPs weighted according to the success of the candidate's school in the ÖSS. AOBPs are a function of the high school's i) average ÖSS in the relevant subject (α), ii) highest OBP (β), and iii) lowest OBP (χ), as well as student i's OBP. Again, each student gets 4 different AOBP scores, one corresponding to each of the ÖSS scores.

Figure 13: Construction of Y-ÖSS scores



Finally, up to four Y-ÖSS scores are obtained from Y-ÖSS $= \rho$AOBP$+$ÖSS, where ρ is equal to 0.5 if the student's high school track and program match and it is 0.2 if there is a mismatch between them. Moreover, if the student was placed in a 2 or 4-year program in the previous year, ρ is reduced by 50%. Applicants placed *before* the previous year are not penalized at all.

Students can include up to 18 regular programs (2 or 4-year programs) in their preference lists in addition to 2 distance education programs. Before a student submits her placement preferences, she has access to all her scores (ÖSS, OBP, AOBP, and Y-ÖSS) as well her percentiles for each score.

[36] Student i's OBP score is obtained in the following way:

$$\text{OBP}_i = 10\left(\frac{\text{GPA}_i - \mu}{\sigma}\right) + 50$$

where μ and σ are the mean and standard deviation of raw GPAs in student i's high school.OBPs are calculated the first time a student takes the ÖSS, relative to the students graduating from her high school in that year, and they are *not* updated over repeated attempts.

C Standardized HS GPA versus quality normalized HS GPA

Raw GPAs and OBPs ignore potential quality heterogeneity and grade inflation across high schools. Since we are interested in obtaining a measure that will allow us to rank students on the same scale based on their high school academic performance, neither of these measures are useful. Obtaining 10/10 at a very selective school is not the same as obtaining 10/10 in a very bad school.

To deal with this issue, we constructed *school quality normalized* GPAs. Within each track k and for each school j, we define the adjustment factor, A_{jk}:

$$A_{jk} = \frac{\overline{\text{GPA}}_{jk}}{\overline{\text{ÖSS}}_{jk}} \frac{\overline{\text{GPA}}_{k}}{\overline{\text{ÖSS}}_{k}} \tag{C.1}$$

where $\overline{\text{GPA}}_{jk}$ and $\overline{\text{ÖSS}}_{jk}$ are the average GPA and ÖSS scores for each high school and track combination. $\overline{\text{GPA}}_{k}$ and $\overline{\text{ÖSS}}_{k}$ are the average GPA and ÖSS score across all comparable students from the same track.[37] The first term in ((C.1)) should go up if the school is inflating grades relative to its true quality. For example, if the average GPA in school j is about 8/10 but the average exam score for its students is only 5/10, school j is worse than the raw GPAs of its students suggest. After all, since the ÖSS is a standardized exam, $\overline{\text{ÖSS}}_{jk}$ should be a good proxy for the true quality of the school on a unique scale. The second term in ((C.1)) is just a constant for all the students in the same database and it takes the adjustment factor to a scale which is relative to everyone in the same track.

Define the school quality normalized GPA for student i in school j and track k as:

$$\text{GPAnorm}_{ijk} = 100 \left(\frac{\widetilde{\text{GPA}}_{ijk}}{\widetilde{\text{GPA}}_{k}^{\max}} \right)$$

where $\widetilde{\text{GPA}}_{ijk}$ is defined as:

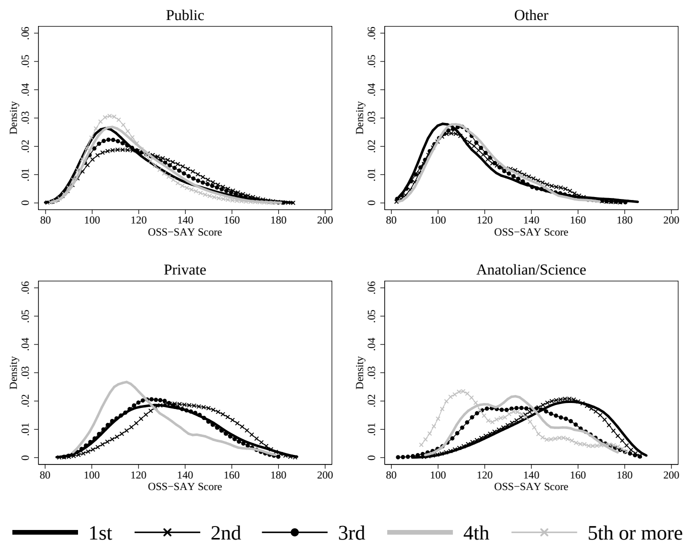
$$\widetilde{\text{GPA}}_{ijk} = \left(\frac{\text{GPA}_{ijk}}{A_{jk}} \right)$$

and $\widetilde{\text{GPA}}_{k}^{\max}$ is just the maximum $\widetilde{\text{GPA}}_{ijk}$ in a given k. Notice that if the student is in a school that tends to inflate the grades relative to true performance, the raw GPA of all the students in such school will be penalized through a higher A_{jk}.

[37]This adjustment factor is constructed using ÖSS-SAY scores for Science students while Social Studies students' factor relies on ÖSS-SÖZ. For Turkish-Math students, we use the ÖSS-EA score.

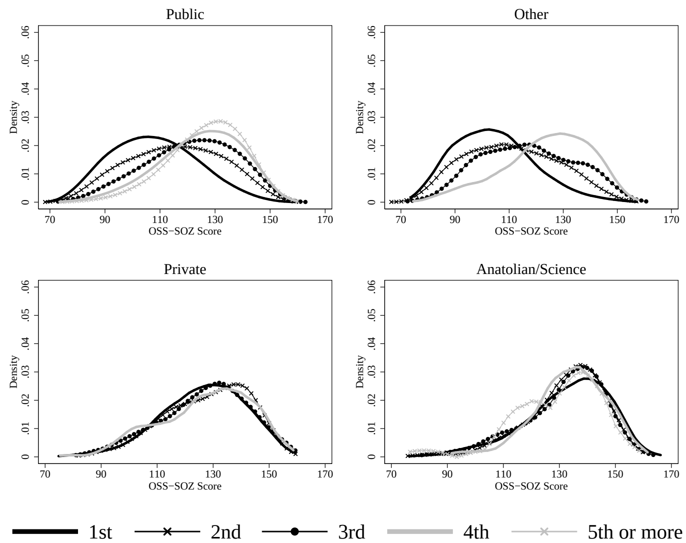
D Additional Tables and Figures

Figure 14: Distribution of ÖSS Score by school type: Science



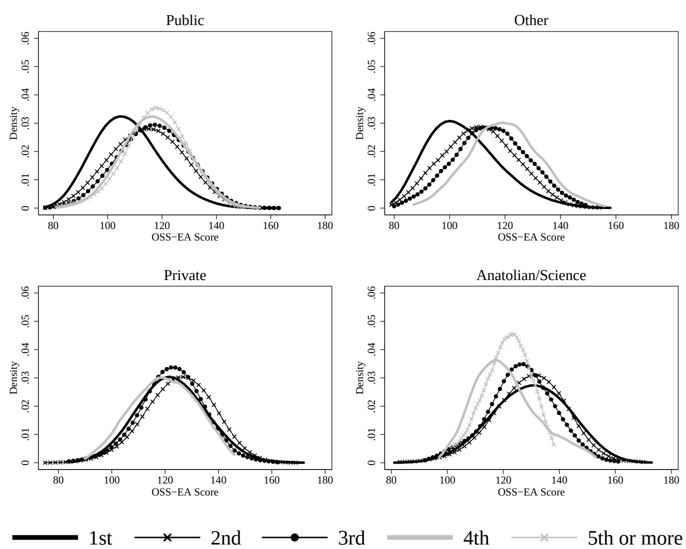
Source: ÖSYM data on 2002 ÖSS applicants.

Figure 15: Distribution of ÖSS Score by school type: Social Studies



Source: ÖSYM data on 2002 ÖSS applicants.

Figure 16: Distribution of ÖSS Score by school type: Turkish-Math



Source: ÖSYM data on 2002 ÖSS applicants.

Table 5: Descriptive Statistics: All Databases

Variable	Obs	Mean	SD	Min	Max
Individual and Family Background					
Gender	119466	0.56		0	1
Raw HS GPA	115892	62.88	14.16	4	100
Standardized HS GPA	115892	49.44	9.10	30	80
Quality Normalized HS GPA (based on ÖSS-SAY)	115892	48.40	10.51	2.38	100
Quality Normalized HS GPA (based on ÖSS-SOZ)	115892	47.94	10.83	2.40	100
Quality Normalized HS GPA (based on ÖSS-EA)	115892	48.46	10.64	2.51	100
School Type					
Public	119421	0.72		0	1
Private	119421	0.11		0	1
Anatolian/Science	119421	0.11		0	1
Other	119421	0.06		0	1
Father's education					
Primary or less	119466	0.46		0	1
Middle/High school	119466	0.30		0	1
2-year higher education	119466	0.04		0	1
College/Master/PhD	119466	0.11		0	1
Missing	119466	0.08		0	1
More than 3 children in the household	119248	0.42		0	1
Household Monthly Income					
<250TL	119466	0.39		0	1
[250 − 500]TL	119466	0.39		0	1
>500TL	119466	0.22		0	1
Preparation for the Exam					
Student was working when exam was taken	119466	0.15		0	1
Expenditures in *dersanes*					
Did not attend	119257	0.20		0	1
Scholarship	119257	0.02		0	1
<1b TL	119257	0.30		0	1
[1 − 2]b TL	119257	0.16		0	1
>2b TL	119257	0.07		0	1
Missing	119257	0.26		0	1
Exam Performance					
Took language exam	119466	0.01		0	1
ÖSS-SAY	119466	110.19	25.41	0	184.26
ÖSS-SOZ	119466	113.57	25.80	0	172.29
ÖSS-EA	119466	111.85	23.63	0	171.25
Number of attempts					
1st attempt	114800	0.38		0	1
2nd attempt	114800	0.27		0	1
3rd attempt	114800	0.19		0	1
4th attempt	114800	0.10		0	1
5th attempt	114800	0.06		0	1
Student was placed	119466	0.29		0	1

Source: ÖSYM data on 2002 ÖSS applicants.

Table 6: Descriptive Statistics: Science

Variable	Obs	Mean	SD	Min	Max
Individual and Family Background					
Gender	39853	0.59		0	1
Raw HS GPA	38691	68.19	15.77	4	100
Standardized HS GPA	38691	51.68	10.01	30	80
Quality Normalized HS GPA (based on ÖSS-SAY)	38691	43.51	10.34	2.38	100
Quality Normalized HS GPA (based on ÖSS-SÖZ)	38691	43.59	10.14	2.62	100
Quality Normalized HS GPA (based on ÖSS-EA)	38691	43.76	10.11	2.55	100
School Type					
Public	39834	0.59		0	1
Private	39834	0.18		0	1
Anatolian/Science	39834	0.20		0	1
Other	39834	0.03		0	1
Father's education					
Primary or less	39853	0.39		0	1
Middle/High school	39853	0.30		0	1
2-year higher education	39853	0.06		0	1
College/Master/PhD	39853	0.17		0	1
Missing	39853	0.08		0	1
More than 3 children in the household	39787	0.38		0	1
Household Monthly Income					
$<$250TL	39853	0.34		0	1
$[250-500]$TL	39853	0.40		0	1
$>$500TL	39853	0.26		0	1
Preparation for the Exam					
Student was working when exam was taken	39853	0.13		0	1
Expenditures in *dersanes*					
Did not attend	39789	0.13		0	1
Scholarship	39789	0.04		0	1
$<$1b TL	39789	0.35		0	1
$[1-2]$b TL	39789	0.20		0	1
$>$2b TL	39789	0.10		0	1
Missing	39789	0.17		0	1
Exam Performance					
Took language exam	39853	0.01		0	1
ÖSS-SAY	39853	124.02	29.99	0	184.26
ÖSS-SÖZ	39853	108.76	26.30	0	172.29
ÖSS-EA	39853	116.64	26.35	0	171.25
Number of attempts					
1st attempt	38771	0.42		0	1
2nd attempt	38771	0.25		0	1
3rd attempt	38771	0.16		0	1
4th attempt	38771	0.09		0	1
5th attempt	38771	0.07		0	1
Student was placed	39853	0.36		0	1

Source: ÖSYM data on 2002 ÖSS applicants.

Table 7: Descriptive Statistics: Social Studies

Variable	Obs	Mean	SD	Min	Max
Individual and Family Background					
Gender	39780	0.57		0	1
Raw HS GPA	38684	57.28	10.64	4	100
Standardized HS GPA	38684	47.66	7.78	30	80
Quality Normalized HS GPA (based on ÖSS-SAY)	38684	53.23	9.45	3.504234	100
Quality Normalized HS GPA (based on ÖSS-SÖZ)	38684	54.36	10.05	3.489486	100
Quality Normalized HS GPA (based on ÖSS-EA)	38684	54.14	9.77	3.514539	100
School Type					
Public	39763	0.86		0	1
Private	39763	0.02		0	1
Anatolian/Science	39763	0.02		0	1
Other	39763	0.09		0	1
Father's education					
Primary or less	39780	0.56		0	1
Middle/High school	39780	0.28		0	1
2-year higher education	39780	0.03		0	1
College/Master/PhD	39780	0.05		0	1
Missing	39780	0.08		0	1
More than 3 children in the household	39695	0.49		0	1
Household Monthly Income					
<250TL	39780	0.45		0	1
$[250-500]$TL	39780	0.38		0	1
>500TL	39780	0.17		0	1
Preparation for the Exam					
Student was working when exam was taken	39780	0.21		0	1
Expenditures in *dersanes*					
Did not attend	39698	0.26		0	1
Scholarship	39698	0.01		0	1
<1b TL	39698	0.22		0	1
$[1-2]$b TL	39698	0.09		0	1
>2b TL	39698	0.03		0	1
Missing	39698	0.38		0	1
Exam Performance					
Took language exam	39780	0.01		0	1
ÖSS-SAY	39780	98.96	19.00	0	160.42
ÖSS-SÖZ	39780	113.53	26.61	0	161.17
ÖSS-EA	39780	105.41	21.91	0	155.59
Number of attempts					
1st attempt	37458	0.25		0	1
2nd attempt	37458	0.25		0	1
3rd attempt	37458	0.25		0	1
4th attempt	37458	0.16		0	1
5th attempt	37458	0.10		0	1
Student was placed	39780	0.23		0	1

Source: ÖSYM data on 2002 ÖSS applicants.

Table 8: Descriptive Statistics: Turkish-Math

Variable	Obs	Mean	SD	Min	Max
Individual and Family Background					
Gender	39833	0.51		0	1
Raw HS GPA	38517	63.16	13.41	4	100
Standardized HS GPA	38517	48.99	8.89	30	80
Quality Normalized HS GPA (based on ÖSS-SAY)	38517	48.48	9.38	2.60	100
Quality Normalized HS GPA (based on ÖSS-SÖZ)	38517	45.85	9.12	2.40	100
Quality Normalized HS GPA (based on ÖSS-EA)	38517	47.48	9.32	2.51	100
School Type					
Public	39824	0.71		0	1
Private	39824	0.14		0	1
Anatolian/Science	39824	0.11		0	1
Other	39824	0.05		0	1
Father's education					
Primary or less	39833	0.44		0	1
Middle/High school	39833	0.33		0	1
2-year higher education	39833	0.04		0	1
College/Master/PhD	39833	0.11		0	1
Missing	39833	0.09		0	1
More than 3 children in the household	39766	0.39		0	1
Household Monthly Income					
$<$250TL	39833	0.37		0	1
$[250-500]$TL	39833	0.40		0	1
$>$500TL	39833	0.23		0	1
Preparation for the Exam					
Student was working when exam was taken	39833	0.10		0	1
Expenditures in *dersanes*					
Did not attend	39770	0.19		0	1
Scholarship	39770	0.01		0	1
$<$1b TL	39770	0.31		0	1
$[1-2]$b TL	39770	0.17		0	1
$>$2b TL	39770	0.08		0	1
Missing	39770	0.23		0	1
Exam Performance					
Took language exam	39833	0.01		0	1
ÖSS-SAY	39833	107.57	18.76	0	180.00
ÖSS-SÖZ	39833	118.41	23.47	0	169.00
ÖSS-EA	39833	113.48	20.82	0	168.00
Number of attempts					
1st attempt	38571	0.46		0	1
2nd attempt	38571	0.30		0	1
3rd attempt	38571	0.16		0	1
4th attempt	38571	0.06		0	1
5th attempt	38571	0.02		0	1
Student was placed	39833	0.26		0	1

Source: ÖSYM data on 2002 ÖSS applicants.

Table 9: Determinants of the Fraction of Second to First Time Takers by Track and Background Characteristics

	Science	Social Studies	Turkish-Math
Constant	1.203	1.229	0.971
	(0.116)	(0.140)	(0.094)
Gender	0.007	0.002	-0.038
	(0.057)	(0.081)	(0.049)
Prep school/tutoring expenditures (Base: no prep school)			
Scholarship	0.116	-0.009	-0.029
	(0.120)	(0.223)	(0.119)
<1b TL	-0.236	0.167	-0.128
	(0.098)	(0.119)	(0.080)
$[1-2]$b TL	-0.002	0.450	0.100
	(0.102)	(0.133)	(0.082)
>2b TL	0.265	1.011	0.484
	(0.109)	(0.170)	(0.092)
Missing	0.115	0.130	0.085
	(0.106)	(0.117)	(0.084)
School Type (Base: Public)			
Private	-0.369	-0.401	-0.309
	(0.072)	(0.131)	(0.061)
Anatolian/Science	-0.948	-0.764	-0.652
	(0.074)	(0.126)	(0.064)
Other	-0.459	-0.592	-0.216
	(0.113)	(0.111)	(0.088)
Father's education (Base: Primary or less)			
Middle/High school	0.032	0.009	-0.068
	(0.088)	(0.111)	(0.072)
2-year higher education	0.188	-0.027	-0.049
	(0.102)	(0.149)	(0.088)
College/Master/PhD	0.029	-0.008	-0.067
	(0.094)	(0.138)	(0.079)
Missing	0.086	0.177	-0.044
	(0.114)	(0.144)	(0.094)
Mother's education (Base: Primary or less)			
Middle/High school	-0.059	-0.257	0.077
	(0.072)	(0.102)	(0.061)
2-year higher education	0.144	-0.101	0.326
	(0.116)	(0.205)	(0.095)
College/Master/PhD	0.098	-0.484	0.062
	(0.113)	(0.194)	(0.109)
Missing	-0.073	-0.153	0.049
	(0.123)	(0.151)	(0.101)
More than 3 children in the household	0.084	0.002	0.135
	(0.063)	(0.091)	(0.055)
Observations	730	404	682
R-squared	0.226	0.226	0.224

Source: ÖSYM data on 2002 ÖSS applicants.
Standard errors in parentheses.

Table 10: Regression Results from ML Estimation: Science

	α_0		α_1	
Constant	50.205	(1.170)	51.604	(0.770)
Individual and Family Background				
Gender	-2.591	(0.024)	2.383	(0.016)
School Type (base: Public)				
Private	5.788	(0.046)	6.160	(0.036)
Anatolian/Science	12.660	(0.049)	13.379	(0.038)
Other	-0.475	(0.298)	0.562	(0.168)
Father's education (base: Primary or less)				
Middle/High school	0.078	(0.050)	0.078	(0.034)
2-year higher education	1.385	(0.133)	1.181	(0.110)
College/Master/PhD	2.041	(0.084)	2.035	(0.060)
Missing	0.360	(0.260)	0.172	(0.157)
Mother's education (base: Primary or less)				
Middle/High school	-0.760	(0.047)	-0.594	(0.033)
2-year higher education	0.956	(0.197)	0.763	(0.147)
College/Master/PhD	1.239	(0.181)	0.849	(0.136)
Missing	-0.110	(0.287)	-0.092	(0.198)
Father's occupation (base: Employer)				
Works for wages/salary	1.468	(0.148)	1.450	(0.117)
Self-employed	1.256	(0.181)	1.371	(0.132)
Unemployed/not in Labor Force	1.264	(0.243)	1.333	(0.201)
Missing	-0.060	(0.385)	0.738	(0.270)
Mother's occupation (base: Employer)				
Works for wages/salary	2.630	(1.176)	0.909	(0.793)
Self-employed	2.458	(1.246)	0.866	(0.847)
Unemployed/not in Labor Force	2.914	(1.143)	1.139	(0.729)
Missing	1.818	(1.382)	-0.354	(0.913)
More than 3 children in the household	0.033	(0.039)	-0.401	(0.028)
Household Monthly Income (base: >500TL)				
<250TL	0.252	(0.074)	0.291	(0.053)
$[250-500]$TL	0.050	(0.047)	-0.002	(0.037)
Preparation for the Exam				
Student was working when exam was taken	-1.682	(0.272)	-1.711	(0.183)
Expenditures in *dersanes* (base: Did not attend)				
Scholarship	12.264	(0.202)	13.647	(0.175)
<1b TL	4.120	(0.097)	6.051	(0.055)
$[1-2]$b TL	2.794	(0.108)	5.070	(0.068)
>2b TL	2.976	(0.164)	5.348	(0.129)
Missing	-0.194	(0.127)	0.556	(0.066)

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Table 10 (continued)

	α_0		α_1	
Other characteristics				
Internet access (base: No internet access)				
At home	0.027	(0.075)	0.560	(0.057)
Not at home	-0.456	(0.034)	0.155	(0.024)
Missing	-1.070	(0.209)	-0.807	(0.140)
Population in Town of HS (base: Over a million)				
<10,000	-0.276	(0.154)	-3.386	(0.095)
10,000-50,000	-1.765	(0.064)	-3.175	(0.060)
50,000-250,000	-0.969	(0.045)	-1.266	(0.035)
250,000-1,000,000	-0.819	(0.063)	-1.178	(0.048)
Missing	-2.155	(0.110)	-2.544	(0.075)
Funds to Pay for College (base: Family funds)				
Student's work	-1.130	(0.046)	-0.863	(0.028)
Loan	0.203	(0.033)	0.381	(0.024)
Other	-1.362	(0.136)	-0.497	(0.095)
Number of Observations	15610			
σ_θ	7.482 (0.002)			
σ_{ϵ_0}	5.753 (0.004)			
σ_{ϵ_1}	3.355 (0.004)			
Log likelihood	106402.8			

Source: ÖSYM data on 2002 ÖSS applicants.

Note: Bootstrapped standard errors in parenthesis.

Table 11: Regression Results from ML Estimation: Social Studies

	α_0		α_1	
Constant	20.997	(0.342)	57.659	(1.469)
Individual and Family Background				
Gender	-1.291	(0.008)	-0.528	(0.028)
School Type (base: Public)				
Private	3.515	(0.063)	7.464	(0.224)
Anatolian/Science	4.553	(0.031)	10.928	(0.182)
Other	-0.506	(0.012)	-0.372	(0.067)
Father's education (base: Primary or less)				
Middle/High school	-0.128	(0.010)	0.186	(0.047)
2-year higher education	0.004	(0.097)	-0.582	(0.343)
College/Master/PhD	0.358	(0.057)	1.397	(0.213)
Missing	-0.163	(0.039)	-0.392	(0.181)
Mother's education (base: Primary or less)				
Middle/High school	-0.589	(0.017)	-0.673	(0.077)
2-year higher education	0.382	(0.240)	0.157	(0.962)
College/Master/PhD	-0.430	(0.179)	0.504	(0.576)
Missing	-0.179	(0.058)	-0.282	(0.279)
Father's occupation (base: Employer)				
Works for wages/salary	0.910	(0.061)	1.614	(0.292)
Self-employed	0.831	(0.066)	1.470	(0.282)
Unemployed/not in Labor Force	0.910	(0.069)	1.315	(0.328)
Missing	0.449	(0.101)	0.816	(0.441)
Mother's occupation (base: Employer)				
Works for wages/salary	1.374	(0.334)	1.595	(1.441)
Self-employed	1.557	(0.335)	1.458	(1.442)
Unemployed/not in Labor Force	1.361	(0.309)	1.012	(1.320)
Missing	1.100	(0.342)	0.051	(1.386)
More than 3 children in the household	0.012	(0.008)	-0.581	(0.033)
Household Monthly Income (base: >500TL)				
<250TL	0.490	(0.017)	0.552	(0.073)
$[250-500]$TL	0.249	(0.016)	0.465	(0.071)
Preparation for the Exam				
Student was working when exam was taken	-0.356	(0.023)	-1.237	(0.106)
Expenditures in *dersanes* (base: Did not attend)				
Scholarship	2.763	(0.282)	7.737	(0.874)
<1b TL	1.547	(0.016)	5.587	(0.056)
$[1-2]$b TL	1.312	(0.039)	6.211	(0.141)
>2b TL	1.302	(0.163)	6.992	(0.527)

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Table 11 (continued)

	α_0		α_1	
Missing	-0.136	(0.011)	-0.433	(0.039)
Other characteristics				
Internet access (base: No internet access)				
At home	-0.555	(0.035)	-0.138	(0.178)
Not at home	-0.407	(0.011)	-0.085	(0.045)
Missing	-0.129	(0.028)	-0.501	(0.123)
Population in Town of HS (base: Over a million)				
<10,000	0.363	(0.024)	-1.728	(0.078)
10,000-50,000	-0.264	(0.020)	-0.878	(0.078)
50,000-250,000	-0.253	(0.017)	-0.303	(0.082)
250,000-1,000,000	-0.363	(0.023)	-0.400	(0.093)
Missing	-0.584	(0.021)	-1.834	(0.090)
Funds to Pay for College (base: Family funds)				
Student's work	-0.006	(0.011)	0.161	(0.044)
Loan	0.296	(0.013)	0.794	(0.049)
Other	-0.006	(0.025)	0.417	(0.111)
Number of Observations	8801			
σ_θ	3.850 (0.004)			
σ_{ϵ_0}	0.007 (0.000)			
σ_{ϵ_1}	6.344 (0.004)			
Log likelihood	53098.7			

Source: ÖSYM data on 2002 ÖSS applicants.

Note: Bootstrapped standard errors in parenthesis.

Table 12: Regression Results from ML Estimation: Turkish-Math

	α_0		α_1	
Constant	53.225	(1.396)	57.202	(0.670)
Individual and Family Background				
Gender	-4.557	(0.023)	-0.620	(0.008)
School Type (base: Public)				
Private	5.787	(0.042)	6.132	(0.018)
Anatolian/Science	9.388	(0.037)	9.953	(0.022)
Other	-0.820	(0.170)	0.464	(0.059)
Father's education (base: Primary or less)				
Middle/High school	-0.163	(0.036)	0.043	(0.013)
2-year higher education	0.907	(0.155)	0.237	(0.065)
College/Master/PhD	1.249	(0.086)	1.109	(0.040)
Missing	0.713	(0.202)	-0.091	(0.072)
Mother's education (base: Primary or less)				
Middle/High school	-0.441	(0.052)	0.109	(0.020)
2-year higher education	1.179	(0.310)	0.965	(0.122)
College/Master/PhD	1.549	(0.285)	1.580	(0.126)
Missing	-0.918	(0.271)	0.100	(0.096)
Father's occupation (base: Employer)				
Works for wages/salary	0.931	(0.155)	0.705	(0.064)
Self-employed	0.822	(0.174)	0.505	(0.073)
Unemployed/not in Labor Force	1.131	(0.233)	0.709	(0.080)
Missing	0.854	(0.334)	0.341	(0.131)
Mother's occupation (base: Employer)				
Works for wages/salary	1.283	(1.397)	0.176	(0.667)
Self-employed	1.922	(1.477)	0.253	(0.694)
Unemployed/not in Labor Force	1.917	(1.332)	0.309	(0.654)
Missing	0.402	(1.396)	-0.680	(0.665)
More than 3 children in the household	0.339	(0.032)	-0.270	(0.014)
Household Monthly Income (base: >500TL				
<250TL	1.257	(0.054)	0.752	(0.026)
$[250-500]$TL	0.741	(0.043)	0.431	(0.021)
Preparation for the Exam				
Student was working when exam was taken	-1.448	(0.159)	-0.878	(0.056)
Expenditures in *dersanes* (base: No prep school)				
Scholarship	8.355	(0.414)	7.088	(0.175)
<1b TL	3.154	(0.047)	4.221	(0.018)
$[1-2]$b TL	3.579	(0.083)	4.970	(0.030)
>2b TL	3.966	(0.142)	5.704	(0.071)

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Table 12 (continued)

	α_0		α_1	
Missing	-0.727	(0.058)	-0.174	(0.017)
Other characteristics				
Internet access (base: No internet access)				
At home	-0.532	(0.073)	0.462	(0.037)
Not at home	-0.917	(0.027)	-0.088	(0.012)
Missing	-1.309	(0.125)	-0.866	(0.047)
Population in Town of HS (base: Over a million)				
<10,000	0.750	(0.124)	-1.791	(0.038)
10,000-50,000	-1.092	(0.053)	-2.032	(0.026)
50,000-250,000	-0.861	(0.043)	-0.841	(0.019)
250,000-1,000,000	-0.865	(0.053)	-0.947	(0.024)
Missing	-2.621	(0.076)	-2.050	(0.030)
Funds to Pay for College (base: Family funds)				
Student's work	-0.203	(0.034)	0.187	(0.014)
Loan	0.641	(0.031)	0.639	(0.011)
Other	-0.686	(0.102)	-0.083	(0.039)
Number of Observations	16675			
σ_θ	5.938 (0.001)			
σ_{ϵ_0}	7.072 (0.002)			
σ_{ϵ_1}	0.030 (0.000)			
Log likelihood	109645.2			

Source: ÖSYM data on 2002 ÖSS applicants.

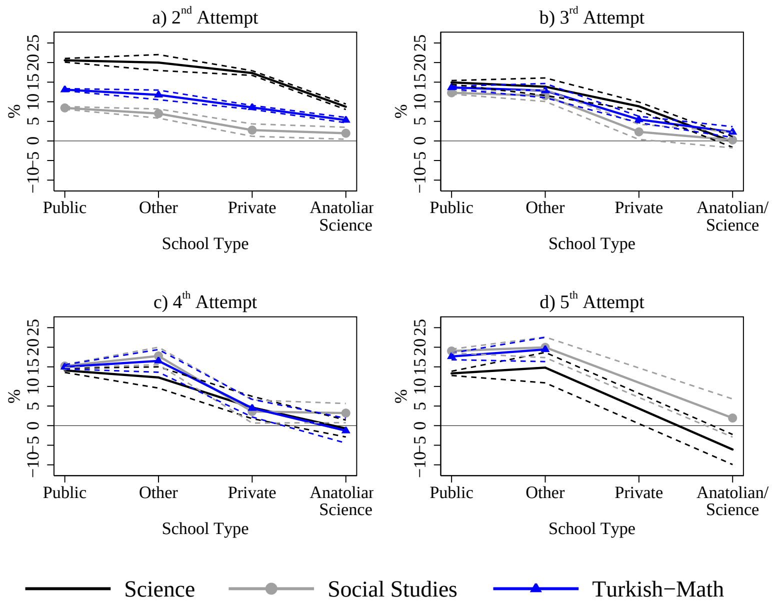
Note: Bootstrapped standard errors in parenthesis.

Table 13: Parameter Values

	Science	Social Studies	Turkish-Math	Source
μ_θ		0		Assumption
μ_0		0		Assumption
$\mu_{n\geq 1}$		0		Assumption
σ_θ		7		Estimates
σ_0		5		Estimates
$\sigma_{n>0}$		3		Estimates
s_*	52.0 (105 points in 100 scale)			Data
δ		0.95		Assumption
υ		0.5		Data[a/]
$E(\lambda_{i2})$	9.65	4.81	6.73	Estimates
$E(\lambda_{i3})$	-2.83	2.30	0.33	Estimates
$E(\lambda_{i4})$	-0.19	1.87	0.89	Estimates
$E(\lambda_{i5})$	-0.40	2.15	1.57	Estimates
$\sigma_{\lambda_{i2}}$	8.69	9.00	6.70	Estimates
$\sigma_{\lambda_{i3}}$	8.59	9.03	6.81	Estimates
$\sigma_{\lambda_{i4}}$	7.54	8.56	6.75	Estimates
$\sigma_{\lambda_{i5}}$	6.92	8.00	6.23	Estimates

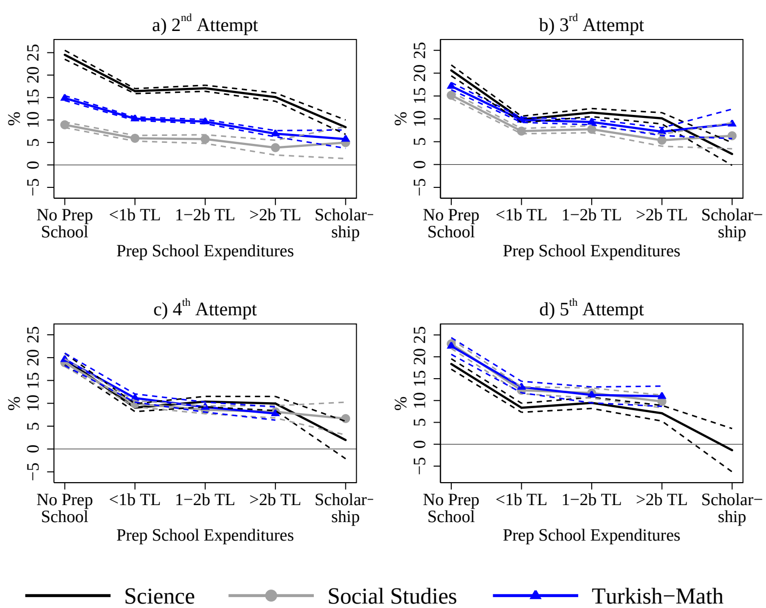
Note: $E(\lambda_{ik})$ and $\sigma_{\lambda_{ik}}$ are obtained from differences between cumulative effects. These are not equivalent but we use them as a reference.
[a/] We ignore the reduction in υ when the student changes track.

Figure 17: Learning by the n^{th} Attempt Relative to First Attempt, by School Type



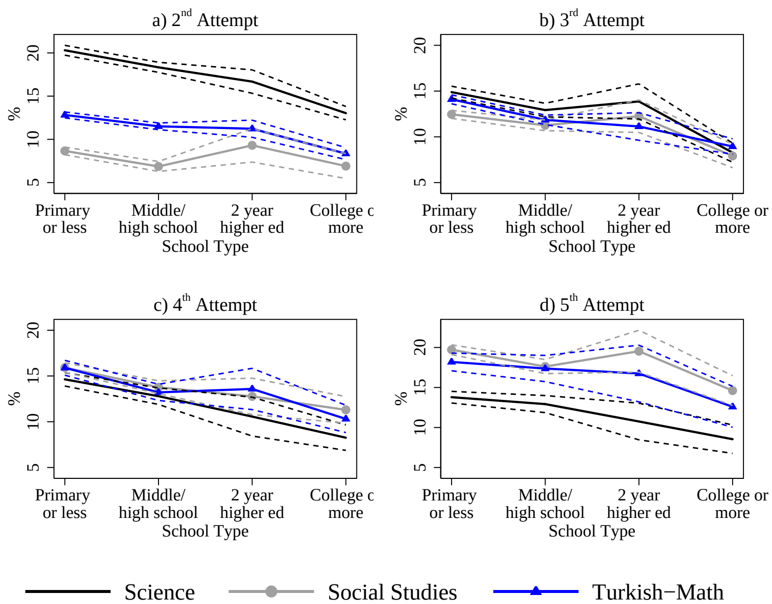
Source: ÖSYM data on 2002 ÖSS applicants.
Note: Dashed lines depict 95% confidence interval.

Figure 18: Learning by the n^{th} Attempt Relative to First Attempt, by Expenditures on *Dersanes*



Source: ÖSYM data on 2002 ÖSS applicants.
Note: Dashed lines depict 95% confidence interval.

Figure 19: Learning by the n^{th} Attempt Relative to First Attempt, by Father's Education Level



Source: ÖSYM data on 2002 ÖSS applicants.
Note: Dashed lines depict 95% confidence interval.

E Evaluating the Normality Assumption: Non-Parametric Estimation of the Factors' Densities

In subsection 6.2 we developed an estimation strategy that assumed that all factors where normally distributed:

$$\begin{aligned} \theta_i &\sim N(0, \sigma_\theta^2) \\ \epsilon_{i0} &\sim N(0, \sigma_0^2) \\ \epsilon_{i1} &\sim N(0, \sigma_1^2) \end{aligned}$$

Under these assumptions, we were able to estimate a system of two equations, GPA (g_i) and score (s_{i1}), in the sample of first time takers. However, applying a result due to Kotlarski (1967) (see Prakasa Rao (1992) for details) it can be shown that the densities of each factor, f_θ, f_{ϵ_0}, and f_{ϵ_1}, can be identified from the knowledge of the joint density of (g, s_1). In this appendix, we briefly review Bonhomme and Robin (2010), who explicitly derive the identifying restrictions for these kind of problems when the factor loadings (coefficients on θ and ϵs) are known. We then implement a non-parametric estimator of the factors' densities[38] and check it against our normality assumptions.

E.1 Non-Parametric Identification

Recall that:

$$\begin{aligned} g_i &= X_i\alpha_0 + \theta_i + \epsilon_{i0} \\ s_{i1} &= X_i\alpha_1 + \theta_i + \epsilon_{i1} \end{aligned}$$

Let $Y_{i0} = g_i - X_i\alpha_0$ and $Y_{i1} = s_{i1} - X_i\alpha_1$ where $\hat{\alpha_0}$ and $\hat{\alpha_1}$ are estimated via OLS. We can write a system for the OLS residuals that is equivalent to the classical measurement error model (Bonhomme and Robin (2010)):

$$Y_{i0} = \theta_i + \epsilon_{i0} \tag{E.1}$$

$$Y_{i1} = \theta_i + \epsilon_{i1} \tag{E.2}$$

Let A be the matrix containing the factor loadings:

$$A = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix},$$

where each column corresponds to one of the three factors, θ, ϵ_0, or ϵ_1.[39] We can represent

[38] We used Bonhomme and Robin (2010)'s codes as a basis for estimation. These are available online at `http://www.cemfi.es/~bonhomme/`.

[39] Notice that any two pair of A's columns are linearly independent and this is required to identify the densities non-parametrically.

system (E.1)-(E.2) using matrices:

$$Y = AW = \sum_{k=1}^{K} A_k W_k$$

where $W' = [\ \theta \quad \epsilon_0 \quad \epsilon_1\ ]$, k indexes the factors and K is the total number of factors. In our case, $K = 3$. Measurements $Y' = [\ Y_0 \quad Y_1\ ]$ are indexed by l and L is the total number of repeated measures. In our data, $L = 2$.

As standard in the factor literature, we assume that both factors are iid shocks and that:

Assumption E.1 *$\theta_i \perp\!\!\!\perp \epsilon_{in} \quad \forall n$ and $\epsilon_{in} \perp\!\!\!\perp \epsilon_{im} \quad \forall n \neq m$. Since Y_{i0} and Y_{i1} are both OLS residuals, this assumption also implies that all factors have zero mean.*

Assumption E.2 *The characteristic functions of the factor variables have no real zeros. In other words, they are not vanishing everywhere.*

Since factors are independent, the variance-covariance matrix of Y is then given by:

$$\mathrm{Var}(Y) = A\mathrm{Var}(W)A^T = \sum_{k=1}^{K} \mathrm{Var}(W_k) A_k A_k^T \tag{E.3}$$

Following Bonhomme and Robin (2010), we use the vech operator. For a 3 by 3 matrix $B = [b_{ij}]$, vech(B) $= (b_{11}, b_{12}, b_{13}, b_{22}, b_{23}, b_{33})$. Since $\mathrm{Var}(Y)$ is symmetric, we can reexpress (E.3) as:

$$\mathrm{vech}(\mathrm{Var}(Y)) = \sum_{k=1}^{K} \mathrm{Var}(W_k)\mathrm{vech}(A_k A_k^T) = Q \begin{bmatrix} \mathrm{Var}(W_1) \\ \vdots \\ \mathrm{Var}(W_K) \end{bmatrix}$$

where

$$Q = [\ \mathrm{vech}(A_1 A_1^T) \quad \dots \quad \mathrm{vech}(A_K A_K^T)\ ]$$

A third assumption required to implement Bonhomme and Robin (2010)'s estimation methodology is given by:

Assumption E.3 *Q has full column rank equal to the number of factors.*

This assumption guarantees that Q is invertible.

Let $i = \sqrt{-1}$. The characteristic function of X_k is given by:

$$\varphi_{W_k}(\tau) = \mathbb{E}(e^{i\tau W_k}) = \int e^{i\tau w} f_{W_k}(w) dw \qquad \tau \in \mathbb{R}$$

Moreover,

$$\kappa_{W_k}(\tau) = \ln[\mathbb{E}(e^{i\tau W_k})]$$

Independence of the factors allows us to write κ_Y as:

$$\kappa_Y(t) = \sum_{k=1}^{K} \kappa_{W_k}(t^T A_k)$$

where $t \in \mathbb{R}^L$. Second-differentiating this system, we get:

$$\nabla\nabla^T \kappa_Y(t) = \sum_{k=1}^{K} \kappa''_{W_k}(t^T A_k) A_k A_k^T$$

But since $\nabla\nabla^T \kappa_Y(t)$ is also symmetric, we can make use of the vech operator once more:

$$\begin{aligned} \text{vech}(\nabla\nabla^T \kappa_Y(t)) &= \sum_{k=1}^{K} \kappa''_{W_k}(t^T A_k)\text{vech}(A_k A_k^T) \\ &= Q \begin{bmatrix} \kappa''_{W_1}(t^T A_1) \\ \vdots \\ \kappa''_{W_K}(t^T A_K) \end{bmatrix} \end{aligned}$$

Under our assumptions, we can identify the second derivatives of the factor variables from:

$$\begin{bmatrix} \kappa''_{W_1}(t^T A_1) \\ \vdots \\ \kappa''_{W_K}(t^T A_K) \end{bmatrix} = Q^- \text{vech}(\nabla\nabla^T \kappa_Y(t)) \tag{E.4}$$

where $Q^- = (Q^T Q)^{-1} Q^T$. Since there are many ways to choose t such that $t^T A_k = \tau$, system (E.4) offers many overidentifying restrictions. For any choice of $\zeta \in \mathbb{R}^L\{0\}$, which Bonhomme and Robin (2010) call direction of integration, we can use $t = \frac{\tau\zeta}{\zeta^T A_k}$ so that:

$$\kappa''_{W_k}(\tau) = Q_k^- \text{vech}\left(\nabla\nabla^T \kappa_Y\left(\frac{\tau\zeta}{\zeta^T A_k}\right)\right) \tag{E.5}$$

where Q_k^- denotes the k^{th} row of Q^-.

The characteristic function of W_k then follows from integrating (E.5) twice and the density function of each factor k is obtained from the inverse Fourier transformation:

$$f_{W_k} = \frac{1}{2\pi} \int e^{-i\tau w} \varphi_{W_k}(\tau) d\tau \tag{E.6}$$

E.2 Density Estimator

To use this result in our sample with N observations, we estimate the characteristic function of the repeated measurements and its derivatives using their empirical analogs:

$$\begin{aligned}
\hat{\kappa}_Y(t) &= \ln\left(\mathbb{E}_N[e^{it^TY}]\right) \\
\widehat{\partial_l \kappa_Y}(t) &= i\frac{\mathbb{E}_N[Y_l e^{it^TY}]}{\mathbb{E}_N[e^{it^TY}]} \\
\widehat{\partial^2_{lm} \kappa_Y}(t) &= -\frac{\mathbb{E}_N[Y_l Y_m e^{it^TY}]}{\mathbb{E}_N[e^{it^TY}]} + \frac{\mathbb{E}_N[Y_l e^{it^TY}]}{\mathbb{E}_N[e^{it^TY}]}\frac{\mathbb{E}_N[Y_m e^{it^TY}]}{\mathbb{E}_N[e^{it^TY}]}
\end{aligned}$$

With these in hand, system (E.4) can be used to recover κ''_{W_k} and the characteristic functions of each factor (after integrating κ''_{W_k} twice). A practical issue first noted by Diggle and Hall (1993) and present in the deconvolution literature since then is the need to rely on a damping or smoothing function that can deal with the sharp fluctuations in the tails that appear when one uses the empirical analog of φ_{W_k}. We follow Li et al. (2000) and introduce a damping factor defined as:

$$d(\tau) = \begin{cases} 1 - |\tau|/T & \text{if} |\tau| \leq T \\ 0 & \text{otherwise} \end{cases}$$

Function $d(\tau)$ is placed inside the integral in (E.6) to smooth the tails of the density estimator.[40] Thus, the density of each factor is finally obtained from:

$$f_{W_k} = d(\tau)\frac{1}{2\pi}\int e^{-i\tau w}\varphi_{W_k}(\tau)d\tau \tag{E.7}$$

In our implementation, the choice of T was arbitrary. We could have chosen T by some data driven process like in Li et al. (2000)[41] but, in practice, the estimated densities in our particular application were barely affected by changes in T.

E.3 Non-Parametric Density Estimates

Figures 20-22 present the non-parametric estimates of the densities of θ, ϵ_0, and ϵ_1 in the Science, Social Sciences, and Turkish-Math tracks. Each estimated plot is compared to a normal distribution with mean μ_k and variance σ_k^2, where $\mu_k = 0 \quad \forall k$. The variances of each factor can

[40] Many other damping functions can be used but one of the most popular ones in the recent deconvolution literature is a second order kernel function. See Bonhomme and Robin (2010) for more details.

[41] To choose T, they minimize the distance between the actual means and variances of each factor and the ones obtained using the non-parametric density estimate.

be obtained from the moments of the joint density of (Y_0, Y_1):

$$\sigma_\theta^2 = E(Y_{i0}Y_{i1}) \tag{E.8}$$

$$\sigma_{\epsilon_0}^2 = E(Y_{i0}^2) - E(Y_{i0}Y_{i1}) \tag{E.9}$$

$$\sigma_{\epsilon_1}^2 = E(Y_{i1}^2) - E(Y_{i0}Y_{i1}) \tag{E.10}$$

In two cases the variances of the factors are very close to zero so we do not present the results for their estimated densities. These are ϵ_0 in the Social Sciences track and ϵ_1 in the Turkish-Math track.

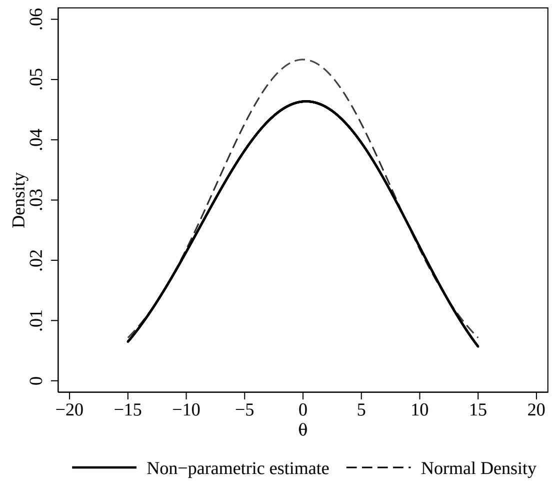
In general, our density estimates look very much like the normal distribution. It seems that our non-parametric estimates of the factors' densities are particularly close to the normal in the Science track. Figure 20 shows that, with the exception of the tails in panels (b) and (c), there is a very good fit of our estimates and the normal distribution. The distribution of θ has greater variance than that of the random shocks, but both ϵ_0 and ϵ_1 still seem to matter in the determination of GPA and exam score.

Figure 21 plots the estimated densities for the unobserved ability and the shock to the exam score in the Social Sciences track. As mentioned before, the shock on the GPA equation does not seem to matter at all in this track. It is clear that the distribution of θ in Social Sciences is close to the normal distribution. However, ϵ_1's density is a little different from the normal. Our estimates show that this shock has two modes that are smoothed over around the mean when the normality assumption is used.

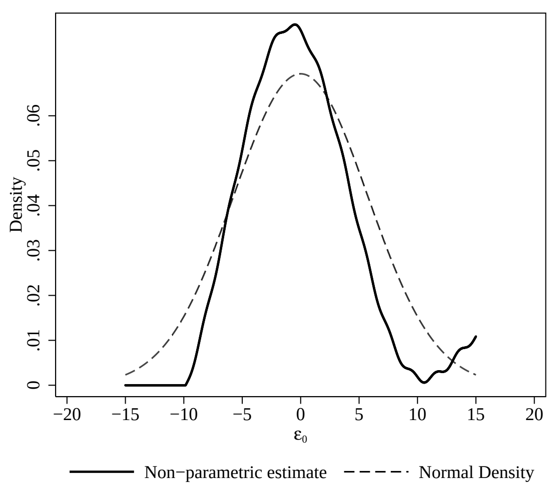
As mentioned before, ϵ_1 seems to matter very little in the determination of the exam scores of Turkish-Math students. However, the estimated densities for the unobserved ability parameter and the shock on GPAs show that they both matter a lot. Moreover, Figure 22 shows that both distributions seem to support the normality assumptions on the shocks, although the estimates for ϵ_0's distribution are less smooth. This, of course, depends on the smoothing function used in E.7.

In sum, our normality assumptions on the shocks seem to be introducing little bias in our estimates. With the exception of the density of ϵ_1 in the Social Sciences track, the distributions of all the other shocks seem to follow closely the normal distribution. In addition, our non-parametric estimates show that the both randomness and unobserved ability affect scores and GPAs differently across tracks.

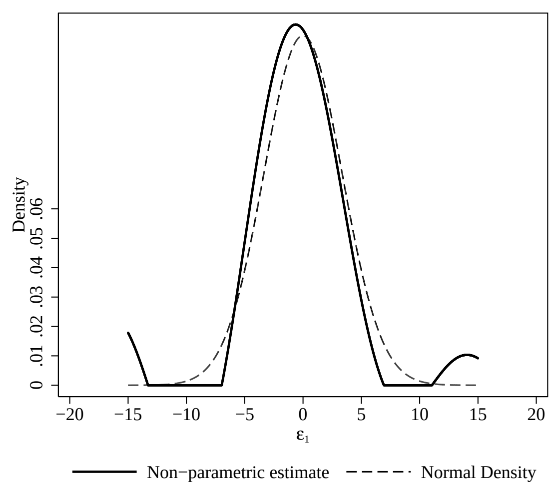
Figure 20: Non-Parametric Density Estimates of θ, ϵ_0, and ϵ_1 in the Science Track



(a) θ



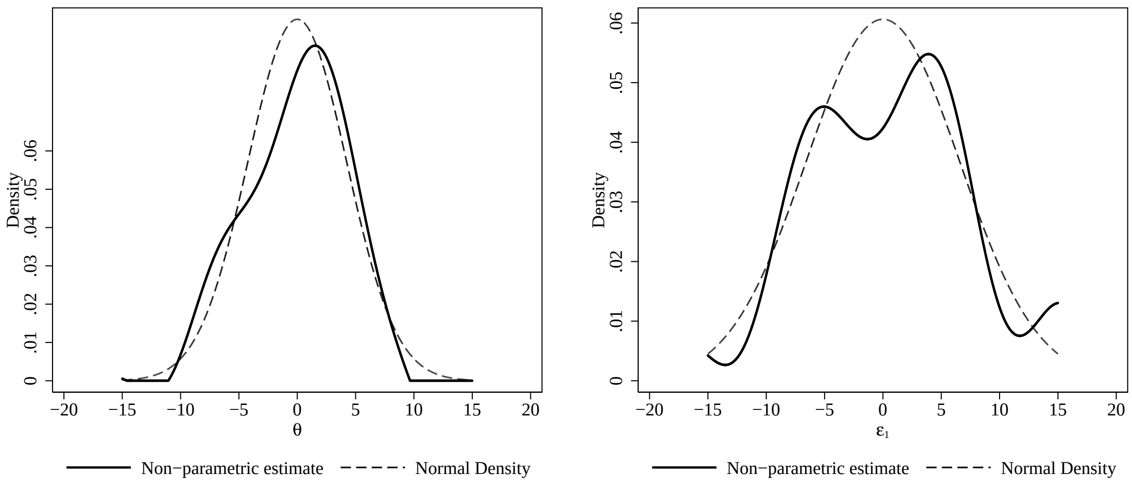
(b) ϵ_0



(c) ϵ_1

Notes: OLS residuals of the GPA and score equations are obtained in the sample of first time takers. Trimming parameter T_N is set at 4. Normal density plotted has mean zero and variance σ_k^2 obtained from (E.8)-(E.10).

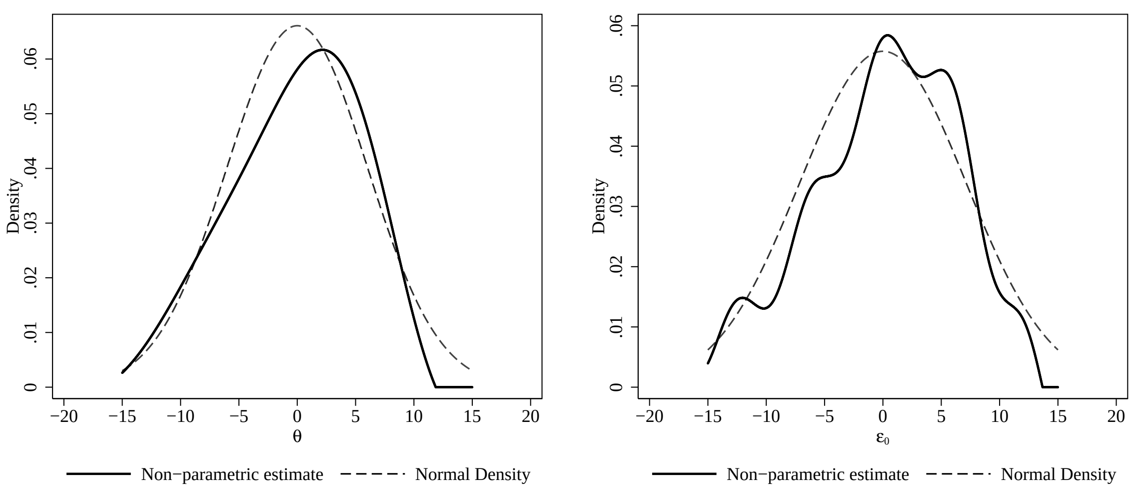
Figure 21: Non-Parametric Density Estimates of θ, ϵ_0, and ϵ_1 in the Social Sciences Track



(a) θ (b) ϵ_1

Notes: OLS residuals of the GPA and score equations are obtained in the sample of first time takers. Trimming parameter T_N is set at 4. Normal density plotted has mean zero and variance σ_k^2 obtained from (E.8)-(E.10).

Figure 22: Non-Parametric Density Estimates of θ, ϵ_0, and ϵ_1 in the Turkish-Math Track



(a) θ (b) ϵ_0

Notes: OLS residuals of the GPA and score equations are obtained in the sample of first time takers. Trimming parameter T_N is set at 4. Normal density plotted has mean zero and variance σ_k^2 obtained from (E.8)-(E.10).