Annenberg Institute
BROWN UNIVERSITY

EdWorkingPaper No. 26-1569

Unpacking the Socioeconomic Status Gap in Exam-Based School Admissions

Andrew Dustan
William & Mary

Diana Ngo
Occidental College

We analyze the large socioeconomic status (SES) gaps in public high school assignments in Mexico City, a centralized choice system with exam-based admissions. Using a rich structural model, decomposition, and simulations, we find that placement score differences explain 83% of the gap in assignment to elite schools, contrasted with preferences (6%) and location (5%). For less-preferred technical schools, preferences explain 64% of the gap, while score differences account for 34%. High-SES students have a substantial advantage on the placement test beyond what is predicted by multiple contemporaneous ability measures, raising concerns about the distributional impacts of exam-based admissions.

VERSION: September 2026

Suggested citation: Dustan, Andrew, and Diana Ngo. (2026). Unpacking the Socioeconomic Status Gap in Exam-Based School Admissions. (EdWorkingPaper: 26-1569). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/qb4d-hv24

Unpacking the Socioeconomic Status Gap in Exam-Based School Admissions

Andrew Dustan *
Department of Economics
William & Mary

Diana Ngo
Department of Economics
Occidental College

August 2026

Abstract

We analyze the large socioeconomic status (SES) gaps in public high school assignments in Mexico City, a centralized choice system with exam-based admissions. Using a rich structural model, decomposition, and simulations, we find that placement score differences explain 83% of the gap in assignment to elite schools, contrasted with preferences (6%) and location (5%). For less-preferred technical schools, preferences explain 64% of the gap, while score differences account for 34%. High-SES students have a substantial advantage on the placement test beyond what is predicted by multiple contemporaneous ability measures, raising concerns about the distributional impacts of exam-based admissions.

Keywords: School choice, inequality, high-stakes exams

*E-mail addresses: addustan@wm.edu, dngo@oxy.edu. We thank Mexico's Secretariat of Public Education for providing the data.

1 Introduction

School choice systems are designed to increase students' access to educational options, often using test-based admissions to ration seats in highly-demanded schools. In practice, highly-demanded schools are disproportionately filled by wealthier students. This is consequential because effective schools improve outcomes, particularly for students with low socioeconomic status (SES) (Jackson et al. 2024; Mbekeani et al. 2026). SES assignment gaps may arise from a combination of heterogeneous preferences, geographical segregation, and achievement gaps. While tests are intended to comparably measure aptitude across students, performance is systematically correlated with SES, and high-SES students often accrue additional advantages in high-stakes testing environments for reasons unrelated to ability. Together, these factors may generate large SES differences in access to quality schools.

To understand the importance of these factors, we examine SES differences in Mexico City high school admissions, a system with centralized school choice and test-based admissions. We focus on two types of schools across the demand spectrum. First, we examine elite schools, which are commonly studied and have been shown to have positive effects on peer quality and long-run outcomes (Gorman and Walker 2021; Beuermann and Jackson 2022).[1] Second, we analyze technical schools, which can benefit vocationally-inclined students (Hemelt, Lenard, and Paeplow 2019; Brunner, Dougherty, and Ross 2023) but may also serve as residual, low-quality options for low-achieving students (Newhouse and Suryadarma 2011; Loyalka et al. 2016).

Using rich administrative data on school choices and assignments, we carefully measure student-level SES using an extensive set of household characteristics to predict consumption. We divide the sample into SES quartiles, focusing our analyses on the gap between high- and low-SES students (wealthiest and poorest quartiles, respectively). We document a large SES gap in placement test scores and use decomposition methods to model high-stakes placement scores as a function of other ability measures. Placement test scores are strongly predicted by middle school GPA and scores from a low-stakes exam taken at a similar time. However, high-SES students have a large, residual advantage on the placement test that is unexplained by these other ability measures. This suggests that high-stakes placement tests may disproportionately disadvantage low-SES

1. There is a large literature showing mixed short-run impacts of selective schools. While some studies show positive effects on academic achievement (Jackson 2010; Berkowitz and Hoekstra 2011; Pop-Eleches and Urquiola 2013; Park et al. 2015), others find no effects on test scores or college quality (Abdulkadiroğlu, Angrist, and Pathak 2014; Dobbie and Fryer Jr 2014; Lucas and Mbiti 2014; Barrow, Sartain, and De La Torre 2020).

students beyond the differences predicted using low-stakes performance measures.

We pair this with a rich structural model of school choice, estimating utilities for different program types by SES, geographic location, academic achievement, and gender. We use the results to formally decompose the SES gap, quantifying the contributions of preferences, placement test scores, and other characteristics. We separate the contribution of placement test scores into the component explained by group differences in other ability measures and the unexplained SES advantage. Finally, we implement counterfactual simulations to further quantify the role of the unexplained SES score advantage. Here, we fully simulate the assignment process, accounting for school capacity constraints, and compute the assignment and welfare effects of removing the residual score advantage.

We find a 1.04 standard deviation difference in mean placement test scores between high- and low-SES students. Of this difference, 34% is unexplained by observable ability measures, constituting a residual high-SES advantage. Overall, the elite school assignment gap is 34 percentage points (p.p.), such that for every five high-SES students assigned to an elite school, only one low-SES student is. The structural demand parameters indicate strong preferences for elite schools across all student types. Marginal utility from elite schools increases modestly with SES. The decomposition analysis shows that preference differences account for only 6% of the assignment gap between the high- and low-SES students. In contrast, placement score differences explain 83% of the gap, with 57% from ability-predicted test score differences and 25% from the unexplained SES test score advantage. These contributions are larger than the roles of location (5%) and other observable characteristics.

The technical school assignment gap is also large; high-SES students are 26.2 p.p. less likely to be assigned to technical schools relative to low-SES students. From the model, technical schools are less preferred than both elite and traditional public schools, and these preferences are more intense for high-SES students. Preferences play a larger role in generating the technical program assignment gap, accounting for 64% of the gap compared to 34% from placement scores (23% explained and 10% unexplained) and -1% from location.

Removing the unexplained score advantage in counterfactual simulations of the assignment process, the SES gap in elite assignment decreases by 7.5 p.p. (22.2%), the gap in technical assignment closes by 3.9 p.p. (15.1%), and the impacts on aggregate commuting distance-denominated welfare are negligible (-0.03 kilometers). We find similar but slightly smaller effects when simulating a simple affirmative action policy that gives additional exam points based on SES quartile.[2]

2. We repeat our analyses with the middle SES quartiles and using alternate measures of SES, including

Together, our results suggest that high-stakes testing has an outsized contribution to the elite school SES gap, beyond what would be expected using other measures of ability. This raises concerns about equitable access to highly-demanded schools and emphasizes the need to consider the distributive implications of exam-based assignment. Preferences account for the majority of the technical school gap, suggesting that technical schools can be helpful in expanding the choice set for low-SES students. At the same time, placement scores account for a third of the technical gap, indicating that continued effort is needed to ensure that low-SES students have access to both technical and traditional academic programs.

In decomposing the contributions of various factors in a rich, unified framework, we consolidate a large literature on the SES gap in education. Existing research consistently shows that disadvantaged students are much less likely to attend high-quality schools, highlighting several important factors. First, families have different preferences, with poorer families often placing stronger priority on attending closer schools (Agarwal and Somaini 2020; Ajayi 2024). Differences in peer networks (Mark, Corcoran, and Jennings 2023) and self-confidence (Hakimov, Schmacker, and Terrier 2023) may also drive differences in how students rank schools. Second, the geographical distribution of schools is unequal, with elite schools located primarily in high-income areas (Burgess et al. 2015; Dustan and Ngo 2018) while technical schools are more dispersed. Finally, students have differential access to schools, as districts set priorities that often result in lower admissions rates for low-SES students (Chetty, Deming, and Friedman 2026). Our results for elite schools show that preference and location differences play relatively small roles, while test-based priorities overwhelmingly contribute to SES gaps in admissions. Preference differences play a larger role in the technical school gap, but test score differences also matter.

We also add to a growing literature on the importance of stakes in a unique dataset with contemporaneous high- and low-stakes test scores for the same individual. Complementing high-quality laboratory studies, we examine a real-world setting where students can adjust both their test-day effort and advanced preparation. Existing studies show that students exert less effort on low-stakes exams, concluding that high-stakes exams are better measures of ability (Schlosser, Neeman, and Attali 2019; Akyol, Krishna, and Wang 2021). Relatedly, Reyes, Riehl, and Xu (2024) study Brazil and show that high-stakes test scores are more informative about later-life outcomes than low-stakes test scores. In contrast, other studies argue that competitive processes can be less effective

self-reported income and parental education. We find similar patterns overall, but the size of the gap differs by group and measure.

in screening for ability (Liu and Neilson 2011; Fang and Noe 2022; Lee and Suen 2023). Similarly, Friedman-Sokuler and Justman (2025) find little empirical relationship between high-stakes test scores and labor market outcomes in Israel, and Arenas and Calsamiglia (2025) show that increasing admission weights on high-stakes test scores causes females to be displaced by males with worse college performance.

Our results emphasize the need for research on the determinants of SES test score gaps, which are large and consistent across contexts (Reardon 2018). Many studies highlight factors unrelated to students' underlying aptitude. High-SES students are more likely to utilize test preparation services (Dang 2007; Buchmann, Condron, and Roscigno 2010; Zhang 2013; Jayachandran 2014), exacerbating the SES gap.[3] Participation is high throughout Latin America (Bray and Ventura 2024). We document, in a cohort of placement test takers subsequent to our analysis period, that students with a college-educated parent are more than three times as likely to participate in a private test preparation course than those whose parents did not complete middle school. Test preparation is expensive (Posso, Saravia, and Uribe 2023). In Mexico City, private courses typically cost between one and three times the monthly per capita urban poverty line (Procuraduría Federal del Consumidor 2022).

Factors beyond test preparation generate SES gaps in high-stakes test scores. Psychological factors like testing anxiety and willingness-to-compete may also play a role (Almås et al. 2016; Heissel et al. 2021). Mani et al. (2013) and Duquennois (2022) argue that poverty itself captures attention and causes distraction, resulting in lower performance on cognitive tasks. Physical factors like hunger have been shown to causally affect test scores (Bond et al. 2022) and disproportionately impact low-SES students. Other contributing factors include environmental concerns like pollution (Ebenstein, Lavy, and Roth 2016; Carneiro, Cole, and Strobl 2021), high temperatures (Park 2022; Garg, Jagnani, and Taraz 2020), distance to testing sites (Hong, Lei, and Li 2025), and exposure to violent crime (Michaelsen and Salardi 2020; Chang and Padilla-Romo 2023). Together, these studies highlight concerns with the equity of high-stakes testing but also offer some implementable solutions.

The rest of the paper proceeds as follows. Section 2 presents context around the school choice system in Mexico City. Section 3 describes the data and preliminary evidence on the SES gap and its correlates. Section 4 describes the methods and results from decomposing the score gradient. Section 5 describes the school assignment decomposition, including the theoretical model, estimation strategy, counterfactual simulations, and re-

3. Posso, Saravia, and Uribe (2023) show that providing a test preparation program to low-SES students in Colombia causally decreases the SES gap by 23%.

sults. Section 6 concludes.

2 Context

Between 1996 and 2024, Mexico City used a centralized school choice system for almost all public high schools in the metropolitan area. It was administered by the Comisión Metropolitana de Instituciones Públicas de Educación Media Superior (COMIPEMS) and processed more than 250,000 applicants per year. The choice process was mandatory for all students interested in attending public schools, and there was full compliance with the mechanism such that students could not attend public schools outside of their assignment. The vast majority of applicants were in their final year (ninth grade) at a Mexico City middle school, though applicants also included some students from outside the Mexico City area, recent graduates, or adults returning to school. Students applied to high schools by submitting a rank-ordered list of up to 20 high school programs, choosing from over 600 options spread throughout the city. Students then took a comprehensive placement test covering content on verbal reasoning, Spanish, history, geography, philosophy/civilization/ethics, quantitative reasoning, math, physics, chemistry, and biology. The placement exam had 128 questions in total, each worth one point, with no penalty for incorrect answers.[4]

Students frequently used private services to prepare for the placement test. The context questionnaire for the 2014 assignment cycle asked students about their participation in test preparation courses and tutoring. While 2014 is six years after the cycles used in this study, the patterns shown in Appendix Table A.1 are informative. Among applicants with at least one college-educated parent, 63.1% reported participating in a test preparation course with a private institution or a private teacher or tutor. Students whose parents did not complete middle school only report an 18.6% participation rate. The between-group difference of 44.5 percentage points is large: the high-education group is more than three times as likely to engage in private test preparation than the low-education group.[5]

Based solely on their test performance and ranked choices, students were accepted into schools under a serial dictatorship mechanism, a special case of the student-proposing

4. Due to historical and political reasons, there was an alternate version of the test for students who ranked a program affiliated with the Universidad Nacional Autónoma de México (UNAM) as their first choice. The two versions of the test were written in collaboration and were perceived to be substantively equivalent.

5. We use parental education as the SES proxy because the 2014 questionnaire does not have sufficient data to reconstruct the SES measures used in the rest of the analysis.

deferred acceptance (SPDA) mechanism that theoretically incentivizes students to truthfully reveal their preferences (Gale and Shapley 1962). A computer sorted students according to their placement test scores and processed each student in turn, beginning with the highest performing student. Each student was assigned to her most-preferred program that had a remaining seat.[6] Approximately 15% of students were not assigned by the algorithm because their placement scores fell below the cutoff scores for all their ranked schools. They could choose among schools with remaining seats in a subsequent assignment round after the main process had finished or could opt out of the public school system entirely. Together, the process generated a cutoff score for each school that filled its capacity, where the cutoff was the score of the final admitted student.

The available high school programs ranged in curriculum and competitiveness, and we classify them into three broad categories. First, there was a small set of elite schools (30 programs), which were affiliated with two different national universities. One group of schools was associated with the Universidad Nacional Autónoma de México (UNAM), a general-interest, prestigious university. The other elite schools were associated with the Instituto Politécnico Nacional and focused on science and engineering. Both sets of elite programs were regularly discussed in the media (Gonzalez 2003) and were highly demanded by students across the metropolitan area. Similar to the broader literature on selective schools, the causal impacts of Mexico City's elite schools are mixed. Dustan, de Janvry, and Sadoulet (2017) find that IPN schools improve math test scores but also increase the likelihood of dropout for students on the margin. In the short- and medium-run, marginal admission to these schools has neutral or negative labor market impacts (Cabrera-Hernández et al. 2026). At the same time, elite high school admission had salient benefits to applicants, as students who attended UNAM-affiliated high schools were offered automatic admission to the university, conditional on meeting certain requirements.[7]

Second, a set of technical schools provided specialized training in job-related skills and were primarily run by the Colegio Nacional de Educación Profesional Técnica (CONALEP) and Dirección General de Educación Tecnológica Industrial (DGETI). These were spread throughout the city, were less highly demanded, and were commonly filled by lower-achieving students. Students applied to specific programs of study within these schools. One study shows that students from these Mexico City technical schools took longer to find jobs but eventually earned higher wages and were more likely to work in jobs

6. When multiple students tied for the final seat(s) in a program, administrators from the corresponding school system decided in real-time whether to admit all, exceeding their seat quota, or to deny them all, leaving the final seats unfilled.

7. There was no such guarantee for IPN high schools.

aligned with their training (Lopez-Acevedo 2003). This is consistent with recent quasi-experimental studies in developing countries that show mixed results from vocational education (Dai and Martins 2020; Kemper and Renold 2024).

The remaining schools were traditional public schools. These covered a broad high school curriculum and tended to be filled by students in the surrounding neighborhoods. During the choice process, students had access to detailed information about all school options in printed materials and a well-attended information fair. Prior year cutoff scores were publicly available on a centralized website and remained relatively stable over time, allowing students to gauge program competitiveness before submitting their rankings.

Appendix Table A.2 presents school characteristics by type, showing meaningful differences in demand, resources, and student experience. Elite schools were more highly demanded, with an average cutoff of 83 compared to 50 for traditional public schools. In comparison, technical schools were less highly demanded, with an average cutoff of 42. Elite schools were much larger, serving over 5,000 students compared to approximately 1,400 students in technical and traditional schools. At the same time, elite schools had the lowest student-to-teacher ratios. Elite schools also had the highest graduation and lowest failure rates. In contrast, technical schools had the lowest graduation rates and similar failure rates compared to traditional schools. Finally, elite schools were slightly less female, due primarily to lower female enrollment at the IPN science-focused elite schools.

During the spring of ninth grade, students also completed a low-stakes standardized exam, Evaluación Nacional del Logro Académico en Centros Escolares de Educación Media Superior (ENLACE). The ENLACE was a national standardized test implemented by the Secretariat of Public Education from 2006 through 2014 to monitor learning outcomes and increase transparency and accountability. The ninth grade exam, ENLACE 9, was taken after students submitted their choice lists, but two months before they took the placement test. Students did not know their ENLACE 9 scores at the time of the placement test, and the ENLACE 9 had no bearing on middle school graduation or other student outcomes. It consisted of math and Spanish subsections, with other subjects rotating annually.

Despite being a low-stakes exam, De Hoyos, Estrada, and Vargas (2021) show that ENLACE scores are effective in measuring skills. Specifically, using a twin fixed effects specification, they find that students with higher sixth grade ENLACE scores were more likely to graduate on time from middle school and high school. Furthermore, twelfth grade ENLACE scores predicted university enrollment and higher wages. Similarly, studies show that middle school GPA is also a meaningful measure in this context; students with higher GPAs are more likely to graduate high school (Dustan, de Janvry, and Sadoulet 2017; Ortega-Hesles and Pariguana 2025).

3 Data

We use administrative data from the COMIPEMS system that covers all students applying to Mexico City public high schools. Since participation is mandatory for enrollment, the data represent the universe of students who eventually attend a public high school. The data include students' full ranked list of preferred programs (up to 20), their scores on the placement test, whether or not they were assigned through the algorithm and their assigned program, if assigned.[8] The administrative data also include information on where students attend middle school and their middle school GPAs, which we normalize within each year. Additionally, students complete a short survey at the time of application, answering questions about basic demographics, family composition, durable goods ownership, housing characteristics, self-reported income, and residential location. We use students' postal code centroids as their residential locations. A small subset of students is missing valid postal codes; we place these students in their middle school postal codes when possible. We exclude students who are missing a valid location (both home and middle school). We also exclude students who graduated middle school in a previous cycle, students who are outside the COMIPEMS zone, and students who are unassignable because they did not complete middle school or did not take the exam.

Separately, we have data on the low-stakes ENLACE 9 exam taken two months prior to the placement test. We match these ENLACE scores to each student in the COMIPEMS system, restricting our analysis to 2007 and 2008, the years for which we are able to match the ENLACE 9 and COMIPEMS datasets. We successfully match 95.5% of ninth grade COMIPEMS applicants to their ENLACE 9 scores. We retain the unmatched students and account for missingness in the analysis.

We construct a measure of student-level SES using the rich survey data on demographics, assets, and self-reported income. Asset ownership, housing characteristics, and demographics are commonly used to proxy for SES in studies where detailed consumption data are lacking (Ngo and Christiaensen 2019), and these proxies produce comparable findings about inequalities in education, health, and labor markets (Filmer and Scott 2012). Similar information is used by the Mexican government's National Population

8. We do not have information on choices made after the assignment algorithm for students who were not initially placed, but Ngo and Dustan (2024) show that assignment gaps are substantively similar when accounting for this final round of assignment.

Council (Consejo Nacional de Población, or CONAPO) to generate a marginalization index (índice de marginación), which is used to monitor socioeconomic disadvantage.

We use the student survey data to generate a measure of predicted household consumption, our preferred measure of SES. Specifically, we use an external survey, the Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH), which has detailed consumption data and a validated consumption aggregate to model the relationship between household consumption and its proxies. We then use the estimates to construct a measure of predicted household consumption in the COMIPEMS data. We use ENIGH data from 2008 and 2010, restricting the sample to municipalities participating in COMIPEMS (INEGI 2008; 2010). We linearly regress the natural log of annual household consumption per capita on asset ownership, parental age categories, parental education categories, family size categories, and household income categories. We allow the relationship to differ between the Federal District and the State of Mexico and include municipality fixed effects. These predictors capture much of the variation in household consumption (r-squared = 0.85), indicating that they can be meaningfully used to measure student SES in the COMIPEMS data. We use our predicted consumption measure to divide students into SES quartiles, with quartile 1 (Q1) and quartile 4 (Q4) indicating the lowest and highest SES, respectively. Appendix Table A.3 presents summary statistics of the underlying SES components for each quartile, showing large gradients across quartiles for all measures with the exception of parental age.

Nine percent of the analytical sample is missing data from the student survey. An additional 18% of students have survey data but are missing one or more items used for measuring SES.[9] To generate SES classifications for these students, we use multiple imputations with chained regressions (MICE) to impute asset ownership, parental age and education, family size, and income. We impute based on student-level information from the COMIPEMS application process. This is available for all students and includes data on placement test score, middle school GPA, gender, distance to closest elite school, total number of choices, fraction of choices that are elite, fraction of choices that are technical, and average distance to chosen schools. We also include postal code average survey responses as predictors (asset ownership, per capita income, parental age and education, and family size). We use 30 imputations, predict consumption for each imputation and use the average predicted consumption to draw the SES quartiles.[10]

Figure 1 shows the geographical distribution of SES across Mexico City, with similar

9. Eight percent are only missing information on father's age or education.

10. In the analyses where we use an asset index as an alternative measure of SES, we run principal component analysis on each imputed dataset and then take the average value over all imputations.

patterns using our preferred student-level predicted consumption measure (top panel) and the neighborhood-level marginalization index constructed by the Mexican government (bottom panel). Higher-SES students are generally more likely to reside close to the city center. At the same time, 40.5% of Q4 students reside in the State of Mexico, and there are several areas in the city center and northern suburbs where the SES distribution is quite mixed. Moreover, household SES varies further within neighborhoods. Overall, this corresponds with Monkkonen, Giottonini, Comandon, et al. (2021), who show that segregation in Mexico City is lower than commonly perceived.

We also use geographical data from Ngo and Dustan (2024) that provide the location of each school program and the driving distances between each postal code-school pair. Figure 2 presents a map of Mexico City and the placement of elite schools. The majority of elite schools are located in the center of the city, in close proximity to the high-SES neighborhoods.

While the COMIPEMS administrative data represent the universe of students who apply to and attend public high schools, students will not appear in the sample if they plan to drop out after middle school or only apply to private schools. We therefore examine selection into the COMIPEMS sample in Appendix Table A.4 to understand the extent to which the SES gap is affected by disproportionate participation in the choice process. As a base, we use the sample of all ENLACE 9 takers (all ninth grade public school students and some private school students) residing within the COMIPEMS geographical boundary. Eighty percent of these students appear in the COMIPEMS sample, with high-SES students participating at slightly lower rates. Among high-SES students,[11] students who participate in COMIPEMS are negatively selected with respect to their performance on the ENLACE 9 exam, with non-participation likely due to exit to the private sector. On the other hand, among low-SES students, students who participate in COMIPEMS are positively selected, with non-participation likely due to dropout. Together, these patterns indicate that selective participation mitigates the observed COMIPEMS SES gap in enrollment, suggesting that the SES gap would be even larger in a system of full participation.

Table 1 presents summary statistics on academic achievement and demographics by student SES. There are large SES gradients in academic achievement according to the COMIPEMS placement test score, the low-stakes ENLACE 9 math and Spanish subscores, and middle school GPA. High-SES students (Q4) score 20.5 points higher on the placement test relative to low-SES students (Q1), and this difference exceeds one standard

11. We have less detailed information on students in this ENLACE sample, so we proxy for SES here by using the government-constructed marginalization index, assigning each student the marginalization index associated with her middle school location and grouping students into evenly-sized SES quartiles.

deviation. Similarly, high-SES students score about three fourths of a standard deviation higher than low-SES students on each of the ENLACE subtests. The gradients move in consistent directions across the middle SES quartiles, and the gaps tend to get larger at higher quartiles. Panels A through D of Figure 3 show the corresponding academic achievement distributions by SES quartile. The figure clearly demonstrates that the mean differences in scores are not due to a small set of outliers. Similar patterns exist for the low-stakes ENLACE 9 math and Spanish subscores as well as middle school GPA, though the differences for GPA are less stark.

Table 1 and Figure 3 also present differences in access and choices by SES. With respect to access, high-SES students live 3 kilometers closer to an elite school compared to low-SES students. This is driven by a large set of high-SES students who live within 5 kilometers of elite schools (Panel E). High-SES students list schools that are slightly farther away on average. However, the differences are small (Panel F), suggesting that willingness-to-travel may not explain a large fraction of the SES assignment gaps. Finally, students across the SES spectrum submit a similar total number of choices, but high-SES students submit a larger number of elite schools and fewer technical and traditional schools.

Table 2 presents the summary statistics for the resulting school assignments. There is a substantial SES gradient in assignment, and the elite SES gap is very large. High-SES students are 5 times more likely to be assigned to elite schools than low-SES students, a difference of 33.8 p.p. over a low-SES assignment rate of 8.5 percent. Conversely, high-SES students are less than half as likely as low-SES students to be assigned to technical schools (18.6% versus 44.8%, respectively). The other differences are more modest. High-SES students are 5.4 p.p. less likely to be assigned to traditional schools. High-SES students are also 2.2 p.p. less likely to go unassigned. Finally, high-SES students are assigned to schools that are 10.5 kilometers away on average, 1.1 kilometers farther than low SES students. Again, the gradients generally move in consistent directions across the middle SES quartiles, with the largest incremental gaps between Q3 and Q4 students.

4 Decomposing the SES test score gradient

4.1 Methods

We use two methods to decompose the SES group differences in placement test score distributions. These decompositions quantify the extent to which differences between high- and lower-SES students' scores are due to group-level differences in observable characteristics, including contemporaneous low-stakes test scores and middle school GPA, and how much they are due to SES advantages that persist after conditioning on these measures of ability. We first decompose group differences in mean placement test scores and subject-specific subtest scores following the semi-parametric reweighting procedure described in DiNardo, Fortin, and Lemieux (1996). Online Appendix B provides more detail.

We then use a distribution regression approach to decompose group differences along the placement test score distribution (Chernozhukov, Fernández-Val, and Melly 2013). This allows us to examine whether the unexplained benefits of SES for placement test scores are concentrated in certain parts of the score distribution, which is important for understanding the role of SES in determining access to elite schools due to their high cutoff scores. While the DiNardo-Fortin-Lemieux decomposition generates an *unconditional* counterfactual test score distribution, the distribution regression approach traces out the full counterfactual *conditional* density function of scores for the lower-SES group. Estimating score distributions conditional on student characteristics allows us to construct student-specific counterfactuals that preserve a student's position in the conditional distribution. This will be valuable for the school assignment decomposition and simulations later in the paper.

The cumulative distribution function of placement test scores S for SES group $W \in \{H, L\}$ is $F_{S|W}$, where H and L represent high and low, respectively. Students have a vector C of observable characteristics that may be correlated with test scores and SES group. The difference between SES group-specific unconditional distributions can be decomposed into a component explained by group differences in the distribution of C and an unexplained component:

$$F_{S|H} - F_{S|L} = \underbrace{F_{S|H} - F_{S|H,C\sim L}}_{\text{Explained component}} + \underbrace{F_{S|H,C\sim L} - F_{S|L}}_{\text{Unexplained component}}, \tag{1}$$

where $F_{S|H,C\sim L}$ is the counterfactual distribution of scores in which the relationship between student characteristics and scores follows that of group H but those characteristics are distributed as in group L. The explained component imposes the relationship between observables and scores in the H group and compares score distributions under W- and L-specific characteristic distributions. The unexplained component imposes the L-specific distribution of characteristics and compares score distributions under the group-specific relationships between characteristics and scores.

Estimating each component of this decomposition requires a model for the conditional placement score distributions. Following Chernozhukov, Fernández-Val, and Melly (2013), we assume:

$$F_{S|W}(s \mid C) = \Lambda(C'\beta_W(s)), \forall s \in \mathcal{S}, \tag{2}$$

where $\mathcal{S}$ is the set of all discrete values taken by the placement test and Λ is the logistic CDF.[12] The $\beta_W(s)$ parameters are estimated with a series of logit regressions, separately by group. The estimated parameters and logistic functional form allow us to estimate the relevant CDFs for the decomposition.[13] We estimate $F_{S|W}$ by computing $\widehat{F}_{S|W}(s \mid C_i)$ for each student i in group W and integrating over students: $\widehat{F}_{S|W} = \frac{1}{N_W}\sum_i \widehat{F}_{S|W}(s \mid C_i)$. We estimate the counterfactual distribution $F_{S|H,C\sim L}$ by using the high-SES parameters to compute, for low-SES students, $\widehat{F}_{S|H}(s \mid C_i)$, and then integrating over students. The characteristics vector C consists of cubic polynomials in low-stakes language and math subscores, a dummy variable for missing low-stakes score, middle school GPA, interactions between subscores and GPA, year-by-municipality of residence fixed effects, gender, and interactions of gender with each of these measures.

With these estimated CDFs constructed, it is straightforward to estimate and decompose group differences at quantiles of the unconditional score distribution. For quantile τ, we compute the quantile function $\widehat{Q}_{S|W}(\tau) = \inf\{s : \widehat{F}_{S|W}(s) \geq \tau\}$ for each group, and similarly compute the counterfactual quantile function $\widehat{Q}_{S|H,C\sim L}(\tau) = \inf\{s : \widehat{F}_{S|H,C\sim L}(s) \geq \tau\}$. Quantile-level differences can then be decomposed as in Equation 1.[14]

4.2 Results

We begin with the DiNardo-Fortin-Lemieux decomposition of SES differences in mean placement test scores. Table 3 shows the results of the mean decomposition, for the overall score and each subject-specific test score. Scores are standardized within the estimation sample to facilitate between-subject comparisons. Overall, Q4 students outperform Q1 students on the placement test by 1.04 standard deviations (SD). Of this difference, 65.8% is explained by differences in observable characteristics including low-stakes ENLACE 9 scores, middle school GPA, residential differences, and gender. The remaining 34.2% of the difference is unexplained, representing a large high-SES residual advantage on the placement test. The results for the subject-specific subtests are similar. While the average subscore differences are smaller, ranging from 0.68 to 0.90 SD, the unexplained

12. Distribution regression directly models $P(S \leq s|C)$ at each point of support, accommodating the discreteness of the test score distribution more straightforwardly than quantile regression approaches.

13. We apply monotonization to individual-level predicted probabilities to ensure valid CDFs, following Chernozhukov, Fernández-Val, and Melly (2013) and Chernozhukov, Fernández-Val, and Galichon (2010).

14. By integrating the estimated quantile functions over $\tau \in [0, 1]$, we can recover mean differences and their decomposition, serving as a consistency check against the reweighting-based mean decomposition.

portion contributes similar amounts to each subscore, accounting for 24.7% to 38.8% of the subscore gaps. The unexplained portions are the lowest for the math and quantitative reasoning subtests, suggesting that mathematical skills may translate more easily between testing scenarios or that differences in effort or studying matter more for other subjects.

Using the subset of students with complete context questionnaires, Appendix Table A.5 repeats the decomposition with additional information on student behaviors. This includes weekly time spent doing homework, time spent reading, subjective measures of self-efficacy, parental investment, and teacher behaviors. Including this rich set of measures into the observables leaves the unexplained portion of the gap almost fully intact.

Comparing quartiles Q2 to Q4 and Q3 to Q4, the total score gaps decrease but remain sizable at 0.73 and 0.42 SD, respectively. The unexplained portions are similar for these comparisons, accounting for 34.9% and 31.9% when comparing Q2 to Q4 and Q3 to Q4, respectively. This indicates that the high-SES residual advantage continues to exist relative to moderate-SES students. Again, the unexplained portions of the subscores are lower for the mathematics and quantitative reasoning subtests but generally similar in magnitude for the other topics.

Repeating this decomposition exercise using alternative measures of SES gives similar qualitative results. Appendix Tables A.6, A.7, and A.8 present the results using per capita household income quartiles, household asset index quartiles, and parental educational attainment levels as the indicators of SES. While the size of the total score gap between high and low groups varies by indicator, the unexplained portion is similar to that of our preferred SES measure. Patterns in the size and proportion unexplained by subtest are also consistent with our preferred measure.[15]

Figure 4 displays the standardized test score differences between SES groups by quantile, for the overall score, the explained component, and the unexplained component. Comparing Q1 to Q4 in Panel A, the lowest-performing high-SES students outperform the lowest-performing low-SES students by approximate half a standard deviation. This difference increases to 1.2 SD at the median. The overall gap decreases slightly at the highest quantiles to approximately 1 SD. The unexplained differences remain relatively consistent throughout the quantile distribution, accounting for a difference of 0.2 to 0.4 SD in test scores. We see similar patterns for the Q2 to Q4 and Q3 to Q4 comparison, with smaller differences for the observed score, explained component, and unexplained component.[16]

15. Appendix Table A.9 repeats the placement test score mean decomposition separately by gender. The magnitudes of the test score gaps and the unexplained proportions are similar across genders.

16. Appendix Table A.10 shows that using distribution regression to estimate mean differences by quar-

Together, the mean and distributional score decompositions indicate that the rich/poor test score gap is very large and remains significant even when comparing middle SES students to the wealthiest quartile. Much of this gap is unexplained by contemporaneous measures of ability and other observable characteristics, suggesting that high-SES students have a notable residual advantage on the placement exam. Given the size of the overall score gap, this residual advantage is likely to be a consequential factor contributing to assignment gaps.

5 Decomposing SES differences in assignments

5.1 Methods

This section describes the specification and estimation of student preferences, the method for decomposing SES gaps in assignment, and the counterfactual simulation exercise.

5.1.1 Student preferences

Student i has preferences over programs $j \in \{1, ..., J\}$ that depend on the interaction between program and individual characteristics. Covariate cells $c(X_i, W_i)$ partition students based on the interaction of gender and an indicator for above-median middle school GPA (X_i) and indicators for predicted consumption quartile (W_i). This results in 16 cells. The utility from assignment to program j for student i in covariate cell $c(X_i, W_i)$ and scalar-valued low-stakes test score A_i (the standardized mean of standardized math and Spanish ENLACE 9 subsection scores) is:

$$\begin{aligned} U_{ij} &= V_{ij} + \varepsilon_{ij} \equiv \widetilde{V}_{ij} + v^d_{ij} + \varepsilon_{ij}, \\ \widetilde{V}_{ij} &= \underbrace{\delta_j + \boldsymbol{T}_j \boldsymbol{\beta}^{\text{type}}_{c(X_i,W_i)} + (\boldsymbol{T}_j \times A_i)\boldsymbol{\gamma}^{\text{type}}_{c(X_i,W_i)}}_{\text{systematic utility excluding distance}}, \\ v^d_{ij} &= \underbrace{\beta^d_{c(X_i,W_i)} d_{ij} + \gamma^d_{c(X_i,W_i)}(d_{ij} \times A_i)}_{\text{distance utility component}}, \end{aligned} \tag{3}$$

where δ_j are program fixed effects, $\boldsymbol{T}_j$ is a vector of indicators for program type, d_{ij} is commuting distance, and ε_{ij} represents i.i.d. unobserved idiosyncratic tastes. The program

tile gives results very similar to the mean decomposition, identifying a 1.04 SD overall placement score advantage for Q4 students with respect to Q1 students that corresponds to a 20.6 point difference in raw scores. Again, about a third of the gap (32.8%) is unexplained by observable characteristics.

fixed effects allow for programs to offer different average utilities, while the $\beta_{c(X_i,W_i)}$ coefficients reflect differences in preferences for different program types and commuting with respect to observable student characteristics. The $\gamma_{c(X_i,W_i)}$ coefficients further allow these preferences to vary linearly with respect to low-stakes scores and for this relationship to depend on the covariate cell $c(X_i, W_i)$. For example, the relationship between low-stakes scores and elite program preferences may differ between low-SES, low-GPA females and high-SES, high-GPA males. The outside option is to remain unassigned by the assignment algorithm, a detail to which we return below.[17]

Equation 3 is estimated using the student-level microdata. We follow the approach in Fack, Grenet, and He (2019), assuming that the matching generated by the assignment algorithm is *stable*. That is, we assume that students choose programs such that each student is assigned to the program that maximizes her utility among all programs that were *ex post* feasible given her placement test score. This student-specific feasible set is denoted $\mathcal{J}_i = \left\{ j : s_i \geq \underline{s}_j \right\}$, where $\underline{s}_j$ is program j's cutoff score. Stability is a weaker assumption than a truth-telling approach that assumes students' rank-order preference lists are ordered by utility and that all listed programs are preferred to all non-listed programs. The benefit of assuming stability is that it does not introduce bias from, for example, students who know they will have low placement scores leaving elite schools off their rank-order lists because they know admission there will be impossible. The cost of this assumption is that it precludes using all information from the rank-order list for estimating preferences, increasing the variance of the parameter estimates.[18]

Estimating Equation 3 under the stability assumption requires limiting each student's "effective choice set" to $\mathcal{J}_i$ (Fack, Grenet, and He 2019). Then, assuming an extreme value type I distribution for the ε_{ij} terms, we estimate a conditional logit using these student-specific effective choice sets, where the "chosen" program is the one to which the student was assigned. This implies that students left unassigned by the mechanism have chosen this outcome, which is reasonable if students prefer the option of private school, exiting the education system entirely, or retaking the following year rather than being assigned to their ex post feasible programs. The relative utility of this outside option is allowed to vary with student characteristics, consistent with literature suggesting that higher-SES students may have more valuable outside options (Akbarpour et al. 2022). We divide the sample into three regions, the Federal District, east state of Mexico, and west

17. Missing low-stakes scores are set to zero, and an indicator for missing scores is interacted with all program type and distance terms.

18. In our case, the reduction in information from the stability assumption would result in many covariate cell-specific program fixed effects being unidentified, given the variation in assignment outcomes in the data.

state of Mexico (Figure 2) to allow for varying preferences among students with differing geographical access.[19] Maximum likelihood estimation of preference parameters is performed separately by region-year.

5.1.2 Summarizing student preferences

The preferences for each SES quartile can be summarized using the average marginal willingness to travel (WTT) and the gradients in WTT with respect to low-stakes test scores. Following Equation 3, marginal utility from distance for student i is $\alpha_i \equiv \beta^d_{c(X_i,W_i)} + \gamma^d_{c(X_i,W_i)} A_i$. Scaling $\widetilde{V}_{ij}$ by $-\alpha_i$ gives the marginal WTT for program j (compared to remaining unassigned):

$$WTT_{ij} = -\frac{1}{\alpha_i}\widetilde{V}_{ij}, \tag{4}$$

which can be estimated for each student-program pair using the preference parameter estimates. The average marginal WTT for all programs of type k across all individuals in group W is thus:

$$WTT_{k,W} = \int WTT_{ij}\, dF_{j|i,T_{j,k}=1}\, dF_{i|W}, \tag{5}$$

which can be estimated using the group-specific sample averages of the estimated student-program WTTs. These averages can then be compared across program types and student groups. Differences in average marginal WTT for a program type between groups are due to differences in preferences parameters and the distribution of observable student characteristics in each group. Standard errors are computed using a parametric bootstrap to account for correlation in estimated WTTs within and between individuals.

The group-specific average WTT gradient in preferences for school type k with respect to low-stakes test scores is the average of individual gradients:

$$\frac{\partial WTT_{k,W}}{\partial A} = -\int \frac{\partial WTT_{ij}}{\partial A_i} dF_{j|i,T_j=k}\, dF_{i|W}, \tag{6}$$

which can be estimated with the sample average of estimated individual gradients.[20] These estimates can then be compared across groups to understand whether, for example, tastes for elite schools are more heterogeneous with respect to low-stakes scores for

19. Because there are many programs, and distant non-elite programs are very rarely chosen, we combine non-elite programs outside the student's region into two aggregated options: traditional and technical. We follow Parsons and Needelman (1992) and Lupi and Feather (1998) to perform this aggregation and account for it appropriately in the likelihood function.

20. The individual-level derivative is the same for all programs j of school type k, so it can be evaluated over individuals, rather than over all individual-program pairs.

high-SES students than for low-SES students.[21]

5.1.3 Assignment gap decomposition

To decompose the between-group differences in program assignments into preference, placement test score (explained and unexplained), distance, and other components, we extend the procedure in Ngo and Dustan (2024). This approach modifies the nonlinear decomposition in Fairlie (1999, 2005, 2017) to aggregate assignment probabilities across programs and to separately incorporate the explained and unexplained components of placement test scores.

The decomposition is applied separately by program type T (elite, technical, traditional, or unassigned) and student group W. Quartile 4 is always the base group, denoted $W = H$, and is compared separately to quartiles 1 through 3, for which $W = L$. The difference in the probability of assignment to school type k between the H and L groups is $P(T = k|H) - P(T = k|L)$. This difference is decomposable into a component reflecting between-group differences in student characteristics and a component reflecting between-group differences in student preferences. Each student i represents a random draw from a population with group-specific joint distributions $F_{\tilde{X}|W}$ of characteristics $\tilde{X}_i = \{X_i, \boldsymbol{d}_i, A_i, s_i(C_i, \tau_i, W_i)\}$. Three elements of $\tilde{X}_i$ require explanation. Student location is reflected in $\boldsymbol{d}_i$, a vector of all student-program distances. Placement test scores are a function of explained and unexplained components, following the distribution regression framework in Section 4: $s_i(C_i, \tau_i, W_i) = \widehat{Q}_{S|W_i, C=C_i}(\tau_i)$, where $\widehat{Q}$ is the quantile function. Student characteristics C_i are the explained component; the unexplained components are the mapping from characteristics to the conditional score distribution, captured here by W_i, and the student's quantile in the conditional distribution, τ_i.

21. Again, standard errors are computed using a parametric bootstrap, accounting for the fact that individual-level low-stakes test score preference gradients are correlated between students (indeed, perfectly correlated for students in the same covariate cell).

The assignment probability decomposition is thus:

$$\begin{aligned} & P\left(T=k|H\right)-P\left(T=k|L\right)= \\ & \int P(T=k|H,\tilde{X})dF_{\tilde{X}|H}-\int P(T=k|L,\tilde{X})dF_{\tilde{X}|L}= \\ & \underbrace{\int P(T=k|H,\tilde{X})dF_{\tilde{X}|H}-\int P(T=k|H,\tilde{X})dF_{\tilde{X}|L}}_{\text{Characteristic component}}+ \\ & \underbrace{\int P(T=k|H,\tilde{X})dF_{\tilde{X}|L}-\int P(T=k|L,\tilde{X})dF_{\tilde{X}|L}}_{\text{Preference component}}. \end{aligned} \tag{7}$$

The overall decomposition procedure requires estimating each component of Equation 7. For each student, we predict conditional assignment probabilities for all feasible programs of type k using the conditional logit probabilities based on the estimated preference parameters. We then sum these program-level probabilities to obtain $\widehat{P}(T=k|W_i,\tilde{X}_i)$. We average over all students by SES group to obtain the group-specific probabilities (the first and last terms of the final expression in Equation 7). The middle terms represent counterfactual probabilities in which low-SES students have high-SES preferences, estimated by predicting low-SES students' conditional assignment probabilities using the high-SES preference parameters.

The preference component reflects the part of the overall gap in assignment to program type k that is due solely to differences in preferences between high- and low-SES groups. The characteristic component reflects the contribution of differences in the joint distribution on students' observable characteristics, conditional on preferences being held constant at those of the high-SES group.

We also perform the nonlinear "detailed" decomposition described in Fairlie (2017) to isolate the contributions of each characteristic. This procedure matches low-SES (ℓ) and high-SES (h) students and progressively replaces elements of $\tilde{X}_\ell$ for low-SES students with those of their high-SES pair, recomputing $\widehat{P}(T=k|H,\tilde{X}_h)$ after each replacement. Two factors are of particular interest. One is the contribution of location, as captured by commuting distances. The other is the separate contributions of the observable and unobservable components of placement test scores, which affect assignment probabilities by changing the feasible set. Placement score differences between matched low- and high-SES students are performed by first writing low-SES student ℓ's test score as $\widehat{Q}_{S|L,C_\ell}(\hat{\tau}_\ell)$, where $\hat{\tau}_\ell$ is the estimated quantile of ℓ's score in his conditional score distribution. The contribution of explained differences in score is obtained by replacing observables C_ℓ with those of the matched high-SES student, C_h. The contribution of unexplained differences is obtained by replacing τ_ℓ with τ_h and evaluating the high-type quantile function ($W = H$). The detailed decomposition is performed 100 times with randomly-ordered variable replacement.

5.2 Counterfactual simulations

The assignment decomposition is a counterfactual exercise that varies preferences and characteristics while holding the other factors constant. We also perform more structured counterfactual simulations that quantify the role of the unexplained portion of the high-SES advantage in placement test scores. These exercises fully simulate the assignment process, accounting for the fact that programs have limited capacities, such that changes in placement test scores for one student can affect the feasible set for others.

We use the estimated preference parameters and the assumption of a stable matching to simulate student assignments. We take the student population in each year as given. First, for each student in the preference estimation sample, we simulate student preferences for all programs using the estimated preference parameters and random draws of the unobserved utility function. Second, we rank all programs by this simulated utility. Third, we submit student preferences and priorities (placement test scores), along with the true portfolios submitted by the students who were not included in the preference estimation sample, to the assignment mechanism, as well as each program's capacity.[22] While the true mechanism only allows students to submit up to 20 ranked options, Artemov, Che, and He (2017) show that under the stability assumption, using the full ranking is valid for simulating assignments. This generates simulated assignments and program-level cutoff scores, which can then be compared between counterfactual priority structures and to the assignment patterns and cutoffs that were actually realized in the true assignment process.

We perform this simulation for three cases. The first is the status quo. The second is a counterfactual in which the unexplained portion of the high-SES score advantage is removed. To do this, for all SES quartiles except the highest, we replace the realized score s_i with the distribution regression-based counterfactual score that keeps student characteristics the same but uses the high-SES conditional distribution: $\widehat{Q}_{S|H,C=C_i}(\tau_i)$. This counterfactual score maintains each student's position in the conditional score distribution (τ_i), so that e.g. a SES quartile 1 student in the 90th percentile of her conditional score distribution is assigned the 90th percentile of the conditional distribution for SES quar-

22. We fix capacities at the number of students assigned in that year of the data. For programs that did not fill up, we assign infinite capacity.

tile 4 students. The final simulation examines whether straightforward affirmative action in the priority structure can achieve similar results to those in which conditional score distributions are fully equalized between SES groups. Specifically, students in quartiles 1 through 3 are given additional points to close the unexplained gap in mean placement test scores.[23]

We compute simulated welfare effects in each counterfactual by comparing the expected commuting distance-denominated surplus with the status quo.[24] Student-level expected surplus depends on the feasible set of programs and the student-specific utilities from those programs. Conditional on estimated preference parameters, student characteristics, and a feasible choice set $\mathcal{J}_i$, expected consumer surplus can be computed up to a constant (Small and Rosen 1981):

$$\mathrm{E}\left(CS_i\right) = -\frac{1}{\alpha_i}\ln\left(\sum_{j\in\mathcal{J}_i}\exp(V_{ij})\right) + K.$$

Holding preferences constant, expanding a student's feasible set increases expected surplus. Differences in expected surplus between two priority structures are due only to the differences in the composition of the resulting feasible sets, $\mathcal{J}_i^0$ and $\mathcal{J}_i^1$:

$$\Delta\mathrm{E}\left(CS_i\right) = -\frac{1}{\alpha_i}\left[\ln\left(\sum_{j\in\mathcal{J}_i^1}\exp(V_{ij})\right) - \ln\left(\sum_{j\in\mathcal{J}_i^0}\exp(V_{ij})\right)\right]. \tag{8}$$

Equation 8 gives student-level counterfactual changes in distance-denominated expected consumer surplus. These student-level changes are then summarized in the relevant groups.

We account for estimation and simulation error in the simulation results by performing a large number of draws from the estimated parameter and idiosyncratic preference distributions, simulating assignment outcomes and welfare using these draws, and presenting their means and standard deviations.

5.3 Results

We first assess model fit. We then describe student preferences, present the the assignment decomposition, and summarize the simulation results.

23. Because scores are discrete, we cannot precisely close the mean gaps in this scheme. Quartile 1 students receive 6 points, Q2 students receive 4 points, and Q3 students receive 2 points.

24. This exposition follows Train (2009) and closely resembles the implementation in Ngo and Dustan (2024).

5.3.1 Model fit

We assess model fit in two ways. The first is to simulate the assignment process under the status quo, and then compare the simulated SES quartile-specific assignment rates to the true proportions in the data. Appendix Table A.11 shows that the model fits the quartile-specific proportions and their differences closely. In particular, the simulated and actual elite gaps between Q4 and Q1 students are nearly identical (33.8 p.p.), and the gaps in assignment to other program types are also very similar.

The second comparison, following Fack, Grenet, and He (2019), is between simulated and true program cutoff scores. These are illustrated in Appendix Figure A.1, with the true year-specific cutoff score on the horizontal axis and the simulated cutoff score on the vertical axis. Markers near on the dashed 45-degree line indicate program-years for which simulated and true cutoffs were similar. Again, the model fits reality closely, with the cutoffs of high-cutoff programs being recovered almost exactly and lower-cutoff programs having slightly higher dispersion. The enrollment-weighted correlation between simulated and actual cutoffs is 0.98.

5.3.2 Preference estimates

Table 4 summarizes the estimated student preference parameters. Traditional academic programs are the base type against which the others (elite, technical, and remaining unassigned) are compared. Columns 1 through 4 show SES-quartile specific estimates, from poorest to richest, while column 5 gives the difference between richest and poorest quartiles. Preferences for different program types are qualitatively similar across groups. All groups strongly prefer elite schools: Q1 students are on average willing to commute 18.99 km farther each way to attend one, and richer students are willing to travel somewhat farther than this. The Q4-Q1 gap in elite WTT is 3.75 km. All SES groups prefer traditional academic programs over technical ones: average marginal WTT for Q1 is -6.12 km, increasing in magnitude to -9.75 km for Q4 students. Richer students are less averse to remaining unassigned: the Q4-Q1 gap is 6.15 km, consistent with the insight in Akbarpour et al. (2022) that richer students often have stronger outside options (such as private school) and may thus find fewer options acceptable to put on their choice lists.

The average low-stakes test score preference gradients reveal similarities and differences between groups. For Q1 students, a 1 standard deviation increase in low-stakes test score is associated with a 0.58 km increase in WTT for elite schools. This is consistent with more-able students preferring elite schools more. This gradient is higher for richer students: for Q4 students it is 1.33 km. Low-stakes scores have a much weaker relationship with preferences for technical schools, and the estimated Q4-Q1 difference in these gradients is zero. Higher low-stakes scores predict a greater willingness to remain unassigned, and this is especially true for Q4 students, suggesting that high-SES, high-ability students have better outside options, including private school.

The distance parameters, used to transform the preference parameters into WTT measures, have similar magnitudes across groups. Thus the SES differences in average marginal WTT are not simply due to differences in the distance coefficients.

5.3.3 Assignment gap decomposition

We focus on the Q4-Q1 gap, presented in Table 5. Comparisons with Q2 and Q3 reflect similar patterns (Appendix Tables A.12 and A.13). Column 1 shows the elite assignment gap decomposition. The base gap is 33.8 p.p. Of this total, only 1.9 p.p. (5.6%) is due to SES differences in preferences. This is consistent with the positive but modest group differences in average WTT for elite programs. Group differences in student characteristics account for the remaining 31.9 p.p. (94.4%) of the elite gap. The detailed decomposition shows that differences in placement test scores account for the large majority of the gap. The explained part of score differences (i.e. the part explained by low-stakes scores, middle school GPA, and gender) accounts for 57.4% of the total gap, while the unexplained high-SES score advantage in test scores is responsible for 25.3%. Not only is the unexplained high-SES score advantage much more important than the role of preferences, but its contribution is also nearly five times as large as that of commuting distance (5.2%). The direct contributions of the remaining student characteristics (low-stakes test score, middle school GPA, and gender) must be interpreted with caution. They only account for these factors' direct contributions through differences in the observable component of program utilities, through X_i and A_i in equation 3. They do not account for these factors' important role in the explained component of the *placement test score* (through C_i in the score distribution function). Group differences in these three characteristics only account for 6.6% of the total elite assignment gap.

The gap in technical program assignment is preference-driven, as detailed in column 2. Q1 students are 26.2 p.p. more likely than Q4 students to be assigned to a technical program, and 16.7 p.p. (63.6%) of this gap is due to preference differences. This is consistent with the WTT results, which showed that, while all groups had low preference for technical programs, this was much more pronounced for Q4 students. Most of the remaining gap is explained by differences in placement test scores, as Q1 students' lower scores result in them being assigned to less-preferred, lower-cutoff programs. The explained difference in scores accounts for 6.1 p.p. (23.4%) of the technical assignment gap, while the unexplained difference in scores accounts for 2.6 p.p. (10.1%) of the gap. The remaining factors explain very little of the technical assignment gap, and commuting distance actually closes the gap slightly (0.2 p.p., or 0.7% of the total).

The assignment gap for traditional academic programs is relatively small, as shown in column 3. Q1 students are 5.4 p.p. more likely than Q4 students to be assigned to a traditional program, and group differences in preferences make this gap 0.6 p.p. (10.6%) smaller than it would be with uniform preferences. Commuting distance explains 3.8 p.p. (70.1%) of the gap, as lower-SES students tend to live farther from elite schools and closer to traditional schools, particularly in the State of Mexico.

While low-SES students remain unassigned only 2.2 p.p. more often than high-SES students, this conceals large, countervailing impacts of group differences in preferences and characteristics. Preference differences make Q4 students 14.2 p.p. more likely to remain unassigned compared to Q1 students, illustrating the importance of these students' relatively favorable outside options. But group differences in placement test scores more than cancel out the impact of preferences: the observed and unobserved components of scores make Q1 students 12.8 p.p. and 6.5 p.p. more likely to remain unassigned than Q4 students, respectively. Group differences in commuting distances make Q4 students relatively more likely to remain unassigned than Q1 students, again indicating that geographical access to schools is not the primary driver of (non-)assignment patterns.

In summary, differences in placement test scores are important determinants of group disparities in assignments, and an important proportion of the score-specific component of the gap is due to socioeconomic differences in test scores that cannot be explained by low-stakes test scores, middle school grade point average, or other observable factors.

5.3.4 Counterfactual simulations

Table 6 shows the results of the counterfactual assignment simulation that equalizes conditional score distributions across SES quartiles. This would reduce the SES gap in elite assignment between Q4 and Q1 groups by 7.5 p.p. (22.2%). Equalizing conditional score distributions closes the elite gap by increasing the rate at which low-SES students are assigned to elite programs and reducing the rate for Q4 students. The increase is largest for Q1 students, whose rate of elite assignment increases by 3.1 p.p. (27.1%), while for Q4 students, the decrease is 4.4 p.p. (11.5%).

Figure 5 plots the counterfactual changes in assignment rates according to students' low-stakes test score and SES quartile. Panel A shows the pattern for elite assignment. Among the poorest students, equalizing conditional placement test score distributions has the largest positive impact for those near the 85th percentile of the low-stakes score distribution. Many of these students have placement test scores near the margin of elite assignment, and eliminating the unexplained portion of the SES placement test score gap is sufficient to increase their elite assignment rates by more than 7 p.p. Among the richest students, the largest negative impacts are for students near the 75th percentile, who are also near the margin of elite admission and are displaced at higher rates when the unexplained portion of the SES score gap is eliminated.

This counterfactual reallocation of students reduces the gap in technical program assignment by 3.9 p.p. (15.1%). The decrease results from a 2.3 p.p. (5.4%) decrease in technical assignment among Q1 students and a 1.7 p.p. (8.2%) increase among Q4 students. As shown in Panel B of Figure 5, this reallocation occurs throughout most of the low-stakes score distribution, as higher placement test scores allow students to access both elite and traditional academic programs. The simulated change in the assignment gap for traditional academic programs is close to zero (1.3%). Panel C of Figure 5 shows that this null average change averages two opposing impacts: low-ability Q4 students are assigned to traditional programs less often, while high-ability Q4 students are assigned to them more often, reflecting displacement from elite schools; the opposite pattern holds for Q1 students.

Equalizing conditional score distributions between SES groups reverses the gap in remaining unassigned. Under this counterfactual reallocation, Q4 students are 1.4 p.p. *more* likely to be unassigned than Q1 students. As shown in Panel D of Figure 5, low-ability Q4 students' probability of going unassigned increases by as much as 3 p.p., as poorer students displace them at their preferred programs. Because high-SES students place a higher value on remaining unassigned, presumably due to stronger outside options, their displacement into unassignment is larger than the transition of previously unassigned low-SES students into assignment.

This reallocation would affect the distribution of student welfare between SES groups. Among the poorest quartile, welfare would rise by the equivalent of 0.78 km of one-way commuting distance per student, while it would fall by 0.97 km for the richest quartile. The overall impact on welfare is a negligible -0.03 km per student. Figure 6 shows that the reallocation of welfare takes place throughout the low-stakes test score distribution, with the largest changes occurring at percentiles where elite impacts are highest.

Table 7 shows the results of simulating the simple SES-based affirmative action assignment rule aimed at closing the unexplained gap in conditional test score means. This rule results in similar assignment patterns as the previous counterfactual, although the gaps are not closed to the same extent. For example, the elite gap closes by 15.0% instead of 22.2%, while the technical gap closes by 9.9% instead of 15.1%. The -0.08 km change in overall welfare is worse than the counterfactual that fully equalizes the conditional score distributions. These differences arise because uniform point bonuses by group do not fully equalize the conditional score distributions.

6 Discussion

We have shown that differences in placement test scores are key determinants of the large SES gaps in high school assignment. For elite schools, score differences are far more important than preference differences or geographical segregation. While low-stakes test scores and other student characteristics explain a significant proportion of SES differences in placement test scores, the residual SES advantage is large and has meaningful consequences. For lower-SES students, these include lower access to elite schools, higher probability of placement into less-preferred technical programs, and lower welfare. Furthermore, this disadvantage increases the probability that low-SES students are unassigned by the mechanism, and these are precisely the students who appear to have the worst outside options. Existing literature suggests that this residual advantage reflects not only ability differences, but also systematic factors disadvantaging low-SES students. A limitation of this study is that it does not identify or quantify the specific explanations that are at play in this context. To do so, we would need student-level data regarding test preparation, day-of-exam effort, testing anxiety, and measures related to other potential factors.

These results do not imply that high-stakes testing is worse than its alternatives.[25] While there are concerns about between-group disparities, high-stakes test scores can be informative about ability, particularly for within-group variation. Moreover, low-stakes performance measures cannot be used for admission without raising their stakes and the corresponding concerns. In contexts where high-stakes exams continue to be used for admission, Posso, Saravia, and Uribe (2023) show that interventions that provide test preparation to low-SES students can be very effective. Alternatively, where politically feasible, point-based affirmative action can be used to reduce the SES gap in places where the residual advantage can be quantified.

25. For example, Riehl (2024) cautions that exam redesign efforts can have negative consequences. Specifically, an effort to reduce test score biases in Colombia lowered the SES gap but also decreased the predictive power of the exam, resulting in worse graduation and labor market outcomes for both high- and low-income students.

References

Abdulkadiroğlu, Atila, Joshua Angrist, and Parag Pathak. 2014. "The elite illusion: Achievement effects at Boston and New York exam schools." *Econometrica* 82 (1): 137–196.

Agarwal, Nikhil, and Paulo Somaini. 2020. "Revealed preference analysis of school choice models." *Annual Review of Economics* 12 (1): 471–501.

Ajayi, Kehinde F. 2024. "School choice and educational mobility: Lessons from secondary school applications in Ghana." *Journal of Human Resources* 59 (4): 1207–1243.

Akbarpour, Mohammad, Adam Kapor, Christopher Neilson, Winnie Van Dijk, and Seth Zimmerman. 2022. "Centralized school choice with unequal outside options." *Journal of Public Economics* 210:104644.

Akyol, Pelin, Kala Krishna, and Jinwen Wang. 2021. "Taking PISA seriously: How accurate are low-stakes exams?" *Journal of Labor Research* 42 (2): 184–243.

Almås, Ingvild, Alexander W Cappelen, Kjell G Salvanes, Erik Ø Sørensen, and Bertil Tungodden. 2016. "Willingness to compete: Family matters." *Management Science* 62 (8): 2149–2162.

Arenas, Andreu, and Caterina Calsamiglia. 2025. "Gender differences in high-stakes performance and college admission policies." *Management Science.*

Artemov, Georgy, Yeon-Koo Che, and Yinghua He. 2017. "Strategic 'mistakes': Implications for market design research." *NBER Working Paper.*

Barrow, Lisa, Lauren Sartain, and Marisa De La Torre. 2020. "Increasing access to selective high schools through place-based affirmative action: Unintended consequences." *American Economic Journal: Applied Economics* 12 (4): 135–163.

Berkowitz, Daniel, and Mark Hoekstra. 2011. "Does high school quality matter? Evidence from admissions data." *Economics of Education review* 30 (2): 280–288.

Beuermann, Diether W, and C Kirabo Jackson. 2022. "The short-and long-run effects of attending the schools that parents prefer." *Journal of Human Resources* 57 (3): 725–746.

Bond, Timothy N, Jillian B Carr, Analisa Packham, and Jonathan Smith. 2022. "Hungry for success? SNAP timing, high-stakes exam performance, and college attendance." *American Economic Journal: Economic Policy* 14 (4): 51–79.

Bray, Mark, and Alexandre Ventura. 2024. "Shadow education in Latin America: Assembling the jigsaw." *Revista Española de Pedagogía.*

Brunner, Eric J, Shaun M Dougherty, and Stephen L Ross. 2023. "The effects of career and technical education: Evidence from the Connecticut technical high school system." *Review of Economics and Statistics* 105 (4): 867–882.

Buchmann, Claudia, Dennis J Condron, and Vincent J Roscigno. 2010. "Shadow education, American style: Test preparation, the SAT and college enrollment." *Social forces* 89 (2): 435–461.

Burgess, Simon, Ellen Greaves, Anna Vignoles, and Deborah Wilson. 2015. "What parents want: School preferences and school choice." *The Economic Journal* 125 (587): 1262–1289.

Cabrera-Hernández, Francisco J, Andrew Dustan, Daniel Osuna Gomez, and María Padilla-Romo. 2026. *Marginal Admission to Elite High Schools: Long-run Effects on Labor Market Outcomes.* Technical report. National Bureau of Economic Research.

Carneiro, Juliana, Matthew A Cole, and Eric Strobl. 2021. "The effects of air pollution on students' cognitive performance: evidence from Brazilian university entrance tests." *Journal of the Association of Environmental and Resource Economists* 8 (6): 1051–1077.

Chang, Eunsik, and María Padilla-Romo. 2023. "When crime comes to the neighborhood: Short-term shocks to student cognition and secondary consequences." *Journal of Labor Economics* 41 (4): 997–1039.

Chernozhukov, Victor, Iván Fernández-Val, and Alfred Galichon. 2010. "Quantile and probability curves without crossing." *Econometrica* 78 (3): 1093–1125.

Chernozhukov, Victor, Iván Fernández-Val, and Blaise Melly. 2013. "Inference on counterfactual distributions." *Econometrica* 81 (6): 2205–2268.

Chetty, Raj, David J Deming, and John N Friedman. 2026. "Diversifying society's leaders? The determinants and causal effects of admission to highly selective private colleges." *The Quarterly Journal of Economics* 141 (1): 51–145.

Dai, Li, and Pedro S Martins. 2020. *Does vocational education pay off in China? Instrumental-variable quantile-regression evidence.* Technical report. GLO Discussion Paper.

Dang, Hai-Anh. 2007. "The determinants and impact of private tutoring classes in Vietnam." *Economics of education review* 26 (6): 683–698.

De Hoyos, Rafael, Ricardo Estrada, and María José Vargas. 2021. "What do test scores really capture? Evidence from a large-scale student assessment in Mexico." *World Development* 146:105524.

DiNardo, John, Nicole M. Fortin, and Thomas Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach." *Econometrica* 64 (5): 1001–1044. https://doi.org/10.2307/2171954.

Dobbie, Will, and Roland G Fryer Jr. 2014. "The impact of attending a school with high-achieving peers: Evidence from the New York City exam schools." *American Economic Journal: Applied Economics* 6 (3): 58–75.

Duquennois, Claire. 2022. "Fictional money, real costs: Impacts of financial salience on disadvantaged students." *American Economic Review* 112 (3): 798–826.

Dustan, Andrew, Alain de Janvry, and Elisabeth Sadoulet. 2017. "Flourish or Fail? The Risky Reward of Elite High School Admission in Mexico City." *Journal of Human Resources* 52 (3): 756–799.

Dustan, Andrew, and Diana KL Ngo. 2018. "Commuting to educational opportunity? School choice effects of mass transit expansion in Mexico City." *Economics of Education Review* 63:116–133.

Ebenstein, Avraham, Victor Lavy, and Sefi Roth. 2016. "The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution." *American Economic Journal: Applied Economics* 8 (4): 36–65.

Fack, Gabrielle, Julien Grenet, and Yinghua He. 2019. "Beyond truth-telling: Preference estimation with centralized school choice and college admissions." *American Economic Review* 109 (4): 1486–1529.

Fairlie, Robert W. 1999. "The absence of the African-American owned business: An analysis of the dynamics of self-employment." *Journal of labor Economics* 17 (1): 80–108.

———. 2005. "An extension of the Blinder-Oaxaca decomposition technique to logit and probit models." *Journal of economic and social measurement* 30 (4): 305–316.

———. 2017. "Addressing path dependence and incorporating sample weights in the nonlinear Blinder-Oaxaca decomposition technique for logit, probit and other nonlinear models." *Stanford Institute for Economic Policy Research, Working Paper (17-013).*

Fang, Dawei, and Thomas Noe. 2022. "Less competition, more meritocracy?" *Journal of Labor Economics* 40 (3): 669–701.

Filmer, Deon, and Kinnon Scott. 2012. "Assessing asset indices." *Demography* 49 (1): 359–392.

Friedman-Sokuler, Naomi, and Moshe Justman. 2025. "Family background, education, and earnings: the limited value of "test-score transmission"." *Review of Economics of the Household* 23 (3): 1075–1112.

Gale, David, and Lloyd S Shapley. 1962. "College admissions and the stability of marriage." *The American Mathematical Monthly* 69 (1): 9–15.

Garg, Teevrat, Maulik Jagnani, and Vis Taraz. 2020. "Temperature and human capital in India." *Journal of the Association of Environmental and Resource Economists* 7 (6): 1113–1150.

Gonzalez, Alberto. 2003. "Ganan preferencia la UNAM y el Poli." February 22. https://www.proquest.com/newspapers/ganan-preferencia-la-unam-y-el-poli/docview/307107613/se-2, *Reforma.*

Gorman, Emma, and Ian Walker. 2021. "Heterogeneous effects of missing out on a place at a preferred secondary school in England." *Economics of Education Review* 81:102082.

Hakimov, Rustamdjan, Renke Schmacker, and Camille Terrier. 2023. *Confidence and college applications: Evidence from a randomized intervention.* Technical report. Working Paper.

Heissel, Jennifer A, Emma K Adam, Jennifer L Doleac, David N Figlio, and Jonathan Meer. 2021. "Testing, Stress, and Performance: How Students Respond Physiologically to High-Stakes Testing." *Education Finance and Policy* 16 (2): 183–208.

Hemelt, Steven W, Matthew A Lenard, and Colleen G Paeplow. 2019. "Building bridges to life after high school: Contemporary career academies and student outcomes." *Economics of Education Review* 68:161–178.

Hong, Justin Jihao, Victor Lei, and Xuan Li. 2025. "Testing Away from One's Own School: Exam Location and Performance in High-Stakes Exams." *Available at SSRN 5251481.*

Instituto Nacional de Estadística y Geografía. 2008. *Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) 2008.* Aguascalientes, Mexico.

———. 2010. *Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) 2010.* Aguascalientes, Mexico.

Jackson, C Kirabo, Sebastián Kiguel, Shanette C Porter, and John Q Easton. 2024. "Who benefits from attending effective high schools?" *Journal of Labor Economics* 42 (3): 717–751.

Jackson, C. Kirabo. 2010. "Do students benefit from attending better schools? Evidence from rule-based student assignments in Trinidad and Tobago." *The Economic Journal* 120 (549): 1399–1429.

Jayachandran, Seema. 2014. "Incentives to teach badly: After-school tutoring in developing countries." *Journal of Development Economics* 108:190–205.

Kemper, Johanna, and Ursula Renold. 2024. "Evaluating the impact of general versus vocational education on labor market outcomes in Egypt by means of a regression discontinuity design." *Journal of Development Economics* 166:103172.

Lee, Frances Xu, and Wing Suen. 2023. "Gaming a selective admissions system." *International Economic Review* 64 (1): 413–443.

Liu, Liqun, and William S Neilson. 2011. "High scores but low skills." *Economics of Education Review* 30 (3): 507–516.

Lopez-Acevedo, Gladys. 2003. "A Reassessment of Technical Education in Mexico." *Journal of Career and Technical Education* 19 (2): 59–81.

Loyalka, Prashant, Xiaoting Huang, Linxiu Zhang, Jianguo Wei, Hongmei Yi, Yingquan Song, Yaojiang Shi, and James Chu. 2016. "The impact of vocational schooling on human capital development in developing countries: Evidence from China." *The World Bank Economic Review* 30 (1): 143–170.

Lucas, Adrienne M, and Isaac M Mbiti. 2014. "Effects of school quality on student achievement: Discontinuity evidence from kenya." *American Economic Journal: Applied Economics* 6 (3): 234–263.

Lupi, Frank, and Peter M Feather. 1998. "Using partial site aggregation to reduce bias in random utility travel cost models." *Water resources research* 34 (12): 3595–3603.

Mani, Anandi, Sendhil Mullainathan, Eldar Shafir, and Jiaying Zhao. 2013. "Poverty impedes cognitive function." *science* 341 (6149): 976–980.

Mark, Nicholas DE, Sean P Corcoran, and Jennifer L Jennings. 2023. "Choosing Alone? Peer Continuity Disparities in Choice-Based Enrollment Systems." *Educational Researcher* 52 (6): 365–376.

Mbekeani, Preeya P, John P Papay, Ann Mantil, and Richard J Murnane. 2026. "Understanding High Schools' Effects on Longer-Term Outcomes." *Journal of Policy Analysis and Management* 45 (2): e70093.

Michaelsen, Maren M, and Paola Salardi. 2020. "Violence, psychological stress and educational performance during the "war on drugs" in Mexico." *Journal of Development Economics* 143:102387.

Monkkonen, Paavo, M Paloma Giottonini, Andre Comandon, et al. 2021. "Socioeconomic segregation in Mexico City: scale, social classes, and the primate city." *Urban socio-economic segregation and income inequality,* 389.

Newhouse, David, and Daniel Suryadarma. 2011. "The value of vocational education: High school type and labor market outcomes in Indonesia." *The World Bank Economic Review* 25 (2): 296–322.

Ngo, Diana, and Andrew Dustan. 2024. "Preferences, access, and the STEM gender gap in centralized high school assignment." *American Economic Journal: Applied Economics* 16 (4): 257–287.

Ngo, Diana KL, and Luc Christiaensen. 2019. "The performance of a consumption augmented asset index in ranking households and identifying the poor." *Review of Income and Wealth* 65 (4): 804–833.

Ortega-Hesles, Marıa Elena, and Marco Pariguana. 2025. "School Choice, Skill Measures, and Graduation."

Park, Albert, Xinzheng Shi, Chang-tai Hsieh, and Xuehui An. 2015. "Magnet high schools and academic performance in China: A regression discontinuity design." *Journal of Comparative Economics* 43 (4): 825–843.

Park, R Jisung. 2022. "Hot temperature and high-stakes performance." *Journal of Human Resources* 57 (2): 400–434.

Parsons, George R, and Michael S Needelman. 1992. "Site aggregation in a random utility model of recreation." *Land economics,* 418–433.

Pop-Eleches, Cristian, and Miguel Urquiola. 2013. "Going to a better school: Effects and behavioral responses." *American Economic Review* 103 (4): 1289–1324.

Posso, Christian, Estefanía Saravia, and Pablo Uribe. 2023. "Acing the test: Educational effects of the SaberEs test preparation program in Colombia." *Economics of Education Review* 97:102459.

Procuraduría Federal del Consumidor. 2022. *Costo de los cursos para entrar a la preparatoria.* Technical report. Ciudad de México, México: Procuraduría Federal del Consumidor (PROFECO), Departamento de Encuestas, Secretaría de Economía. Accessed August 13, 2026. https://www.gob.mx/cms/uploads/attachment/file/809473/COSTO_DE_LOS_CURSOS_PARA_ENTRAR_A_LA_PREPARATORIA.pdf.

Reardon, Sean F. 2018. "The widening academic achievement gap between the rich and the poor." In *Social stratification,* 536–550. Routledge.

Reyes, Germán J, Evan Riehl, and Ruqing Xu. 2024. *Stakes and Signals: An Empirical Investigation of Muddled Information in Standardized Testing.* Technical report. National Bureau of Economic Research.

Riehl, Evan. 2024. "Do less informative college admission exams reduce earnings inequality? evidence from Colombia." *Journal of Labor Economics* 42 (4): 1009–1047.

Schlosser, Analia, Zvika Neeman, and Yigal Attali. 2019. "Differential performance in high versus low stakes tests: evidence from the GRE test." *The Economic Journal* 129 (623): 2916–2948.

Small, Kenneth A, and Harvey S Rosen. 1981. "Applied welfare economics with discrete choice models." *Econometrica: Journal of the Econometric Society,* 105–130.

Train, Kenneth E. 2009. *Discrete choice methods with simulation.* Cambridge university press.

Zhang, Yu. 2013. "Does private tutoring improve students' National College Entrance Exam performance?—A case study from Jinan, China." *Economics of Education Review* 32:1–28.

Tables

Table 1: Choice and demographic summary statistics

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q4-Q1
Academic achievement					
Placement test score	55.71	61.71	68.10	76.24	20.53
	(17.540)	(18.593)	(19.210)	(20.093)	(0.084)
ENLACE 9 math subscore	0.09	0.30	0.51	0.83	0.74
	(0.917)	(0.963)	(0.997)	(1.051)	(0.005)
ENLACE 9 Spanish subscore	0.18	0.40	0.61	0.91	0.73
	(0.849)	(0.872)	(0.882)	(0.913)	(0.004)
Middle school GPA (standardized)	-0.10	-0.05	0.03	0.12	0.22
	(0.967)	(0.999)	(1.010)	(1.009)	(0.004)
School choices					
Total number of choices listed	9.40	9.75	9.89	9.68	0.28
	(3.531)	(3.642)	(3.735)	(3.923)	(0.017)
Percent of choices that are elite	26.55	35.89	46.56	59.56	33.01
	(28.880)	(31.412)	(32.984)	(33.205)	(0.139)
Percent of choices that are technical	37.67	31.26	24.28	16.57	-21.11
	(30.611)	(29.159)	(26.762)	(22.926)	(0.121)
Percent of choices that are traditional academic	35.78	32.85	29.16	23.87	-11.91
	(27.732)	(26.894)	(26.172)	(25.304)	(0.119)
Average driving distance to all choices (km)	11.63	12.03	12.37	12.46	0.84
	(5.659)	(5.837)	(6.000)	(6.041)	(0.026)
Demographics and geography					
Male	0.42	0.45	0.47	0.50	0.08
	(0.493)	(0.497)	(0.499)	(0.500)	(0.002)
Driving distance to closest elite program (km)	10.76	9.74	8.87	7.68	-3.08
	(6.789)	(6.605)	(6.534)	(6.207)	(0.029)
Observations	99982	99982	99982	99981	199963

Note: Calculations are for all students in the analysis sample for the 2007 and 2008 COMIPEMS cycles. Standard deviations are in parentheses in columns 1 through 4; standard errors are in parentheses in column 5. Placement test score is raw score out of 128. ENLACE 9 subscores are standardized with respect to the national population. Middle school GPA is normalized by year within analysis sample.

Table 2: Program assignment summary statistics

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q4-Q1
Geography					
Driving distance to assigned program (km)	9.3	9.8	10.2	10.5	1.1
	(7.62)	(7.81)	(8.13)	(8.14)	(0.04)
Program Types					
Elite assigned program	8.5	15.5	26.1	42.3	33.8
	(27.82)	(36.17)	(43.93)	(49.40)	(0.18)
Technical assigned program	44.8	38.4	29.2	18.6	-26.2
	(49.73)	(48.63)	(45.46)	(38.88)	(0.20)
Traditional academic assigned program	29.6	30.0	29.0	24.2	-5.4
	(45.66)	(45.84)	(45.39)	(42.85)	(0.20)
Unassigned	17.1	16.1	15.7	14.9	-2.2
	(37.66)	(36.75)	(36.34)	(35.66)	(0.16)
Observations	99982	99982	99982	99981	199963

Note: Calculations for driving distance are conditional on assignment. Program assignment variables do not condition on assignment. Indicator variables are percentages. Standard deviations are in parentheses in columns 1 through 4; standard errors are in parentheses in column 5.

Table 3: Decomposition of SES differences in mean placement test scores

	Q1 vs. Q4		Q2 vs. Q4		Q3 vs. Q4	
	(1) Total	(2) Unexplained	(3) Total	(4) Unexplained	(5) Total	(6) Unexplained
Overall score	1.04	0.36	0.73	0.25	0.42	0.13
	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)
		[34.2%]		[34.9%]		[31.9%]
Verbal reasoning	0.90	0.32	0.61	0.23	0.33	0.11
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
		[35.0%]		[37.4%]		[32.7%]
Spanish	0.78	0.30	0.54	0.20	0.31	0.11
	(0.004)	(0.006)	(0.004)	(0.005)	(0.004)	(0.003)
		[38.8%]		[37.2%]		[34.4%]
History	0.69	0.26	0.51	0.20	0.31	0.12
	(0.004)	(0.007)	(0.004)	(0.005)	(0.005)	(0.004)
		[38.0%]		[39.9%]		[38.7%]
Geography	0.79	0.30	0.56	0.22	0.33	0.13
	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
		[38.3%]		[40.0%]		[39.2%]
Civics and Ethics	0.81	0.31	0.57	0.23	0.33	0.12
	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
		[38.5%]		[39.6%]		[37.6%]
Quantitative reasoning	0.77	0.19	0.50	0.12	0.27	0.04
	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)
		[25.1%]		[23.3%]		[16.7%]
Math	0.68	0.17	0.48	0.11	0.28	0.05
	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
		[24.7%]		[23.4%]		[18.0%]
Physics	0.72	0.25	0.52	0.18	0.30	0.10
	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.004)
		[34.6%]		[35.5%]		[32.4%]
Chemistry	0.73	0.25	0.53	0.18	0.31	0.10
	(0.005)	(0.007)	(0.004)	(0.005)	(0.005)	(0.004)
		[34.2%]		[34.7%]		[32.4%]
Biology	0.80	0.30	0.57	0.22	0.33	0.12
	(0.005)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)
		[37.6%]		[39.1%]		[37.6%]

Note: Rows represent subtests from the placement test. Odd columns contain estimated differences between the indicated predicted consumption quartiles in means of the standardized (mean zero, standard deviation 1) subscores. Even columns contain the portion of the mean difference that is not explained by observable characteristics in the DiNardo-Fortin-Lemieux decomposition. Bootstrapped standard errors are in parentheses. Unexplained proportion of the overall gap is in square brackets.

Table 4: Summary of estimated student preferences from choice model

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q4-Q1
Average marginal willingness to travel by program type					
Elite	18.99	20.20	21.63	22.73	3.75
	(0.273)	(0.180)	(0.160)	(0.123)	(0.290)
Technical	-6.12	-7.08	-8.27	-9.75	-3.63
	(0.051)	(0.068)	(0.070)	(0.085)	(0.079)
Unassigned	-4.25	-2.53	-0.80	1.90	6.15
	(0.075)	(0.077)	(0.093)	(0.100)	(0.133)
Average low-stakes score willingness to travel gradients					
Low-stakes $\times$ elite	0.58	0.66	0.77	1.33	0.75
	(0.216)	(0.158)	(0.126)	(0.118)	(0.254)
Low-stakes $\times$ technical	0.04	0.19	0.07	0.04	0.00
	(0.053)	(0.061)	(0.062)	(0.072)	(0.093)
Low-stakes $\times$ unassigned	0.14	0.18	0.30	1.08	0.94
	(0.093)	(0.094)	(0.083)	(0.094)	(0.122)
Average distance coefficient					
Distance (km)	-0.22	-0.21	-0.21	-0.21	0.01
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Note: Columns 1-4 refer to predicted consumption quartiles over which preference estimates are averaged. Column 5 is the difference between the highest and lowest quartiles. Average marginal willingness to travel (WTT) estimates are computed using Equation 4. Average WTT gradient estimates are computed using Equation 6. Units of measure for both are kilometers of one-way commuting distance. Bootstrapped standard errors in parentheses.

Table 5: Decomposition of assignment gaps, highest vs. lowest SES quartiles

	(1) Elite	(2) Technical	(3) Traditional academic	(4) Unassigned
Q4 assignment rate	42.3	18.6	24.2	14.9
Q1 assignment rate	8.5	44.8	29.6	17.1
Assignment gap	33.8	-26.2	-5.4	-2.2
Contribution of preference parameter differences	1.9	-16.7	0.6	14.2
	(0.07)	(0.24)	(0.25)	(0.26)
	[5.6%]	[63.6%]	[-10.6%]	[-660.1%]
Contributions of differences in student characteristics				
Placement test score (explained)	19.4	-6.1	-0.5	-12.8
	(0.08)	(0.06)	(0.07)	(0.06)
	[57.4%]	[23.4%]	[9.2%]	[591.2%]
Placement test score (unexplained)	8.5	-2.6	0.6	-6.5
	(0.04)	(0.03)	(0.03)	(0.03)
	[25.3%]	[10.1%]	[-10.7%]	[299.9%]
Commuting distance	1.7	0.2	-3.8	1.9
	(0.04)	(0.09)	(0.09)	(0.09)
	[5.2%]	[-0.7%]	[70.1%]	[-86.2%]
ENLACE 9 score	1.1	-1.0	-1.3	1.2
	(0.10)	(0.14)	(0.16)	(0.15)
	[3.3%]	[3.7%]	[24.9%]	[-55.6%]
Middle school GPA	0.9	-0.4	-0.5	0.0
	(0.02)	(0.03)	(0.03)	(0.03)
	[2.8%]	[1.6%]	[9.6%]	[-0.3%]
Gender	0.2	0.5	-0.4	-0.2
	(0.02)	(0.03)	(0.02)	(0.03)
	[0.5%]	[-1.7%]	[7.5%]	[11.1%]
Total	31.9	-9.6	-6.0	-16.4
	(0.07)	(0.24)	(0.25)	(0.26)
	[94.4%]	[36.4%]	[110.6%]	[760.1%]

Note: Entries correspond to the nonlinear decomposition of the probability of assignment to programs of the type specified in the column header, following the decomposition procedure described in Section 5.1.3. SES quartiles are determined by predicted consumption. Detailed decomposition contributions are means across 100 simulations. Bootstrapped standard errors using 50 repetitions per simulation are in parentheses. Proportions of total gap explained are in square brackets.

Table 6: Simulated effects of equalizing conditional placement test score distributions on SES assignment gaps and welfare

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q4-Q1	(6) Overall
Elite	3.1	2.0	-0.8	-4.4	-7.5	
	(0.05)	(0.04)	(0.04)	(0.04)	(0.07)	
	[27.1%]	[11.5%]	[-3.1%]	[-11.5%]	[-22.2%]	
Technical	-2.3	-1.2	0.6	1.7	3.9	
	(0.06)	(0.05)	(0.05)	(0.06)	(0.09)	
	[-5.4%]	[-3.2%]	[1.9%]	[8.2%]	[-15.1%]	
Traditional academic	0.5	-0.3	-0.6	0.4	-0.1	
	(0.06)	(0.05)	(0.05)	(0.06)	(0.10)	
	[1.5%]	[-1.1%]	[-2.2%]	[1.5%]	[1.3%]	
Unassigned	-1.3	-0.5	0.9	2.3	3.7	
	(0.04)	(0.03)	(0.03)	(0.05)	(0.06)	
	[-8.9%]	[-3.2%]	[5.6%]	[14.0%]	[-157.7%]	
Welfare	0.78	0.36	-0.27	-0.97		-0.03
	(0.01)	(0.00)	(0.00)	(0.01)		(0.00)

Note: Entries in columns 1 through 4 are simulated effects on students in the indicated predicted consumption quartile of changing conditional placement test score distributions (for all quartiles Q1-Q3) to match those of Q4, as described in Section 5.2. The first three rows are the change in simulated proportion of assigned students who are assigned to a program of the specified type. The final row is the change in simulated welfare, computed using Equation 8. Column 5 contains simulated changes in the Q4-Q1 assignment gap. Point estimates are the mean of 200 simulations. Standard deviations from the 200 simulations are in parentheses. Proportion changes compared to the status quo proportion or gap are in square brackets.

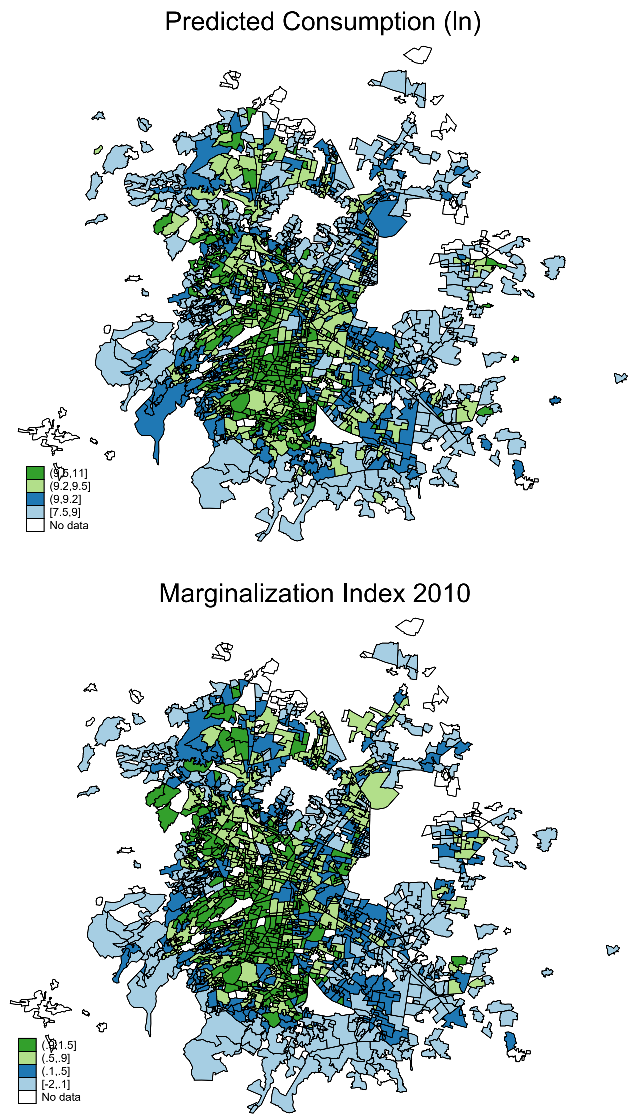
Table 7: Simulated effects of point-based affirmative action on SES assignment gaps and welfare

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q4-Q1	(6) Overall
Elite	2.2	1.3	-0.7	-2.8	-5.1	
	(0.04)	(0.04)	(0.04)	(0.06)	(0.08)	
	[20.8%]	[7.9%]	[-2.7%]	[-7.2%]	[-15.0%]	
Technical	-1.5	-0.7	0.4	1.0	2.6	
	(0.05)	(0.04)	(0.04)	(0.05)	(0.09)	
	[-3.6%]	[-2.0%]	[1.3%]	[5.3%]	[-9.9%]	
Traditional academic	0.5	-0.3	-0.5	0.1	-0.4	
	(0.06)	(0.04)	(0.04)	(0.06)	(0.09)	
	[1.6%]	[-0.9%]	[-1.6%]	[0.4%]	[7.0%]	
Unassigned	-1.2	-0.3	0.8	1.7	2.9	
	(0.03)	(0.02)	(0.03)	(0.04)	(0.06)	
	[-7.7%]	[-2.0%]	[4.9%]	[10.8%]	[-125.0%]	
Welfare	0.52	0.16	-0.33	-0.68		-0.08
	(0.01)	(0.01)	(0.01)	(0.01)		(0.01)

Note: Entries in columns 1 through 4 are simulated effects on students in the indicated predicted consumption quartile of instituting a point-based affirmative action policy that gives 6 entrance exam points to Q1 students, 4 points to Q2 students, and 2 points to Q1 students, roughly equating *conditional* means between groups as described in Section 5.2. The first three rows are the change in simulated proportion of assigned students who are assigned to a program of the specified type. The final row is the change in simulated welfare, computed using Equation 8. Column 5 contains simulated changes in the Q4-Q1 assignment gap. Point estimates are the mean of 200 simulations. Standard deviations from the 200 simulations are in parentheses. Proportion changes compared to the status quo proportion or gap are in square brackets.

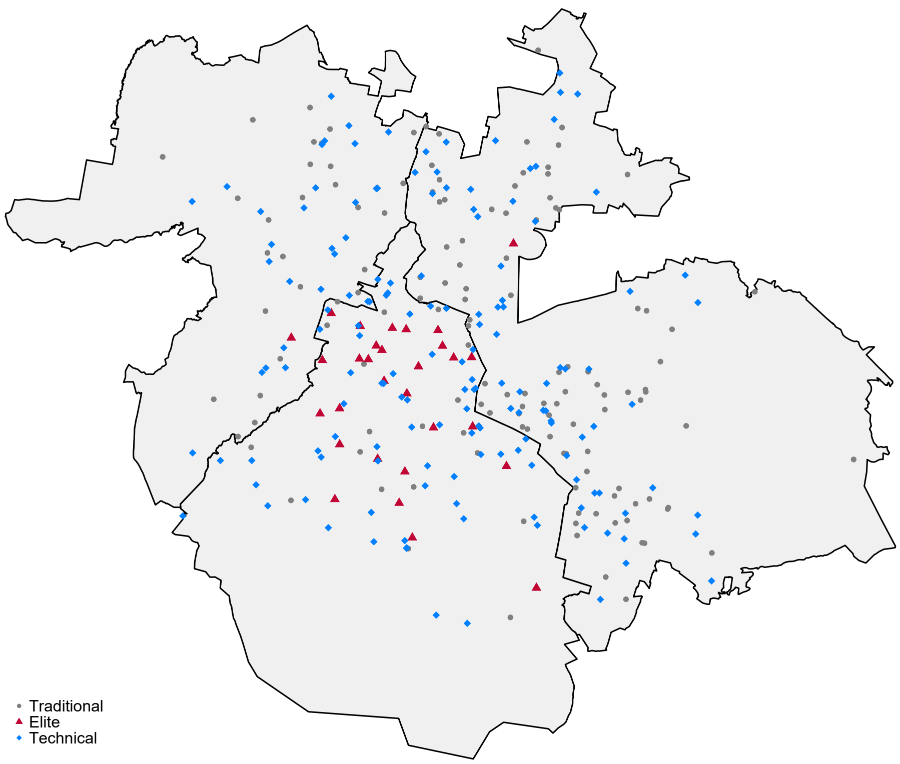
Figures

Figure 1: Geographical Distribution of Socioeconomic Status



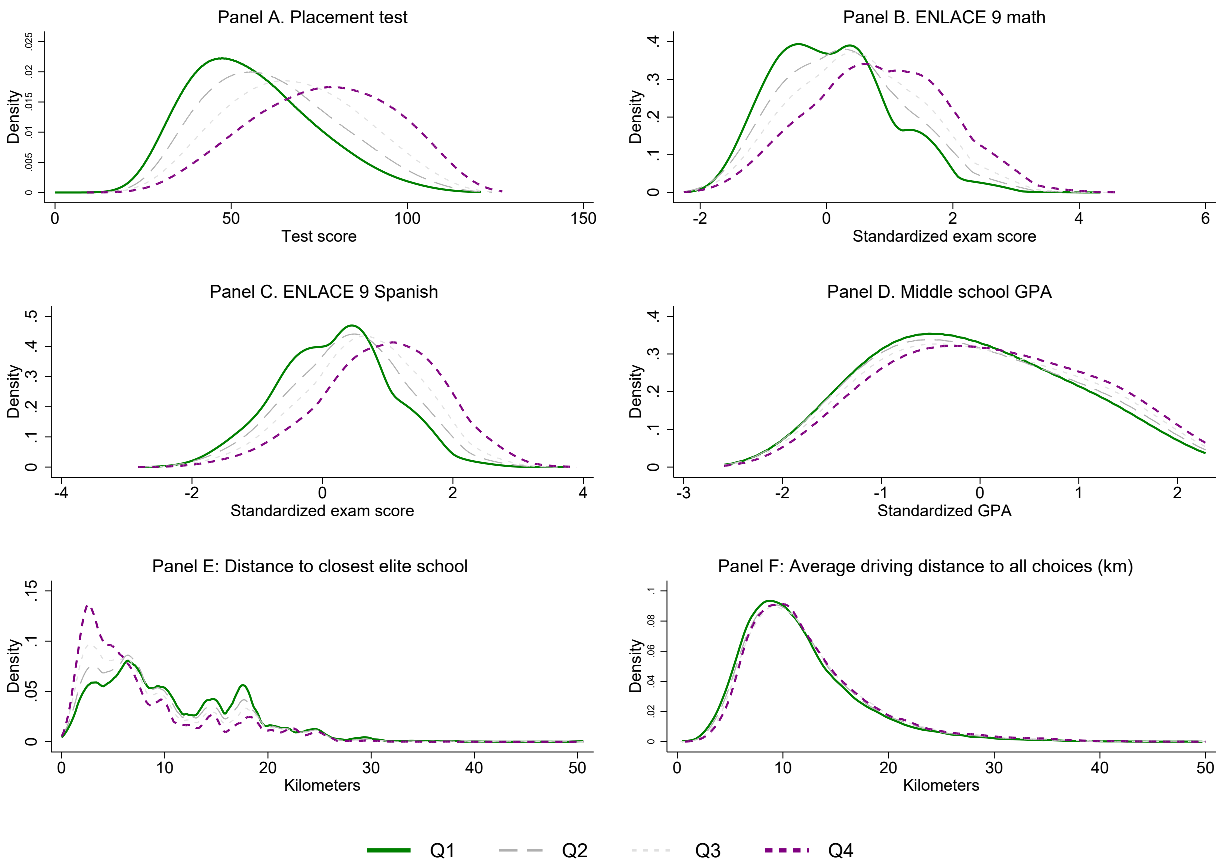
Note: The top panel presents our constructed student-level predicted consumption measure, where higher values (green) represent wealthier neighborhoods. The bottom panel shows the neighborhood-level marginalization index constructed by Mexico's National Population Council (CONAPO). We use the negative marginalization index to match the direction of predicted consumption.

Figure 2: School locations



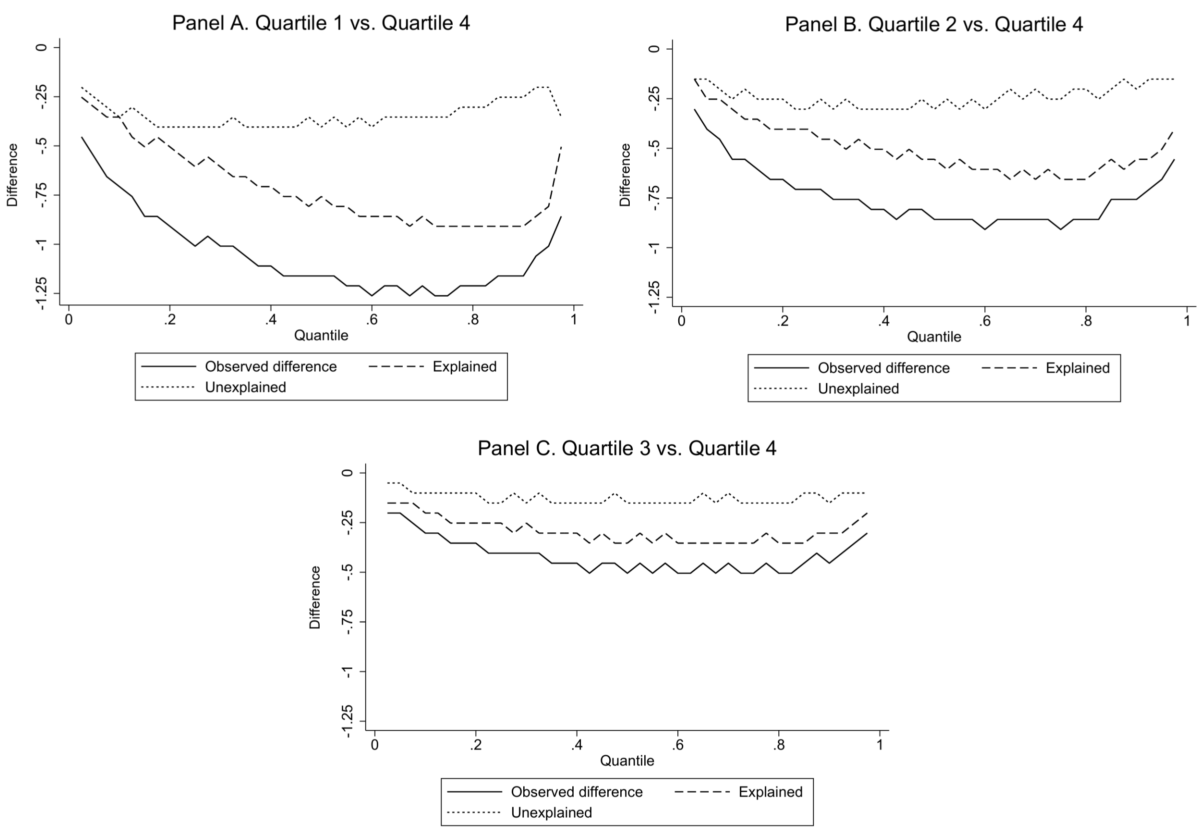
Note: Markers correspond to public high schools in the COMIPEMS zone. School classifications are on the basis of programs available for students to choose in the choice process. Regions are those used to partition the student sample in the preference estimation.

Figure 3: Test score, GPA, and distance distributions by SES quartile



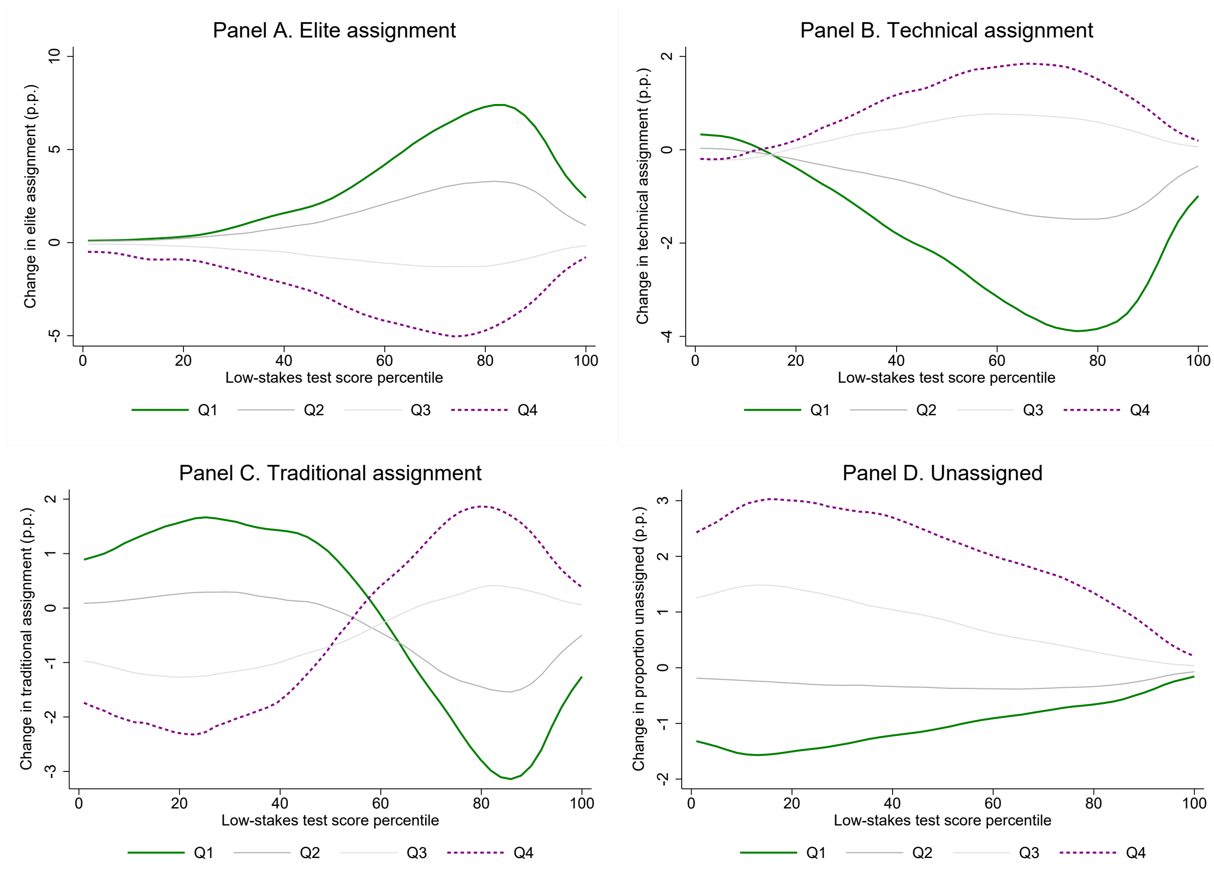
Note: Plots are for all students in analysis sample in the 2007 and 2008 COMIPEMS cycles. Placement test score is raw score out of 128. ENLACE 9 subscores are nationally standardized. Middle school GPA is standardized by year within the analysis sample.

Figure 4: Decomposition of distributional differences in placement test score distributions between SES quartiles



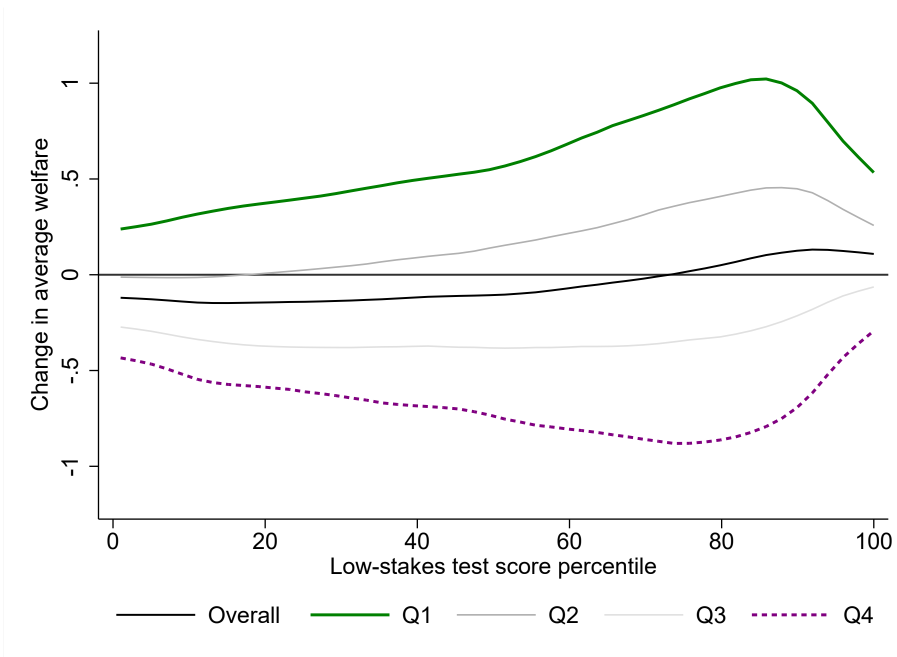
Note: Solid lines represent quantile-specific differences in standardized (mean zero, standard deviation 1) placement test scores between the specified predicted consumption quartiles. Dashed and dotted lines represent, respectively, the contribution of explained (characteristic) and unexplained (parameter) differences to this total. Decompositions are performed following the distribution regression approach in Chernozhukov, Fernández-Val, and Melly (2013).

Figure 5: Equilibrium effects of equalizing conditional score distributions on SES group-specific assignment rates, by low-stakes test score percentile



Note: Lines represent simulated effects on students in the indicated predicted consumption quartile and low-stakes test score percentile of changing conditional placement test score distributions (for all quartiles Q1-Q3) to match those of Q4, as described in Section 5.2. Vertical axis is the change in simulated proportion of students who are assigned to the indicated program type.

Figure 6: Equilibrium effects of equalizing conditional score distributions on welfare, by low-stakes test score percentile



Note: Lines represent simulated effects on students in the indicated predicted consumption quartile and low-stakes test score percentile of changing conditional placement test score distributions (for all quartiles Q1-Q3) to match those of Q4, as described in Section 5.2. Vertical axis is the change in simulated welfare, denominated in kilometers of one-way commuting distance.

Online Appendix A: Additional Tables and Figures

Table A.1: Private placement test preparation course participation by parental education level, 2014

	(1)	(2)	(3)	(4)	(5)
	< MS	MS	HS	College	College vs. < MS
Took private prep course	0.186	0.249	0.424	0.631	0.445
					(0.004)
Observations	20285	75884	88091	44089	64374

Note: The data source is the context questionnaire completed by COMIPEMS applicants for the 2014 cycle. Sample is limited to ninth graders in the COMIPEMS geographical zone with valid parental education measures. Parental education refers to level of attainment of the highest-educated parent. Columns 1 through 4 are proportions of students reporting participation in a placement test preparation course with a private institution or private teacher/tutor. Standard error for the difference between college and below middle school means is in parentheses in column 5.

Table A.2: School demographics, staffing, and academics by type

	(1) Elite	(2) Technical	(3) Traditional
Demographics and staffing			
Total number of students	5221.4	1357.5	1380.4
	(3118.51)	(628.48)	(1563.84)
Student-to-teacher ratio	16.8	20.1	18.3
	(3.07)	(5.92)	(3.69)
Percent of entering class that is female	45.6	47.4	54.3
	(11.46)	(13.80)	(5.62)
Academics			
Placement cutoff score	83.1	41.8	49.5
	(8.13)	(8.38)	(11.22)
Graduation rate	66.9	45.9	56.7
	(11.65)	(9.35)	(11.42)
Failure rate	16.7	31.0	31.7
	(21.30)	(9.24)	(8.45)
Observations	30	151	133

Note: Data are from the school census from 2004 through 2009, which provides data for aggregate campuses as opposed to COMIPEMS programs. Each observation represents the mean value for a campus from 2004 through 2009. Statistics, excluding total number of students, are weighted by average student population of each campus. The graduation rate is computed as the number of graduating students divided by the number of entering students in the corresponding cohort. Failures are defined as students failing between one and five subjects in a given year. Placement cutoff scores are from the 2007 and 2008 admissions cycle. Undersubscribed schools are given cutoff scores of 31, the minimum score to be assignable.

Table A.3: Household characteristics by consumption quartile

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q4-Q1
Asset Ownership					
Has housing with drainage	86.7	92.8	95.8	97.6	10.8
	(32.92)	(24.21)	(19.23)	(15.22)	(0.11)
Has housing with piped water	81.8	90.5	94.7	97.3	15.5
	(37.34)	(27.09)	(21.21)	(15.89)	(0.13)
Has garbage collection services	62.5	77.7	85.9	92.6	30.1
	(46.85)	(38.46)	(32.81)	(25.61)	(0.17)
Has hot water heater	37.4	60.2	79.9	94.2	56.8
	(46.89)	(45.54)	(37.82)	(22.66)	(0.16)
Has family automobile	16.7	26.7	40.8	67.8	51.1
	(35.77)	(40.61)	(46.15)	(45.68)	(0.18)
Has landline telephone	64.6	75.5	84.3	93.3	28.7
	(46.31)	(39.89)	(34.26)	(24.33)	(0.17)
Has cellular phone	39.5	48.9	61.1	80.0	40.5
	(47.23)	(46.32)	(45.84)	(38.95)	(0.19)
Has television	97.1	98.3	98.6	98.7	1.6
	(16.11)	(11.90)	(10.85)	(11.07)	(0.06)
Has cable or satellite television	4.9	9.3	17.0	39.5	34.6
	(20.57)	(25.98)	(34.79)	(47.96)	(0.17)
Has video recorder	27.3	35.0	44.3	62.3	35.0
	(42.93)	(43.99)	(46.64)	(47.42)	(0.20)
Has DVD player	66.7	78.3	85.8	93.1	26.4
	(45.69)	(38.27)	(32.69)	(24.49)	(0.16)
Has computer	19.0	34.2	53.0	80.4	61.4
	(37.79)	(43.82)	(46.96)	(38.70)	(0.17)
Has internet connection	4.4	9.9	20.1	49.1	44.7
	(19.60)	(26.94)	(37.19)	(49.00)	(0.17)
Geographical Location					
Resides in Federal District	31.6	38.8	47.6	58.5	27.0
	(46.48)	(48.72)	(49.94)	(49.26)	(0.21)
Resides in State of Mexico	68.4	61.2	52.4	41.5	-27.0
	(46.48)	(48.72)	(49.94)	(49.26)	(0.21)
Observations	99982	99982	99982	99981	199963

Continued: Household characteristics by consumption quartile

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q4-Q1
Income					
Monthly income per capita	321.3	703.4	1135.3	2459.0	2137.7
	(157.74)	(172.91)	(265.05)	(1143.66)	(3.65)
Demographics					
Father's age	43.0	42.1	42.3	43.3	0.3
	(6.85)	(5.99)	(5.92)	(6.14)	(0.03)
Mother's age	40.5	39.8	40.0	40.9	0.4
	(6.16)	(5.36)	(5.30)	(5.53)	(0.03)
Missing father's age	7.1	6.2	7.0	6.5	-0.6
	(24.05)	(20.99)	(23.03)	(23.38)	(0.11)
Missing mother's age	0.4	0.4	0.4	0.4	0.1
	(5.03)	(4.52)	(5.15)	(5.97)	(0.02)
Family size	5.8	4.9	4.4	3.9	-1.9
	(1.72)	(1.12)	(1.06)	(1.05)	(0.01)
Father's Education					
Less than primary	10.7	4.2	1.8	0.6	-10.1
	(29.38)	(17.88)	(12.51)	(7.21)	(0.10)
Primary	34.5	22.1	12.2	4.4	-30.2
	(45.43)	(38.00)	(30.62)	(19.85)	(0.16)
Secondary	34.8	41.0	35.1	18.6	-16.1
	(45.60)	(45.23)	(44.60)	(37.82)	(0.19)
Preparatoria/bachillerato/normal	11.8	23.0	34.1	37.5	25.7
	(30.90)	(38.72)	(44.20)	(47.07)	(0.18)
Technical/professional or higher	1.2	3.7	9.7	32.5	31.3
	(10.09)	(16.42)	(26.98)	(45.70)	(0.15)
Missing education	7.0	6.1	6.9	6.4	-0.6
	(24.58)	(21.40)	(23.41)	(23.89)	(0.11)
Mother's Education					
Less than primary	15.7	5.2	2.1	0.7	-15.0
	(34.78)	(19.93)	(13.32)	(7.97)	(0.11)
Primary	41.6	28.8	16.7	5.9	-35.7
	(47.20)	(41.60)	(34.94)	(22.91)	(0.17)
Secondary	32.2	40.9	37.0	21.0	-11.2
	(44.88)	(45.31)	(45.16)	(39.62)	(0.19)
Preparatoria/bachillerato/normal	9.6	23.1	38.8	51.3	41.6
	(28.09)	(38.75)	(45.51)	(48.67)	(0.18)
Technical/professional or higher	0.5	1.6	4.9	20.7	20.2
	(6.27)	(10.41)	(19.33)	(39.53)	(0.13)
Missing education	0.4	0.4	0.4	0.4	0.0
	(5.69)	(4.86)	(5.45)	(6.25)	(0.03)
Observations	99982	99982	99982	99981	199963

Note: Categories are aggregated or presented as continuous for display. Full model includes nine age categories, nine education categories, ten family size categories, and eighteen income categories.

Table A.4: Selection into COMIPEMS participation

	(1) Appears in COMIPEMS	(2) ENLACE 9 math score, normalized	(3) ENLACE 9 Spanish score, normalized
SES Quartile by Middle School Marginalization			
Q2	0.02	0.25	0.30
	(0.002)	(0.009)	(0.008)
Q3	0.03	0.47	0.50
	(0.002)	(0.009)	(0.008)
Q4	-0.03	1.05	1.10
	(0.002)	(0.008)	(0.008)
Appers in COMIPEMS X SES Quartile			
Appears in COMIPEMS sample		0.53	0.54
		(0.007)	(0.006)
Appears in COMIPEMS X Q2		-0.17	-0.19
		(0.010)	(0.009)
Appears in COMIPEMS X Q3		-0.28	-0.27
		(0.010)	(0.009)
Appears in COMIPEMS X Q4		-0.72	-0.72
		(0.010)	(0.009)
Constant	0.80	-0.31	-0.25
	(0.001)	(0.006)	(0.006)
Observations	541709	541709	541709

Note: Data are from 2007 and 2008 ENLACE 9 test takers who reside within the COMIPEMS geographical boundary. SES quartiles are based on a government-constructed marginalization index, where each student is assigned the index associated with her middle school location.

Table A.5: Decomposition of SES differences in mean placement test scores, including survey-based behavioral indices

	Q1 vs. Q4		Q2 vs. Q4		Q3 vs. Q4	
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Unexplained	Total	Unexplained	Total	Unexplained
Overall score	0.95	0.30	0.64	0.20	0.40	0.12
	(0.005)	(0.007)	(0.005)	(0.004)	(0.004)	(0.003)
		[31.6%]		[31.1%]		[29.3%]
Verbal reasoning	0.83	0.26	0.54	0.18	0.32	0.10
	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
		[31.9%]		[33.0%]		[31.1%]
Spanish	0.72	0.27	0.48	0.16	0.31	0.10
	(0.005)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
		[36.9%]		[33.3%]		[33.1%]
History	0.63	0.20	0.46	0.17	0.30	0.11
	(0.005)	(0.008)	(0.005)	(0.006)	(0.005)	(0.005)
		[32.5%]		[37.1%]		[36.3%]
Geography	0.73	0.26	0.51	0.19	0.31	0.12
	(0.005)	(0.008)	(0.005)	(0.006)	(0.004)	(0.004)
		[35.6%]		[37.4%]		[36.9%]
Civics and Ethics	0.74	0.25	0.51	0.18	0.33	0.12
	(0.004)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
		[34.1%]		[34.9%]		[36.4%]
Quantitative reasoning	0.70	0.17	0.43	0.08	0.24	0.03
	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
		[24.0%]		[18.1%]		[10.9%]
Math	0.63	0.14	0.41	0.07	0.25	0.03
	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)
		[23.2%]		[18.2%]		[13.5%]
Physics	0.66	0.22	0.45	0.15	0.29	0.09
	(0.005)	(0.008)	(0.005)	(0.004)	(0.005)	(0.004)
		[33.7%]		[32.2%]		[30.4%]
Chemistry	0.66	0.20	0.46	0.14	0.29	0.08
	(0.005)	(0.008)	(0.005)	(0.005)	(0.005)	(0.004)
		[30.9%]		[31.2%]		[27.4%]
Biology	0.73	0.26	0.51	0.18	0.32	0.11
	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)
		[35.1%]		[35.9%]		[35.3%]

Note: Rows represent subtests from the placement test. Odd columns contain estimated differences between the indicated predicted consumption quartiles in means of the standardized (mean zero, standard deviation 1) subscores. Even columns contain the portion of the mean difference that is not explained by observable characteristics in the DiNardo-Fortin-Lemieux decomposition. Bootstrapped standard errors are in parentheses. Unexplained proportion of the overall gap is in square brackets. Estimation sample is a subset of the non-survey sample because it drops students with missing responses to survey questions. Behavioral measures include information on weekly time spent doing homework, time spent reading, and subjective measures of self-efficacy, parental investment, and teacher behaviors.

Table A.6: Decomposition of SES differences in mean placement test scores, per capita household income

	Q1 vs. Q4		Q2 vs. Q4		Q3 vs. Q4	
	(1) Total	(2) Unexplained	(3) Total	(4) Unexplained	(5) Total	(6) Unexplained
Overall score	0.98	0.34	0.67	0.23	0.37	0.12
	(0.004)	(0.005)	(0.004)	(0.003)	(0.005)	(0.003)
		[34.6%]		[33.8%]		[32.9%]
Verbal reasoning	0.84	0.30	0.56	0.20	0.29	0.10
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
		[35.4%]		[35.9%]		[33.3%]
Spanish	0.73	0.28	0.50	0.18	0.28	0.10
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
		[38.8%]		[36.1%]		[34.9%]
History	0.65	0.24	0.48	0.19	0.29	0.12
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
		[37.6%]		[39.4%]		[41.4%]
Geography	0.75	0.29	0.53	0.21	0.30	0.12
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
		[39.0%]		[39.3%]		[40.7%]
Civics and Ethics	0.75	0.29	0.53	0.21	0.29	0.12
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
		[38.0%]		[39.0%]		[39.1%]
Quantitative reasoning	0.73	0.20	0.47	0.11	0.23	0.03
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.003)
		[26.7%]		[23.5%]		[14.9%]
Math	0.65	0.16	0.45	0.09	0.24	0.04
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.003)
		[24.6%]		[20.3%]		[16.5%]
Physics	0.68	0.24	0.48	0.16	0.28	0.09
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
		[35.8%]		[33.4%]		[34.0%]
Chemistry	0.69	0.24	0.49	0.16	0.29	0.10
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
		[34.7%]		[33.5%]		[35.2%]
Biology	0.75	0.28	0.53	0.20	0.30	0.12
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
		[37.8%]		[37.8%]		[38.7%]

Note: Rows represent subtests from the placement test. Odd columns contain estimated differences between the indicated household per capita income quartiles in means of the standardized (mean zero, standard deviation 1) subscores. Even columns contain the portion of the mean difference that is not explained by observable characteristics in the DiNardo-Fortin-Lemieux decomposition. Bootstrapped standard errors are in parentheses. Unexplained proportion of the overall gap is in square brackets.

Table A.7: Decomposition of SES differences in mean placement test scores, household asset index

	Q1 vs. Q4		Q2 vs. Q4		Q3 vs. Q4	
	(1) Total	(2) Unexplained	(3) Total	(4) Unexplained	(5) Total	(6) Unexplained
Overall score	0.75	0.24	0.60	0.19	0.32	0.09
	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.003)
		[31.9%]		[31.4%]		[28.6%]
Verbal reasoning	0.67	0.23	0.51	0.17	0.25	0.08
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
		[34.2%]		[33.9%]		[32.2%]
Spanish	0.57	0.21	0.45	0.15	0.23	0.07
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
		[36.8%]		[34.1%]		[30.0%]
History	0.49	0.16	0.40	0.14	0.22	0.07
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
		[32.2%]		[33.6%]		[30.0%]
Geography	0.59	0.21	0.46	0.17	0.25	0.09
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
		[36.6%]		[35.6%]		[35.6%]
Civics and Ethics	0.59	0.22	0.47	0.17	0.23	0.08
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
		[36.7%]		[36.8%]		[32.6%]
Quantitative reasoning	0.56	0.14	0.44	0.10	0.22	0.04
	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)
		[24.9%]		[23.2%]		[19.3%]
Math	0.48	0.10	0.40	0.08	0.21	0.03
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
		[20.2%]		[20.4%]		[14.3%]
Physics	0.52	0.16	0.42	0.13	0.23	0.07
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)
		[31.0%]		[31.1%]		[28.3%]
Chemistry	0.52	0.16	0.44	0.14	0.24	0.07
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
		[30.8%]		[31.9%]		[30.4%]
Biology	0.58	0.20	0.46	0.16	0.25	0.08
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)
		[35.3%]		[34.6%]		[32.3%]

Note: Rows represent subtests from the placement test. Odd columns contain estimated differences between the indicated household asset index quartiles in means of the standardized (mean zero, standard deviation 1) subscores. Even columns contain the portion of the mean difference that is not explained by observable characteristics in the DiNardo-Fortin-Lemieux decomposition. Bootstrapped standard errors are in parentheses. Unexplained proportion of the overall gap is in square brackets.

Table A.8: Decomposition of SES differences in mean placement test scores, parental education

	< MS vs. College		MS vs. College		HS vs. College	
	(1) Total	(2) Unexplained	(3) Total	(4) Unexplained	(5) Total	(6) Unexplained
Overall score	1.08	0.36	0.90	0.28	0.51	0.15
	(0.005)	(0.007)	(0.005)	(0.004)	(0.005)	(0.003)
		[33.5%]		[30.4%]		[28.5%]
Verbal reasoning	0.93	0.31	0.75	0.24	0.40	0.12
	(0.005)	(0.007)	(0.005)	(0.004)	(0.005)	(0.003)
		[34.0%]		[31.3%]		[29.9%]
Spanish	0.83	0.30	0.68	0.21	0.39	0.12
	(0.005)	(0.008)	(0.005)	(0.004)	(0.005)	(0.004)
		[36.5%]		[31.3%]		[30.0%]
History	0.76	0.30	0.66	0.26	0.40	0.15
	(0.005)	(0.007)	(0.006)	(0.005)	(0.005)	(0.004)
		[39.4%]		[38.6%]		[38.6%]
Geography	0.82	0.32	0.70	0.25	0.40	0.14
	(0.005)	(0.008)	(0.005)	(0.005)	(0.005)	(0.004)
		[38.3%]		[36.5%]		[35.3%]
Civics and Ethics	0.85	0.31	0.71	0.25	0.41	0.14
	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)
		[37.0%]		[35.5%]		[34.1%]
Quantitative reasoning	0.75	0.16	0.59	0.09	0.31	0.03
	(0.006)	(0.007)	(0.005)	(0.005)	(0.004)	(0.003)
		[21.2%]		[14.6%]		[9.2%]
Math	0.70	0.15	0.59	0.10	0.35	0.05
	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)
		[21.3%]		[17.2%]		[13.2%]
Physics	0.76	0.26	0.65	0.20	0.38	0.11
	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)
		[34.8%]		[31.3%]		[29.2%]
Chemistry	0.78	0.27	0.67	0.21	0.40	0.12
	(0.006)	(0.008)	(0.005)	(0.005)	(0.005)	(0.004)
		[34.8%]		[31.5%]		[30.4%]
Biology	0.86	0.34	0.73	0.28	0.41	0.14
	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)
		[40.0%]		[37.7%]		[34.9%]

Note: Rows represent subtests from the placement test. Odd columns contain estimated differences between the indicated parental education groups in means of the standardized (mean zero, standard deviation 1) subscores. Categories reflect the parent with the highest level of education. Even columns contain the portion of the mean difference that is not explained by observable characteristics in the DiNardo-Fortin-Lemieux decomposition. Bootstrapped standard errors are in parentheses. Unexplained proportion of the overall gap is in square brackets.

Table A.9: Decomposition of SES differences in mean placement test scores, by gender

	Pooled		Female		Male	
	(1) Total	(2) Unexplained	(3) Total	(4) Unexplained	(5) Total	(6) Unexplained
Overall score	1.04	0.37	1.00	0.33	1.05	0.37
	(0.004)	(0.005)	(0.006)	(0.007)	(0.006)	(0.009)
		[35.9%]		[33.3%]		[35.1%]
Verbal reasoning	0.91	0.34	0.91	0.31	0.90	0.33
	(0.004)	(0.005)	(0.006)	(0.007)	(0.006)	(0.008)
		[37.2%]		[34.3%]		[36.7%]
Spanish	0.78	0.30	0.78	0.27	0.80	0.31
	(0.004)	(0.006)	(0.005)	(0.008)	(0.006)	(0.010)
		[38.8%]		[34.8%]		[38.8%]
History	0.69	0.26	0.63	0.23	0.71	0.28
	(0.004)	(0.006)	(0.006)	(0.008)	(0.006)	(0.010)
		[38.6%]		[36.8%]		[39.1%]
Geography	0.80	0.33	0.76	0.30	0.79	0.31
	(0.004)	(0.006)	(0.006)	(0.008)	(0.006)	(0.010)
		[41.4%]		[39.4%]		[39.4%]
Civics and Ethics	0.81	0.32	0.80	0.29	0.83	0.32
	(0.004)	(0.006)	(0.006)	(0.008)	(0.006)	(0.009)
		[39.8%]		[36.0%]		[39.0%]
Quantitative reasoning	0.78	0.21	0.75	0.19	0.77	0.20
	(0.004)	(0.005)	(0.006)	(0.007)	(0.006)	(0.009)
		[27.6%]		[25.3%]		[26.4%]
Math	0.68	0.18	0.63	0.14	0.69	0.18
	(0.004)	(0.006)	(0.006)	(0.008)	(0.007)	(0.008)
		[26.4%]		[22.2%]		[26.4%]
Physics	0.72	0.26	0.68	0.24	0.73	0.26
	(0.004)	(0.006)	(0.006)	(0.008)	(0.006)	(0.011)
		[36.3%]		[35.9%]		[34.9%]
Chemistry	0.72	0.25	0.69	0.23	0.75	0.27
	(0.004)	(0.005)	(0.006)	(0.009)	(0.006)	(0.009)
		[35.2%]		[33.1%]		[35.7%]
Biology	0.80	0.32	0.75	0.28	0.81	0.30
	(0.004)	(0.006)	(0.005)	(0.007)	(0.007)	(0.010)
		[39.5%]		[37.6%]		[36.9%]

Note: Rows represent subtests from the placement test. Odd columns contain estimated differences between the indicated predicted consumption quartiles in means of the standardized (mean zero, standard deviation 1) subscores. Even columns contain the portion of the mean difference that is not explained by observable characteristics in the DiNardo-Fortin-Lemieux decomposition. Bootstrapped standard errors are in parentheses. Unexplained proportion of the overall gap is in square brackets.

Table A.10: Decomposition of SES differences in mean placement test scores, from distribution regression

	(1) Q1 vs. Q4	(2) Q2 vs. Q4	(3) Q3 vs. Q4
Total (raw)	-20.60	-14.56	-8.20
	(0.096)	(0.100)	(0.128)
Explained	-13.84	-9.84	-5.74
	(0.120)	(0.086)	(0.093)
	[67.2%]	[67.6%]	[70.0%]
Unexplained	-6.76	-4.72	-2.46
	(0.112)	(0.078)	(0.092)
	[32.8%]	[32.4%]	[30.0%]
Total (standardized)	-1.04	-0.74	-0.41
	(0.005)	(0.005)	(0.006)
Explained	-0.70	-0.50	-0.29
	(0.006)	(0.004)	(0.005)
	[67.2%]	[67.6%]	[70.0%]
Unexplained	-0.34	-0.24	-0.12
	(0.006)	(0.004)	(0.005)
	[32.8%]	[32.4%]	[30.0%]

Note: Raw scores are placement test scores (ranging from 0 to 128). Standardized scores are transformations of the raw scores (mean zero, standard deviation 1). Total differences are between the specified predicted consumption quartile and Q4. Explained and unexplained entries represent, respectively, the contribution of explained (characteristic) and unexplained (parameter) differences to this total. Decompositions are performed following the distribution regression approach in Chernozhukov, Fernández-Val, and Melly (2013). The resulting quantile-specific estimates are integrated to obtain the mean decomposition. Bootstrapped standard errors are in parentheses. Contributions as a percentage of the overall difference are in square brackets.

Table A.11: Model fit

	Simulated					Actual				
	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q4-Q1	(6) Q1	(7) Q2	(8) Q3	(9) Q4	(10) Q4-Q1
Elite	8.5	15.5	26.1	42.2	33.8	8.5	15.5	26.1	42.3	33.8
	(0.07)	(0.09)	(0.09)	(0.10)	(0.14)					
Technical	44.5	38.1	29.0	18.5	-25.9	44.8	38.4	29.2	18.6	-26.2
	(0.20)	(0.19)	(0.17)	(0.16)	(0.26)					
Traditional academic	30.6	31.2	30.1	25.0	-5.5	29.6	30.0	29.0	24.2	-5.4
	(0.18)	(0.17)	(0.17)	(0.17)	(0.27)					
Unassigned	16.5	15.3	14.8	14.2	-2.3	17.1	16.1	15.7	14.9	-2.2
	(0.13)	(0.14)	(0.13)	(0.13)	(0.19)					

Note: Columns 1 through 4 report the simulated predicted consumption quartile-specific proportions of assigned students who were assigned to the indicated program type. Column 5 shows the simulated Q4-Q1 difference. Proportions are means over 100 independent simulations of the assignment process accounting for uncertainty in student preference parameters, idiosyncratic student preferences, and random tie-breakers in assignment. Standard deviations of the simulated proportions are in parentheses. Columns 6 through 10 show the actual proportions (and differences) in the data. Proportions are reported in percentages. Simulations are as described in Section 5.2, using estimated student preferences from the procedure described in Section 5.1.1.

Table A.12: Decomposition of elite and technical program assignment gaps, SES quartile 2 vs quartile 4 (richest)

	(1) Elite	(2) Technical	(3) Traditional academic	(4) Unassigned
Q4 assignment rate	42.3	18.6	24.2	14.9
Q2 assignment rate	15.5	38.4	30.0	16.1
Assignment gap	26.8	-19.8	-5.8	-1.2
Contribution of preference parameter differences	1.9	-11.2	-0.3	9.6
	(0.05)	(0.12)	(0.02)	(0.09)
	[7.2%]	[56.8%]	[4.4%]	[-837.5%]
Contributions of differences in student characteristics				
Placement test score (explained)	16.8	-4.9	-2.0	-9.9
	(0.01)	(0.10)	(0.03)	(0.07)
	[62.8%]	[24.6%]	[34.0%]	[870.4%]
Placement test score (unexplained)	6.7	-2.4	0.1	-4.4
	(0.01)	(0.03)	(0.01)	(0.02)
	[25.0%]	[11.9%]	[-2.1%]	[388.6%]
Commuting distance	0.9	-0.4	-3.0	2.4
	(0.01)	(0.03)	(0.02)	(0.04)
	[3.5%]	[2.1%]	[51.0%]	[-212.8%]
ENLACE 9 score	0.2	-1.0	-0.7	1.4
	(0.02)	(0.20)	(0.02)	(0.24)
	[0.8%]	[4.8%]	[11.4%]	[-123.2%]
Middle school GPA	0.1	-0.3	0.1	0.1
	(0.01)	(0.02)	(0.07)	(0.11)
	[0.3%]	[1.4%]	[-2.2%]	[-5.9%]
Gender	0.1	0.3	-0.2	-0.2
	(0.02)	(0.02)	(0.05)	(0.01)
	[0.4%]	[-1.7%]	[3.6%]	[20.2%]
Total	24.8	-8.6	-5.5	-10.7
	(0.05)	(0.12)	(0.02)	(0.09)
	[92.8%]	[43.2%]	[95.6%]	[937.5%]

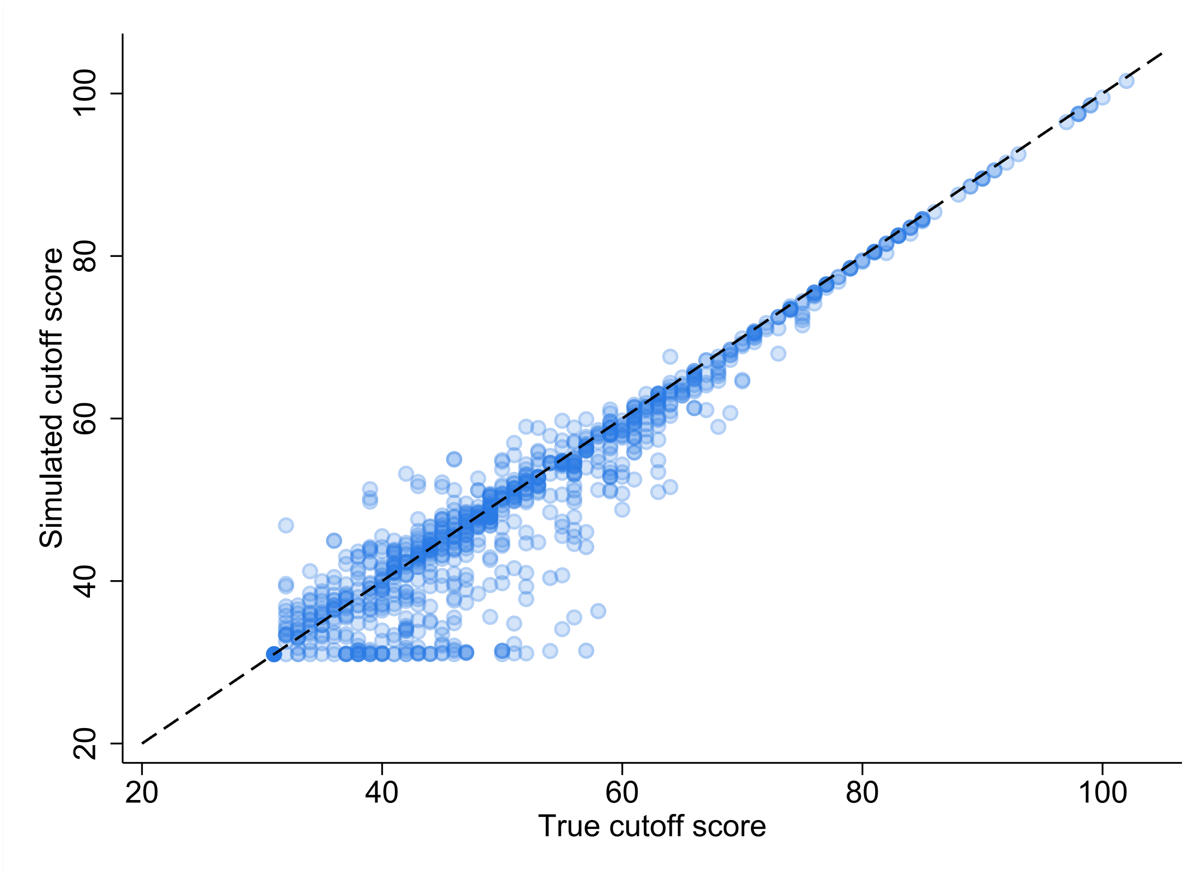
Note: Entries correspond to the nonlinear decomposition of the probability of assignment to elite (column 1) or technical (column 2) programs among students receiving any assignment, following the decomposition procedure described in Section 5.1.3. SES quartiles are determined by predicted consumption. Detailed decomposition contributions are means across 50 simulations. Bootstrapped standard errors are in parentheses. Proportions of total gap explained are in square brackets.

Table A.13: Decomposition of elite and technical program assignment gaps, SES quartile 3 vs quartile 4 (richest)

	(1) Elite	(2) Technical	(3) Traditional academic	(4) Unassigned
Q4 assignment rate	42.3	18.6	24.2	14.9
Q3 assignment rate	26.1	29.2	29.1	15.6
Assignment gap	16.2	-10.6	-4.9	-0.7
Contribution of preference parameter differences	1.1	-5.3	-0.7	4.9
	(0.04)	(0.32)	(0.20)	(0.09)
	[6.6%]	[50.4%]	[14.0%]	[-715.9%]
Contributions of differences in student characteristics				
Placement test score (explained)	10.9	-2.9	-1.8	-6.2
	(0.00)	(0.08)	(0.03)	(0.05)
	[67.5%]	[27.4%]	[37.7%]	[891.9%]
Placement test score (unexplained)	3.8	-1.4	-0.5	-1.9
	(0.01)	(0.02)	(0.01)	(0.01)
	[23.4%]	[13.1%]	[10.9%]	[269.5%]
Commuting distance	0.6	-0.3	-1.5	1.3
	(0.02)	(0.03)	(0.02)	(0.03)
	[3.6%]	[2.6%]	[31.9%]	[-181.5%]
ENLACE 9 score	-0.0	-0.8	-0.4	1.2
	(0.02)	(0.14)	(0.01)	(0.15)
	[-0.2%]	[7.3%]	[8.9%]	[-178.4%]
Middle school GPA	-0.2	-0.1	0.3	0.1
	(0.01)	(0.00)	(0.07)	(0.09)
	[-1.2%]	[1.3%]	[-5.8%]	[-7.7%]
Gender	0.1	0.2	-0.1	-0.2
	(0.03)	(0.02)	(0.05)	(0.00)
	[0.3%]	[-2.1%]	[2.5%]	[22.1%]
Total	15.1	-5.3	-4.2	-5.6
	(0.04)	(0.32)	(0.20)	(0.09)
	[93.4%]	[49.6%]	[86.0%]	[815.9%]

Note: Entries correspond to the nonlinear decomposition of the probability of assignment to elite (column 1) or technical (column 2) programs among students receiving any assignment, following the decomposition procedure described in Section 5.1.3. SES quartiles are determined by predicted consumption. Detailed decomposition contributions are means across 50 simulations. Bootstrapped standard errors are in parentheses. Proportions of total gap explained are in square brackets.

Figure A.1: Model fit: simulated versus actual program cutoffs



Note: Markers and lines correspond to program-by-year cutoff score pairs, where the x-axis is the true cutoff score and the y-axis is the simulated cutoff score resulting from simulating assignment under the status quo priority structure as described in Section 5.2. Cutoff scores are the lowest placement test score a student could obtain and be assigned, and are set to 31 (the minimum to be eligible for assignment) for programs that are not oversubscribed. Opacity is determined by true enrollment counts in the respective year, such that darker points indicate higher enrollment. Dashed line is a 45-degree line.

Online Appendix B: Decomposition details

Here we provide more detail on our implementation of DiNardo, Fortin, and Lemieux (1996) for decomposing placement test scores. The method decomposes group differences using a semi-parametric reweighting procedure, allowing for a flexible relationship between student characteristics and test scores. Students belong to SES groups $W \in \{H, L\}$. While we divide students into quartiles based on predicted consumption, each decomposition will restrict the sample to compare the top quartile ($W = H$) and one of the three lower quartiles, setting that group to $W = L$, and dropping the other quartiles. Students have a vector C of characteristics that may predict test scores and SES group. The difference in mean scores between groups is $\Delta = E[S|W = H] - E[S|W = L]$. The overall difference is composed of a component explained by group differences in C and an unexplained (residual) component: $\Delta = \Delta_C + \Delta_U$. To quantify these components, we estimate the counterfactual distribution of test scores for low SES students if they were to have the same observable characteristics as high SES students. We first calculate the probability of being high-SES conditional on observables, next reweight the low SES score distribution, and then estimate Δ_U by comparing the means of the reweighted data. Following DiNardo, Fortin, and Lemieux (1996), the reweighting function for low-SES students is:

$$\psi(C) = \frac{Pr(W = H|C)}{1 - Pr(W = H|C)} \cdot \frac{1 - Pr(W = H)}{Pr(W = H)}.$$

We estimate $Pr(W = H)$ using the sample proportion of high-SES students and $Pr(W = H|C)$ using a logit function, where C consists of cubic polynomials in low-stakes language and math subscores, a dummy variable for missing low-stakes score, middle school GPA, interactions between subscores and GPA, year-by-municipality of residence fixed effects, gender, and interactions of gender with each of these measures.[1] The estimated overall difference $\widehat{\Delta}$ is computed using the sample conditional means. After estimating $\widehat{\Delta}_U$ using the reweighted means, we estimate the explained component by the difference $\widehat{\Delta}_C = \widehat{\Delta} - \widehat{\Delta}_U$. Standard errors for the difference and its components are computed using a bootstrap procedure.

1. The gender interactions are motivated by the observation in Ngo and Dustan (2024) that male students have higher placement test scores than female students conditional on low-stakes test scores.