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【要旨】

This study constructs and estimates a structural equilibrium model of the medical school market in which students strategically apply to schools, and admission probabilities at specific institutions are endogenously determined. It empirically analyzes how gender differences in preferences related to distance from home impact gender disparities in public medical school admissions in Japan. Our results indicate that females incur greater costs associated with distance compared to males. While financial aid to offset distance-related costs can increase the proportion of female applicants to medical schools, it does not lead to a corresponding increase in female admissions due to the effects of competition. We propose a financially feasible alternative affirmative action policy that provides financial aid exclusively to female students to reduce the gender gap.

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Distance to Medical Schools and Its Impact on the Gender Gap in Admissions: An Equilibrium Approach*

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April 25, 2025

Abstract

This study constructs and estimates a structural equilibrium model of the medical school market in which students strategically apply to schools, and admission probabilities at specific institutions are endogenously determined. It empirically analyzes how gender differences in preferences related to distance from home impact gender disparities in public medical school admissions in Japan. Our results indicate that females incur greater costs associated with distance compared to males. While financial aid to offset distance-related costs can increase the proportion of female applicants to medical schools, it does not lead to a corresponding increase in female admissions due to the effects of competition. We propose a financially feasible alternative affirmative action policy that provides financial aid exclusively to female students to reduce the gender gap.

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1 Introduction

Evidence suggests that the distance to a college impedes students from applying to that particular college (e.g., Acton et al. (2024)). Additionally, research indicates that improving access to schools increases enrollment among girls more than boys in many developing countries (e.g., Burde and Linden (2013) and Muralidharan and Prakash (2017)). While many developed countries have numerous schools within reach, gender differences in the costs associated with distance from home may still persist. Consequently, even in developed countries, the economic significance of college distance may vary between men and women. As college choice can substantially impact lifetime earnings in many developed countries (e.g., Hoekstra (2009) and Dale and Krueger (2014)), disparities in access to colleges could contribute to gender income differences.

This effect may be particularly pronounced for medical schools. Graduating from a medical school is a prerequisite for sitting for the national examination required for a medical license, which qualifies one for a medical profession. Therefore, if gender differences in preferences about distance from home exist, the distance to medical schools could lead to an uneven gender representation in the medical profession, leading to gender income differences as this is one of the high-income occupations.

This study examines the geography of public medical school opportunities by constructing an equilibrium model of the medical school market wherein students strategically apply to schools and admission probabilities at particular institutions are endogenously determined. Relying on entrance examination data for Japanese public medical schools, we use this model to estimate gender differences in preferences related to distance from home and analyze how these differences affect gender disparities in medical school admissions in Japan.

Focusing on the entrance examination for Japanese public medical schools offers several advantages for our analysis. First, the proportion of female students is smaller than that of male students in Japan, indicating a significant gender gap in admissions to Japanese medical schools (MEXT, School Basic Survey). Importantly, the gender gap in admission may be at least partially attributed to the distance to public medical schools. As shown in Table 1, female applicants, on average, apply to medical schools situated approximately 20 kilometers (or 10%) closer to their residence than their male counterparts. This pattern may reflect structural and socio-cultural factors, including familial expectations, safety concerns, or limited access to information and preparatory resources. Notably, public medical schools in Japan are geographically dispersed to promote equitable access to healthcare across regions. However, their admissions capacity does not necessarily correspond to the regional distribution of applicants. Consequently, applicants residing in areas with smaller admission capacities may face intensified competition. If female applicants are more geographically constrained in their application choices, such regional imbalances may disproportionately hinder their admission prospects. Thus, the spatial distribution of medical schools may serve as a structural barrier contributing to persistent gender disparities in medical school admissions.

Table 1: Distance (km) by gender: Students who applied to medical schools

	mean	sd	p25	p50	p75
Female	205.1	256.7	39.5	93.1	266.6
Male	228.2	287.0	43.1	117.8	284.2
Total	220.4	277.4	39.5	109.3	280.7

Note: The distance is determined by calculating the distance from the address of each municipal office in the student's high school's prefecture to the university's address and then taking the median of these distances. Authors constructed this table using data provided by a college Prep School in Japan

Second, focusing on Japanese public medical schools has several technical advantages. A key characteristic of the higher education market is that students cannot purchase a service from a school without an admission, and the probability of admission is influenced by the school's demand and supply, which is constrained by its capacity. This feature complicates the construction of an equilibrium model, which can partially be mitigated by narrowing our focus to Japanese public medical schools. This enables the construction of a relatively simple equilibrium model, as follows:

1) As each student in Japan is allowed to apply to only one public university, or at most two, we can avoid the complexities associated with a multiple-choice model. 2) The number of Japanese public medical schools is limited to 50, which constrains the choice set for each applicant. 3) Because the capacity and tuition of Japanese public universities are heavily regulated, we can treat the supply-side decision as fixed. 4) Public medical schools have lower tuition fees compared to private medical schools and are generally more prestigious. It is, therefore, reasonable to assume that admitted students will enroll and treat entering private medical schools as an option, in the event of failing the examination for public universities. 5) Because enrollment in medical school implies students' primary aim to become qualified doctors, we assume that students applying to medical schools do not seriously consider other departments. Thus, it is reasonable to treat medical school admissions as a distinct market, with other departments serving as outside options. These factors contribute to a more manageable modeling environment for analyzing the admissions market in Japanese public medical schools.

This model incorporates the institutional features of the Japanese public university entrance examination. As explained in more detail below, applicants to public universities in Japan must take two examinations whose combined results determine the applicants' admission outcomes. The first exam is the National Center Test for University Admissions (hereafter referred to as the Center Test)[1]. After receiving their Center Test scores, students decide which public university to apply to. Thereafter, each public university conducts its own entrance examination as a second exam and selects successful candidates based on both the Center Test scores and the results of the second exam.

We obtain individual-level micro data collected by a preparatory school in Japan for students who took the Center Test in 2011. These data include the university each student applied to, the results of their applications (success or failure), Center Test scores, gender,

[1]This test was renamed the Center Test for University Admissions in 2021. As this study analyzes data from before 2021, we use the term "the Center Test."

and the prefecture of the high school that students belong to. Additionally, we use market –level data, which include the number of applicants and admitted students by university.

Combining the individual- and market-level datasets, we adopt an estimation approach developed and widely applied in industrial organization literature (e.g., Petrin, 2002; Berry, Levinsohn, and Pakes, 2004; Goolsbee and Petrin, 2004; Train and Whinston, 2007). A key distinction from previous studies is that our estimation explicitly incorporates the equilibrium condition determining the minimum admission scores. Specifically, for each parameter value in the model, we simultaneously derive both the college-specific mean utilities and the equilibrium minimum scores through a contraction mapping procedure: the former is obtained by matching predicted application shares to their observed counterparts, as proposed by Berry, Levinsohn, and Pakes (1995), and the latter by ensuring that the predicted numbers of admitted students align precisely with the observed admission capacities at each institution.

Our results suggest that females incur greater costs associated with distance, measured by the Euclidean distance between the prefecture of the student's high school and that of the university. In other words, we find evidence that gender differences in the costs associated with distance from home impact college choice decisions in a developed country such as Japan.

Based on the estimated model, we conduct two counterfactual simulations. First, we consider a policy in which the government provides financial aid to offset distance-related costs. We find that this policy increases the number of male applicants by 98 percent and that of female applicants by 130 percent. Consequently, as expected, this policy increases the proportion of female applicants to medical schools from 0.33 to 0.37.

In actuality, however, this policy reduces the proportion of admitted females from 0.23 to 0.21. This is due to competition effects: while the number of applicants increases, the capacity of medical schools remains unchanged. Consequently, admission to medical schools becomes more competitive, crowding out less qualified students and leading to a decline in the share of female admits.

After obtaining a seemingly surprising result from the previous counterfactual simulation, we conduct a second one. Assuming that gender differences in preferences regarding the distance from home reflect social constraints on female students, we consider an affirmative action policy in which the government provides financial aid exclusively to females to offset gender differences in the cost of distance. It should be noted that, unlike the proposal to introduce a gender quota as an affirmative action policy for female students, our proposed affirmative action policy allows female students to compete under the same conditions as male students. Therefore, an increase in female student dropouts owing to this affirmative action policy is not a matter of concern.

We find that this policy increases the number of female applicants to medical schools by 10 percent, while reducing that of male applicants by 2 percent. Consequently, the proportion of admitted females rises from 0.23 to 0.28. Furthermore, this affirmative action policy is financially feasible, with the average financial aid per admitted female students by university ranging from 10,000 to 150,000 Japanese yen per year. These figures can serve as a basis for a constructive policy debate.

Several studies analyze college choice models through the lens of structural models (e.g., Arcidiacono (2005), Howell (2010) and Fu et al. (2022)). The closest related work is by Fu et al. (2022), who estimate a model of high school students' college choices and analyze how uneven access to colleges impacts student welfare. Compared to their study, we focus on a different question: how distance to colleges affects gender differences in medical school admissions. Additionally, we construct an equilibrium model, whereas their study addresses a decision problem. This equilibrium model is crucial for our analysis, as we cannot assess competition effects without it. Our results suggest that reducing distance costs increases the share of female applicants, but it does not increase the share of admitted females due to competition effects. Therefore, without considering equilibrium dynamics, policy implications may be misleading.

Equilibrium models of the college market have been analyzed in various studies (e.g., Epple et al. (2006), Bordon and Fu (2015), Epple et al. (2017), Epple et al. (2019), and Fillmore (2023)). Following the pioneering work of Fu (2014), more recent studies, such as Kapor (2020), Bleemer (2021), and Cook (2024), have explicitly modeled application decisions while accounting for the possibility of rejection after applying.

Although we build on this line of research, the specific structure of the Japanese public education system allows us to construct a much more simplified model. This simplification makes the identification of our model and the interpretation of the results more transparent and intuitive. We can apply standard discrete choice demand estimation methods that incorporate both micro-level and aggregate data (e.g., Petrin (2002), Berry et al. (2004), Goolsbee and Petrin (2004), and Train and Winston (2007)). Equipped with this simple model, we address the economic impact of college distance on gender disparities in admissions—an issue not explored in previous literature.

Some studies have argued that gender differences in time flexibility (e.g., Bertrand et al. (2010) and Goldin (2014)) and willingness to commute (e.g., Barbanchon et al. (2021)) help to explain the persistent gender wage gap in developed countries. This study examines a related but somewhat overlooked factor: how gender differences in preferences on distance from home influence college choices, potentially affecting future earnings. We find existence of such gender differences, which impact the gender composition in Japanese medical schools.

The paper is organized as follows. The next section explains the institutional background of the Japanese medical education system and the entrance examination for medical schools. In the third section, we present our equilibrium model for the medical school admission market. The fourth section describes the dataset, model specification, and empirical procedure and presents estimation results and model fits. In the fifth section, we conduct two counterfactual policy experiments: financial aid to offset distance-related costs and financial aid exclusively for females to mitigate gender differences in the cost of distance. The final section concludes.

2 Institutional Background

2.1 Medical Education System in Japan

In Japan, medical education is offered through 81 medical schools across the nation, categorized into three types: 42 national, 8 prefectural, and 31 private institutions[2]. In this study, we collectively refer to national and prefectural institutions as public universities (50 medical schools in total). Tuition fees differ significantly between public and private medical schools, with the latter being approximately ten times more expensive. Additionally, public medical schools limit applicants to only one institution per application round, whereas private medical schools allow unrestricted applications. Due to these fundamental differences between the two types, we consider them as separate markets; therefore, this study's main analysis focuses on public medical schools.

Unlike in the United States, where medical school typically follows undergraduate education, Japanese medical schools provide a six-year continuous program that students enter directly after graduating from high school. This structure resembles the systems in some European countries.[3] Although some Japanese medical schools have introduced programs for college graduates, these positions represent less than 10% of the total enrollment (Kozu, 2006).

Japan's rapidly aging population has led to increasing healthcare demands, but the supply of physicians has remained insufficient. Recognizing this growing disparity between healthcare demand and physician supply, the Japanese government has gradually increased its medical school enrollment capacity. In the early 2000s, the enrollment capacity was just

[2]The National Defense Medical College operates independently from the framework of these universities. Its entrance examination schedule differs significantly from that of other universities, and due to the lack of applicant data, it has been excluded from this analysis.

[3]In many European countries, such as Germany, France, Italy, and the UK, students join medical school directly after obtaining a high school qualification. These programs typically provide six years of continuous medical education (or 5-6 years in the UK), combining foundational and clinical training in one integrated pathway that leads directly to licensure. Unlike in the United States and Canada, where medical school requires an undergraduate degree, this approach allows students to qualify as doctors without prior university study.

under 8,000 students; by 2019, this increased to nearly 9,500 students (MEXT, School Basic Survey). Despite this increase, significant challenges persist in both the geographical and demographic distribution of medical students and practicing physicians.

First, the geographical distribution of Japan's medical schools reflects the regional disparities, influencing both access to medical education and healthcare delivery. Public medical schools are located across the country, with at least one institution in almost every prefecture, indicating a deliberate effort to enhance regional healthcare and ensure equitable distribution of physicians. By contrast, private medical schools are disproportionately concentrated in urban areas, particularly in the greater Tokyo region. This urban concentration contributes to persistent disparities in physician density across regions. For instance, Tokyo boasts 11 doctors per 1,000 people, compared to just 0.4 per 1,000 in northeastern Japan (Suzuki et al., 2008).

Second, gender disparity is another significant characteristic of Japanese medical education. While the proportion of female medical students has gradually increased over time, their representation remains low compared to that in other developed countries. Since the early 2000s, the percentage of female students in Japanese medical schools has increased from approximately 30% to over 40% in the 2020s (MEXT, School Basic Survey). Despite this progress, women remain underrepresented relative to their share in the general population. Additionally, the acceptance rate for female applicants has consistently been lower than that for male applicants. For instance, in 2017, 5.9% of female applicants successfully gained admission to medical schools compared to 6.6% of male applicants. This is a significant disparity compared to other competitive fields in Japan, such as science, where the acceptance rates for male and female applicants were equal (11.6%), or engineering, where female applicants had a slightly higher acceptance rate (12.2%) than their male counterparts (Fukami et al., 2022).[4]

[4]In 2018, Tokyo Medical University, a private medical school, was found to have systematically discriminated against female applicants by manipulating their entrance examination scores. This scandal prompted investigations into other medical schools and led to subsequent reforms in the admissions process (Wheeler, 2018). Responding to these findings, MEXT conducted an emergency investigation into fairness in medical

2.2 Entrance Examination to Medical School

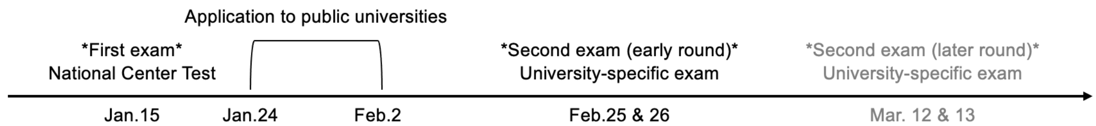
The admission process for Japanese medical schools is complex and distinct from those in other countries, with written examinations serving as the primary selection criterion. Japanese medical school admissions are integrated into the broader university entrance system, differing from those in some countries where medical school admissions follow a separate track. Medical school admissions are widely regarded as among the most challenging in Japan, often considered significantly more difficult than entry into other academic programs. This is due to the limited available capacity in medical schools compared to the high number of applicants, as well as the demanding curriculum and societal expectations on future medical professionals.

The entrance exams to public universities, including public medical schools in Japan, comprise two stages. Applications to public universities are submitted after the completion of the first exam and before the second exam. The timeline of the 2011 university entrance examination is illustrated in Figure 1. The Japanese university entrance examination system is decentralized rather than centralized, with each university conducting its own examinations and independently determining successful applicants. Each university determines the weighting of the scores of the first and second stages in the overall evaluation and the distribution of the subject scores within each stage. These weightings are disclosed to the applicants in advance. The enrollment capacity for each university and faculty is predetermined, and each university sets its admission cutoff scores to ensure that the number of admitted students remains within this limit.

The first stage, known as the Center Test for University Admissions, is a standardized national exam. The Center Test is conducted only once in a year. Students choose and take subjects from the five available options (Japanese, Mathematics, English, Science, and Social

school admissions, covering entrance exams from 2016 to 2018 (MEXT, 2018). The investigation identified six private universities that engaged in score manipulation based on gender and age, but no public universities were named for such misconduct. As our study focuses on entrance exams for public medical schools, the impact of such discrimination against female applicants is expected to be minimal.

Figure 1: Timeline of the 2011 University Entrance Examination



Studies), considering the subject requirements of the universities to which they will apply. Additionally, each subject consists of multiple disciplines (for instance, Science includes Physics, Chemistry, Biology, and Earth Science), and students can select their preferred discipline from among them. As the results of the Center Test serve as a comparable metric, this study also treats Center Test scores as individual attributes. Specifically, the three subjects—English, Mathematics, and Japanese—are referred to as "core subjects" in this study as they are required by many universities. For the medical schools examined in this study, applicants must take all five subjects[5].

The second stage examinations conducted by public universities are divided into two types: early round and later round examinations. These two rounds provide applicants with the opportunity to apply to different universities, with the later round serving as a fallback for those who did not pass their preferred university in the early round. Early round examinations are the primary focus for most applicants, as they are conducted by almost all public medical schools and offer most available slots. By contrast, later round examinations typically have fewer available slots and involve alternative assessment formats, such as comprehensive questions, essays, and interviews, which may prioritize holistic evaluation over purely academic performance[6]. Therefore, we focus solely on early round examinations. In this case, applicants are restricted to applying to only one public university. As medical

[5] In each subject, the specific disciplines required may be determined by each medical school. In some cases, applicants can choose from a set of disciplines. For example, for Science, some schools require Physics and Chemistry, whereas others allow applicants to select two subjects from Physics, Chemistry, and Biology.

[6] Due to the impact of the Great East Japan Earthquake that occurred on March 11, 2011, some universities did not conduct their later round individual entrance exams. For these universities, admission decisions were made based solely on the Center Test outcomes.

school of University of Yamanashi does not conduct an early round examination and only offers a later round exam, it is excluded from our analysis. Thus, the number of schools considered is reduced by 1, from 50 to 49.

The second stage is administered independently by each medical school, with subject requirements varying by institution[7]. For the early round, Mathematics is mandatory in all medical schools, while English (47 out of 49) and Science (41 out of 49) are required in most schools. However, Japanese is required in only a few schools (4 out of 49) and Social Studies is not required in any of the schools. In addition to these written exams, some medical schools conduct interviews and essay tests.

A distinctive feature of the Japanese public university entrance examination system is the self-assessment process following the Center Test. Shortly after the test, official answers are released, allowing applicants to estimate their scores. Most applicants then report their self-assessed scores to major preparatory schools, which aggregate the data and provide detailed reports before the secondary examination application period.[8] These reports help applicants gauge their relative standing among others applying to the same universities and programs, enabling them to make well-informed decisions about their applications for the secondary examination. This system is widely used by medical school applicants, as the ability to assess one's performance and strategically select a medical school is crucial in the competitive admissions process, which we model in the next section.

3 Model

In this section, we model the admission process for public university medical schools in Japan. We focus on the early round selection stage of the secondary examination in which

[7]Kochi and Saga University Medical Schools use a "comprehensive exam" as their written test in the second stage. However, as the exam includes questions from English, Mathematics, and Science, it is treated as a test covering these three subjects, with each subject contributing equally (one-third) to the total score.

[8]Preparatory schools are a ubiquitous feature of the Japanese education landscape, providing supplementary education and test-preparation services for university applicants. They play a significant role in helping students prepare for entrance examinations, offering comprehensive courses, mock exams, and detailed study materials.

students apply to a single medical school. Before making this decision, they estimate their Center Test scores through self-assessment and use this information to gauge their chances of acceptance to different institutions. Based on these perceived probabilities, students select the medical school that offers the highest expected utility. Noteworthy, students may also consider applying to non-medical programs, although our analysis focuses on applications and selection processes for public medical schools. To account for this, our model treats applying to other programs as an outside option.

Admission probability: Assume that there are K types of subjects relevant to applications to Japanese medical schools. Let $\mathbf{y}^1 = (y^1(1), ..., y^1(K))$ denote a student's $K \times 1$ score vector for these subjects in the first-stage Center Test, $\mathbf{y}_j^2 = \left(y_j^2(1), ..., y_j^2(K)\right)$ denote their $K \times 1$ score vector in the second-stage exam for the jth university, and $\gamma_j^s = \left(\gamma_j^s(1), ..\gamma_j^s(K)\right)'$ with $\sum_{k=1}^K \gamma_j^s(k) = 1$ denote the weights assigned to each subject in the sth exam for the jth university. Assume that the minimum score required to get accepted in the jth university is $s_j^m \in \mathbb{R}$. We later set a reasonable restriction on the range of s_j^m to ensure the existence of the market equilibrium.

We can observe the scores at the first-stage Center Test of each student, $\mathbf{y}^1$, but not those at the second-stage exam, $\mathbf{y}_j^2$. Hence, we consider $\mathbf{y}_j^2$ as a random vector. The admission probability for the student with $\mathbf{y}^1$ at the Center Test to the jth university can be modeled as follows.

$$\begin{aligned} q_j\left(s_j^m; \mathbf{y}^1\right) &= \Pr\left(\omega_j \gamma_j^{1\prime} \mathbf{y}^1 + (1-\omega_j)\gamma_j^{2\prime}\mathbf{y}_j^2 \geq s_j^m | \mathbf{y}^1\right) \\ &= \Pr\left(\gamma_j^{2\prime}\mathbf{y}_j^2 \geq \frac{s_j^m - \omega_j \gamma_j^{1\prime}\mathbf{y}^1}{1-\omega_j} | \mathbf{y}^1\right) \end{aligned} \quad (1)$$

where ω_j is the weight assigned to the Center Test. We assume that the $\gamma_j^{2\prime}\mathbf{y}_j^2$ follows a continuous distribution. Hence, $\frac{\partial q_j\left(s_j^m; \mathbf{y}^1\right)}{\partial s_j^m} < 0$. This means that an increase in the minimum score always reduces the admission probability. Each student chooses their preferred university with knowledge of this probability.

Student's Choice: As explained in the introduction, we assume that all admitted students enroll in the university to which they are admitted. Hence, we only need to model students' application decisions. A student maximizes her expected utility by choosing a preferred university, given the vector of the minimum scores, $\{s_j^m\}$, as follows:

$$\max \left\{ \begin{array}{c} \max_{j\in\{1,\ldots,J\}} \left\{ q_j \left(s_j^m; \mathbf{y}^1\right) U_j\left(\varepsilon_j\right) + \left[1 - q_j\left(s_j^m; \mathbf{y}^1\right)\right] U_f \right\}, \\ U_0^e\left(\varepsilon_0\right) \end{array} \right\}$$

where $\{1,..,J\}$ is the set of universities and 0 represents the outside option. The variables, $U_j\left(\varepsilon_j\right)$, U_f, and $U_0^e\left(\varepsilon_0\right)$ are the utility derived from admission to the medical school of the jth university, failing to be admitted, and choosing the outside option, which is the expected benefit of applying to other department or not applying, respectively, and the random variables ε_j and ε_0 are taste shocks when the applicant enters the jth university and applies to another department, respectively[9]. The utility derived from failing to be admitted, U_f, is interpreted as the maximum utility among the utility derived from taking the "later round examination" at a public university, enrolling in a private university, or preparing and reapplying for a university next year.

We assume that $U_j\left(\varepsilon_j\right)$ and $U_0^e\left(\varepsilon_0\right)$ have the following functional forms:

$$U_j\left(\varepsilon_j\right) = \tilde{U}_j \exp\frac{\varepsilon_j}{\lambda} + U_f, \tag{2}$$

$$U_0^e\left(\varepsilon_0\right) = \tilde{U}_0^e \exp\frac{\varepsilon_0}{\lambda} + U_f, \tag{3}$$

where $\tilde{U}_j$ and $\tilde{U}_0^e$ are the average value added from being admitted to the medical school of the jth university and applying to other departments, respectively, $\lambda > 0$ is a scale parameter, and ε_j follows the distribution $\exp\left[-\exp-\left(\varepsilon_j+\gamma\right)\right]$, where γ is Euler's constant (≈ 0.577).

[9]The utility function and budget constraint explicitly including composite goods are presented in the Appendix.

For the purpose of estimation, we also assume that the relative value added is as follows:

$$\ln \frac{\tilde{U}_j}{\tilde{U}_0^e} = \frac{\delta_j + b_j\left(\mathbf{y}^1, \mathbf{x}\right)}{\lambda},$$

where δ_j is the part of utility obtained from university j that is common across all applicants, and $\mathbf{x}$ is the vector of the applicant's characteristics other than test scores $\mathbf{y}^1$. Then, as shown in the Appendix, the choice probability is given by

$$p_j\left(\mathbf{s}^m, \boldsymbol{\delta}; \mathbf{y}^1, \mathbf{x}\right) = \frac{\exp\left\{\lambda q_j\left(s_j^m; \mathbf{y}^1\right) + \delta_j + b_j\left(\mathbf{y}^1, \mathbf{x}\right)\right\}}{1 + \sum_{i \neq 0} \exp\left\{\lambda q_i\left(s_i^m : \mathbf{y}^1\right) + \delta_i + b_i\left(\mathbf{y}^1, \mathbf{x}\right)\right\}}, \forall j, \tag{4}$$

where $\mathbf{s}^m = \left(s_1^m, .., s_J^m\right) \in \left[\underline{\mathrm{s}}, \bar{s}\right]^J$ and $\boldsymbol{\delta} = \left(\delta_1, .., \delta_J\right) \in \mathbf{R}^J$.

Market Equilibrium for Medical School Admission: The minimum score of the jth university, $s_j^m \in \mathbb{R}$, is determined by the following equilibrium condition:

$$\frac{M_j}{N} = \int q_j\left(s_j^m; \mathbf{y}^1\right) p_j\left(\mathbf{s}^m, \delta; \mathbf{y}^1, \mathbf{x}\right) dG\left(\mathbf{y}^1, \mathbf{x}\right), \ \forall j \tag{5}$$

where M_j represents the capacity of the jth university, N is the total number of students taking the Center Test, and $G\left(\mathbf{y}^1, \mathbf{x}\right)$ is the distribution function of $\mathbf{y}^1$ and $\mathbf{x}$. Equation (5) implies that the minimum score is adjusted such that the number of successful applicants equals the capacity of each university.

Definition 1 *The market equilibrium for medical school admission comprises* $\left(\left\{p_i\right\}_i, \ \mathbf{s}^m\right)$ *that satisfies Equations (4) and (5), where* $\left\{q_i\right\}_i$ *is expressed by Equation (1).*

We assume that there exists $\underline{M}$ and $\bar{M}$ such that $0 < \frac{M}{N} = \min\left\{\frac{M_i}{N}\right\}_i$ and $\max\left\{\frac{M_i}{N}\right\}_i = \frac{\bar{M}}{N} < \min_j \int p_j^*\left(\delta; \mathbf{y}^1, \mathbf{x}\right) dG\left(\mathbf{y}^1, \mathbf{x}\right)$ where $p_j^*\left(\delta; \mathbf{y}^1, \mathbf{x}\right) = \frac{\exp\left\{\lambda + \delta_j + b_j\left(\mathbf{y}^1, \mathbf{x}\right)\right\}}{1 + \sum_{i \neq 0} \exp\left\{\lambda + \delta_i + b_i\left(\mathbf{y}^1, \mathbf{x}\right)\right\}}$. The Appendix shows that we can find $\left\{\underline{s}_j\right\}$ and $\left\{\bar{s}_j\right\}$ for any $M_j \in \left[\underline{M}, \bar{M}\right]$ such that if there exists s_j^m that satisfies the Equation (5), $s_j^m \in \left[\underline{s}_j, \bar{s}_j\right]$ for all j. Hence, to guarantee the existence of the equilibrium, we can assume that $\mathbf{s}^m \in \mathbf{S}^m$, where $\mathbf{s}^m = \left\{s_j^m\right\}_j$ and $\mathbf{S}^m = \mathbf{\Pi}_j \left[\underline{s}_j, \bar{s}_j\right]$. The Appendix provides the proof of the following theorem.

Theorem 2 *Suppose that* $\mathbf{s}^m \in \mathbf{S}^m$ *and that the scale parameter* $\lambda > 0$ *is sufficiently small. Then, there exists a unique* $(\{p_i\}_i, \ \mathbf{s}^m)$ *that satisfies the market equilibrium for medical school admission.*

Theorem 2 guarantees the existence of a unique market equilibrium. This ensures that we are prepared to conduct the structural estimation of the market equilibrium for medical school admissions and perform a quantitative analysis in the subsequent sections.

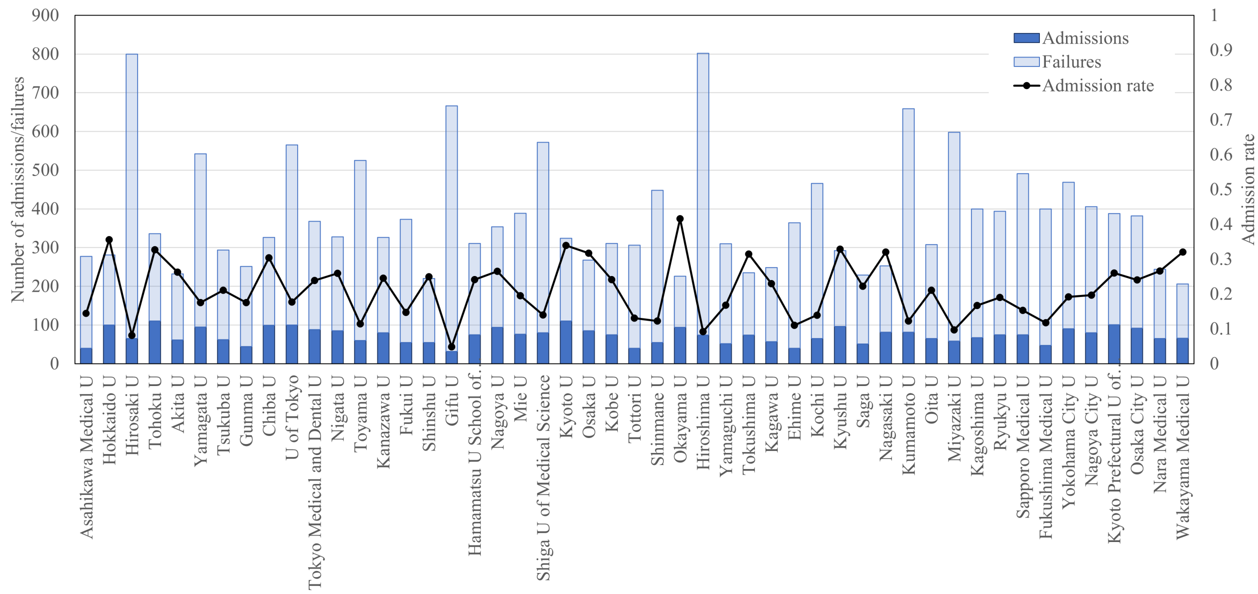
4 Estimation

We specify the parametric forms of the model based on the aforementioned theoretical model for estimation purposes. The parameters in the model are estimated using the individual- and the market-level data for medical school choice. First, we explain our data. Second, we describe how we specify the model to appropriately utilize these data. Third, we introduce the estimation procedure. Fourth, we show our estimation results. Finally, we assess the predictions of the estimated structural model.

4.1 Data

The dataset used in this study primarily comprises market-level (school-level) and individual-level (student-level) data. The market-level data is sourced from *Keisetsu-Jidai*, a monthly magazine published by Obunsha Publishing that provides detailed college information with a focus on entrance examinations. Specifically, we retrieve the data for 49 public medical schools that held entrance examinations on February 25, 2011. The market-level data include the number of applicants and admissions for each school. Figure 2 illustrates the number of applicants for these 49 schools. The heights of the stacked bars represent the total number of applicants, divided into admitted and failed students. The figure also shows the admission rate for each school with a line, varying across institutions, from 0.05 for Gifu University to 0.42 for Okayama University. The total number of applicants for these 49 schools is 18763.

Figure 2: Number of applications and admissions by university



Note: This figure presents the number of applicants for 49 public medical schools. The stacked bars represent the total number of applicants, with the dark blue part indicating admitted students and light blue indicating failed applicants. The left y-axis, measured in number of applicants, corresponds to the bars. The black line represents the admission rate for each school, which is shown on the right y-axis as a proportion.

The individual-level data used in this study were obtained from one of the major preparatory schools, which remains anonymous. The data include personal attributes such as gender, prefecture of the high school which a student attended or graduated from, student's self-assessed Center Test score, and names of the public universities and programs to which they applied. Additionally, the preparatory school provided information on the admission outcomes of each applicant, obtained through a follow-up survey conducted after the examinations.

The individual-level data comprise $N^p = 321,172$ observations, representing approximately 61% of the total population of $N = 558,984$ students who took the Center Test in the target year. The total population number (N) is obtained from the National Center for University Entrance Examinations' website.[10] Within the individual-level observations, $N^m = 8,543$ individuals applied to medical schools.[11]

Given the coverage of the individual-level data, we consider the distribution of student attributes constructed from this data as representative of the population distribution. This approach contrasts that of Train and Whinston (2007), where individual-level data are limited to consumers who choose the inside option. Due to this data limitation, the distribution of individual attributes in their study may not be representative, excluding the possibility of consumers substituting between inside and outside options by assumption. The richness of our individual-level data allows us to incorporate the outside option into the model and analyze how the number of medical school applicants (i.e., inside option) varies in counterfactual scenarios through the substitution with the outside options.

4.2 Model specification

Suppose that $\mathbf{y}_j^2 = \mathbf{y}^1 + \mathbf{1}_K u_j$, where $\mathbf{1}_K$ is a K-dimensional vector of ones, and u_j follows a logistic distribution with a mean of 0 and a variance of $\frac{\pi^2 \sigma_j^2}{3}$. We consider that u_j captures the results of interview, the luck of a student, and so on. This assumption implies that an applicant's academic skills, on average, for each subject do not change between the first-and the second-stage exams. This allows us to define the measure of her academic skills that can be valuable when she applies to the jth university, as $z_j(\mathbf{y}^1) = \sum_{k=1}^{K} \left[\omega_j \gamma_j^1(k) + (1-\omega_j)\gamma_j^2(k)\right] y^1(k)$. We refer to $z_j(\mathbf{y}^1)$ as the z-score of the applicant who applies to the jth university. The z-score, $z_j(\mathbf{y}^1)$, is constructed as the weighted average of the scores for each subject in the Center Test, $y^1(k)$, where the weights

[10] See `https://www.dnc.ac.jp/`(in Japanese).

[11] Our sample of $N^m = 8,543$ accounts for approximately 46% of all medical school applicants (i.e., 18763 applicants). The coverage rate of public medical school applicants within our sample is lower, given that the individual data we obtained from the anonymous preparatory school cover 58% of all Center Test takers. Several factors may explain this discrepancy. One key reason is the existence of specialized preparatory schools that cater specifically to medical school applicants, leading to a more dispersed distribution of self-assessment score submissions among different institutions.

are determined by each university, $\omega_j \gamma_j^1(k) + (1-\omega_j)\gamma_j^2(k)$. Using the z-score, we show that the admission probability is a function of the z-score, $z_j(\mathbf{y}_n^1)$:

$$q_j\left(\mu_j, \mathbf{y}_n^1; \alpha_j\right) = \frac{1}{1 + \exp\left[\mu_j - \alpha_j z_j\left(\mathbf{y}_n^1\right)\right]} \tag{6}$$

where $\mu_j = \alpha_j s_j^m$ and $\alpha_j = \frac{1}{(1-\omega_j)\sigma_j}$[12]. μ_j represents the modified minimum score, which is the focus of the estimation and simulation analyses conducted below. For the exposition, we treat α_j as a parameter in the admission probability function.

For estimation purposes, the vector of student attributes, $\mathbf{x}$, is divided into the observable attribute $\mathbf{x}^o$ and the unobservable attribute ν. The n-th student attribute is denoted as $\mathbf{x}_n = (\mathbf{x}_n^o, \nu_n)$. The observable attribute vector includes the scores of the Center Test, namely $\mathbf{y}_n^1 \subset \mathbf{x}_n^o$. Hence, we hereafter denote the admission probability as $q_j(\mu_j, \mathbf{x}_n^o; \alpha_j)$. ν_n represents the n-th applicant's unobserved preference for medical schools (i.e., the inside option). The empirical distribution of $\mathbf{x}^o$ is defined as $G^o(\mathbf{x}^o)$, while ν is assumed to be independently and identically distributed according to the standard normal distribution, $\Phi(\nu)$.

Then, the empirical version of the application probability to university j for student n is expressed as follows:

$$p_j\left(\boldsymbol{\mu}, \boldsymbol{\delta}, \mathbf{x}_n^o, \nu_n; \boldsymbol{\theta}\right) = \frac{\exp\left\{\lambda \ln q_j\left(\mu_j, \mathbf{x}_n^o; \alpha_j\right) + \delta_j + b_j\left(\mathbf{x}_n^o, \nu_n; \boldsymbol{\beta}\right)\right\}}{1 + \sum_{i \neq 0} \exp\left\{\lambda \ln q_i\left(\mu_i, \mathbf{x}_n^o; \alpha_i\right) + \delta_i + b_i\left(\mathbf{x}_n^o, \nu_n; \boldsymbol{\beta}\right)\right\}}, \tag{7}$$

where $\boldsymbol{\mu} = (\mu_1, \cdots, \mu_J)$ is the vector of the modified minimum score, $b_j(\cdot)$ represents the student-specific preference for university j, which is parameterized by $\boldsymbol{\beta}$[13], and $\boldsymbol{\theta} = (\lambda, \boldsymbol{\alpha}, \boldsymbol{\beta})$ is a parameter vector to be estimated. The cost of distance, taste heterogeneity for university characteristics based on student attributes (including gender), and other factors are measured from $b_j(\cdot)$. The specification of $b_j(\cdot)$ is introduced following the construction of the variables discussed in Section 4.3.1.

[12]To simplify our notation, we use the same q function defined in Section 3 for the admission probability, although the independent variable changes from s_j^m to μ_j.

[13]For the same reason explained in Footnote 12, we use the same functions, p for the application probability and b for the student-specific preference, as in Section 3.

By integrating the student-level application choice probability over the student attributes $(\mathbf{x}_n^o, \nu_n)$, we can derive the application share function for university j as

$$P_j(\boldsymbol{\mu}, \boldsymbol{\delta}; \boldsymbol{\theta}) = \int\int p_j(\boldsymbol{\mu}, \boldsymbol{\delta}, \mathbf{x}_n^o, \nu_n; \boldsymbol{\theta})\, dG^o(\mathbf{x}_n^o)\, d\Phi(\nu_n), \forall j, \tag{8}$$

and the admission share function for university j as

$$Q_j(\boldsymbol{\mu}, \boldsymbol{\delta}; \boldsymbol{\theta}) = \int\int q_j(\mu_j, \mathbf{x}_n^o; \alpha_j)\, p_j(\boldsymbol{\mu}, \boldsymbol{\delta}, \mathbf{x}_n^o, \nu_n; \boldsymbol{\theta})\, dG^o(\mathbf{x}_n^o)\, d\Phi(\nu_n), \forall j. \tag{9}$$

Under the market equilibrium for medical school admission, the modified minimum score $\boldsymbol{\mu}$ is determined such that the admission share function for each university is consistent with its (observed) admission capacity, M_j; specifically,

$$\frac{M_j}{N} = Q_j(\boldsymbol{\mu}, \boldsymbol{\delta}; \boldsymbol{\theta}), \forall j. \tag{10}$$

N denotes the market size, which is defined as the number of students taking the Center Test (i.e., $N = 527,993$). Given this specification, we introduce a procedure to estimate the parameter $\boldsymbol{\theta}$ below.

4.3 Estimation procedure

The estimation is implemented using both the individual- and market-level data. The individual-level data comprise N^m observations of medical school applicants, whereas the market-level data comprise the numbers of admissions and applications for each university, as illustrated in Figure 2.

Note that we use the individual-level data for only students choosing the inside option (i.e., $j = 1, \ldots, J$), thereby excluding students choosing the outside option. However, we can identify the substitution between the inside and the outside options by incorporating the market-level data. The details of the estimation procedure are outlined below.

Using the individual-level data, we first construct the likelihood function for student n based on their application choice and the admission outcomes:

$$L_n(\boldsymbol{\mu}, \boldsymbol{\delta}; \boldsymbol{\theta}) = \prod_{j=1}^{J} \left[\bar{p}_j\left(\boldsymbol{\mu}, \boldsymbol{\delta}, \mathbf{x}_n^o; \boldsymbol{\theta}\right) q_j(\mu_j, \mathbf{x}_n^o; \alpha_j)^{I_{nj}^m} (1 - q_j(\mu_j, \mathbf{x}_n^o; \alpha_j))^{1-I_{nj}^m} \right]^{I_{nj}}, \tag{11}$$

where I_{nj} (I_{nj}^m) takes 1 if student n applies (is admitted) to school j and 0 otherwise, and the n-th student choice probability is,

$$\bar{p}_j\left(\boldsymbol{\mu}, \boldsymbol{\delta}, \mathbf{x}_n^o; \boldsymbol{\theta}\right) = \int p_j\left(\boldsymbol{\mu}, \boldsymbol{\delta}, \mathbf{x}_n^o, \nu_n; \boldsymbol{\theta}\right) d\Phi(\nu_n). \tag{12}$$

Following previous studies (e.g., Goolsbee and Petrin, 2004; Train and Whinston, 2007), we focus on maximizing the likelihood function over $\boldsymbol{\theta}$ only, by incorporating the market-level data into the estimation. Specifically, we introduce equality constraints such that the model predictions are consistent with the market-level data. The first equality constraint relates to the applications for each school:

$$\frac{A_j}{N} = P_j\left(\boldsymbol{\mu}, \boldsymbol{\delta}; \boldsymbol{\theta}\right), \forall j, \tag{13}$$

where A_j is the number of applications for school j observed in the market-level data. This ensures that the application shares predicted by Equation (8) align with the observed shares, which is commonly incorporated into the estimation of demand for differentiated products (e.g. Berry et al., 1995) to calculate the mean utility vector $\boldsymbol{\delta}$ given the model parameters.

A key difference with a standard demand estimation is the need to calculate the minimum score vector $\boldsymbol{\mu}$. Hence, we introduce the second equality constraint regarding the admissions for each school to calculate the modified minimum score vector $\boldsymbol{\mu}$. Specifically, using the condition for the medical school admission market equilibrium shown in Equation (10), we impose the constraint such that the observed admission rates are consistent with the model prediction:

$$\frac{M_j}{A_j} = \frac{Q_j\left(\boldsymbol{\mu}, \boldsymbol{\delta}; \boldsymbol{\theta}\right)}{P_j\left(\boldsymbol{\mu}, \boldsymbol{\delta}; \boldsymbol{\theta}\right)}, \forall j. \tag{14}$$

These two equality constraints ensure that the applications and admissions for each school are consistent with the actual numbers shown by stacked bars in Figure 2.

For any value of $\boldsymbol{\theta}$, $\boldsymbol{\delta}$ and $\boldsymbol{\mu}$ can be computed numerically from these constraints and are thus expressed as a function of $\boldsymbol{\theta}$: $\boldsymbol{\delta}(\boldsymbol{\theta})$ and $\boldsymbol{\mu}(\boldsymbol{\theta})$. Substituting these functions into Equation (11), the likelihood can be rewritten as a function of $\boldsymbol{\theta}$ only: $L_n\left(\boldsymbol{\delta}(\boldsymbol{\theta}), \boldsymbol{\mu}(\boldsymbol{\theta}); \boldsymbol{\theta}\right) \equiv L_n(\boldsymbol{\theta})$. Then, the maximum likelihood estimation is performed for N^m observations of medical school applicants:

$$\max_{\boldsymbol{\theta}} \sum_{n=1}^{N^m} \ln L_n\left(\boldsymbol{\theta}\right).$$

Appendix B discusses the details of the estimation algorithm, including the contraction mapping method used to compute the $\boldsymbol{\delta}$ and $\boldsymbol{\mu}$ values, approximation of application and admission shares in Equation (8), Equation (9), and approximation of a student's choice probability in Equation (12).

To perform the estimation, we need to specify the student-specific preference for each school, $b_j\left(\mathbf{x}_n^o, \nu_n; \boldsymbol{\beta}\right)$ in Equation (7). For this purpose, we first introduce the variables included in $b_j(\cdot)$ with their summary statistics in the following.

4.3.1 Variables and summary statistics

Our dataset is constructed from the individual-level and market-level data. In this section, we introduce key variables used in the estimation and present their summary statistics.

Score variables: Using the score data, we construct two types of aggregate score variables. The first is the core subject scores, which are English (250), Japanese (200), and Mathematics (200), with the maximum score for each subject shown in parentheses. We define these subjects as core because their scores were required for the examinations in majority of the public medical schools, leading most students to choose them in the Center Test. We denote

S_n as the total score, which is the sum of these three core subject scores.

Table 2 shows the summary statistics for total scores (i.e., S_n) and scores for each subject by gender for all students, medical school applicants, and medical school admittees in the individual-level dataset. The average score for all students is higher for males, which is primarily due to their higher scores in mathematics. However, when limiting the sample to medical school applicants, the total score is comparable between males and females, and the difference in the math score reduces between genders.

Table 2: Core Subject Scores by Gender

(a)All students		Total Score		English		Japanese		Mathematics	
	Obs.	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Female	139422	352.0	113.6	153.5	46.5	115.9	34.9	82.6	59.2
Male	181750	366.3	122.5	152.3	49.0	110.9	36.9	103.2	61.5
Total	321172	360.1	119.0	152.8	48.0	113.0	36.1	94.2	61.4

(b)Applicants only		Total Score		English		Japanese		Mathematics	
	Obs.	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Female	2888	519.3	63.0	206.5	26.9	147.7	23.1	165.0	27.5
Male	5655	519.6	60.6	204.6	26.7	142.3	23.8	172.7	25.3
Total	8543	519.5	61.4	205.2	26.8	144.2	23.7	170.1	26.3

(c)Admittees only		Total Score		English		Japanese		Mathematics	
	Obs.	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Female	756	566.2	31.7	223.2	13.5	159.9	17.0	183.2	16.4
Male	1668	561.8	33.2	220.1	16.0	154.0	19.3	187.7	15.2
Total	2424	563.2	32.8	221.1	15.3	155.8	18.8	186.3	15.7

Note: This table presents core subject scores by gender. We define "core subject scores" by English (250), Japanese (200) and Mathematics (200) with the maximum score for each subject shown in parentheses. The "total score" is the sum of these three core subject scores. "All students", "Applicants only" and "Admittees only" refers to all students who take the Center Test in our sample, all students who apply to medical schools, and all students who are admitted in medical schools in our sample, respectively.

The second is the z-score, z_{nj}, defined in the admission probability model. As stated in Section 4.2, z-score is calculated using the student's first exam scores $(\mathbf{y}^1)$[14] and the

[14] If a student did not take the subject specified by the medical school and, therefore, had no score, the

subject weights assigned by each medical school. Specifically, the calculation incorporates the weighted sum of subject scores, where the weights—denoted as γ_j^1, γ_j^2, and ω_j for medical school j—are set by each institution. Consequently, the z-score calculation varies across medical schools.

Distance: The distance variable is defined as $D_{nj} = d(l_n, l_j)$, where l_n and l_j are the locations of student n's high school and university j, respectively, and $d(\cdot)$ is a function that calculates the distance between the two locations.[15] Table 3 presents the summary statistics for the distance, pooling data from all students and universities (i.e., $N^p \times J$ observations), and the statistics broken down by gender.

Table 3: Summary Statistics for Distance (km) for all Students

	Mean	SD	Min	Max
Female	510.6	367.1	12.5	2346.6
Male	516.4	368.6	12.5	2346.6
All students	513.1	367.8	12.5	2346.6

Note: This table presents the summary statistics for the distance, pooling data from all students and universities (i.e., $N^p \times J$ observations). The distance is determined by calculating the distance from the address of each municipal office in the student's high school's prefecture to the university's address and then taking the median of these distances.

The results in table show that the average distance for all students is 513.1km with a standard deviation of 367.8km, indicating that most of the distances between students and universities fall within 1250km (i.e., within two standard deviations from the mean). However, the distance can exceed 2000km when students from Hokkaido, the northernmost prefecture, attend a university in Okinawa, the southernmost prefecture, or vice versa. The summary statistics for the distance varies minimally between genders; for instance, the

subject was considered to have a score of zero. When multiple disciplines are available within a subject, the highest scores among them are used.

[15] The university's location (l_n) is precisely known by its detailed address, whereas the student's location (l_s) is only known at the prefectural level; specifically, the prefecture where the student's high school is located. Because of this difference in geographical granularity, the distance between l_s and l_n is calculated as a representative value. The distance, $d(l_s, l_n)$, is determined by calculating the distance from the address of each municipal office in the student's high school's prefecture to the university's address and then taking the median of these distances.

difference in average distance between genders is approximately 6km.

To capture the school-level variation in distance, we calculate the average distance of each student to each school by gender, using the individual-level data (N^p observations), as follows:

$$\frac{1}{N_M^p}\sum_{n=1}^{N^p} D_{nj} \times (1 - Female_n) \text{ and } \frac{1}{N_F^p}\sum_{n=1}^{N^p} D_{nj} \times Female_n, \tag{15}$$

where N_M^p and N_F^p represent the number of male and female students, respectively, in the sample of N^p observations. These distances between students and medical schools are simply calculated based on each student's and each medical school's location, irrespective of whether the student actually applied to the school.

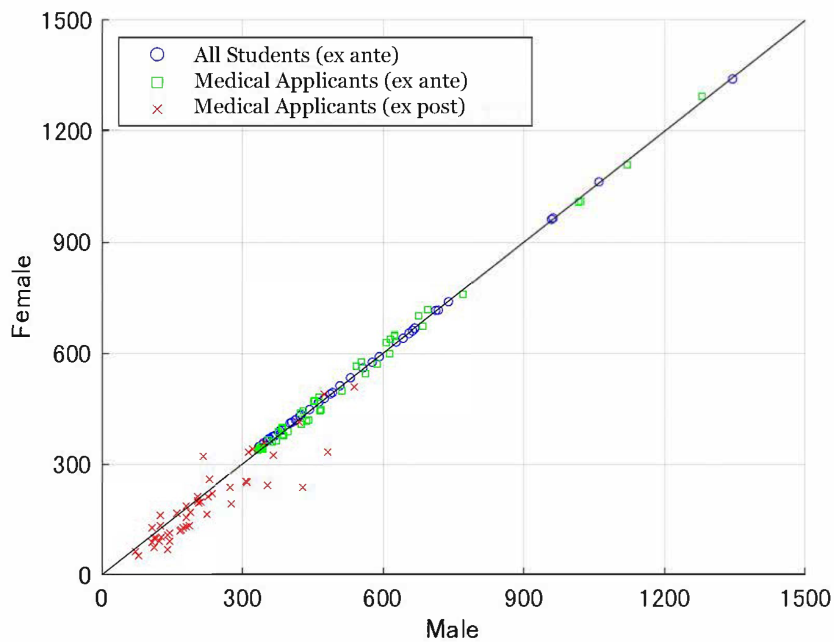
While the ex-ante distance to each school is comparable between genders, the distance between each applicant and the school they ultimately applied to— the *ex post* distance in the sense that it is measured after the application decision has been made—differs substantially between genders, as shown in Table 1. To examine these gender differences at the school level, we compute the following ex-post average distances by school:

$$\frac{1}{N_M^m}\sum_{n=1}^{N^m} D_{nj} \times (1 - Female_n) \times I_{nj} \text{ and } \frac{1}{N_F^m}\sum_{n=1}^{N^m} D_{nj} \times Female_n \times I_{nj}, \tag{16}$$

where N_M^m and N_F^m represent the number of male and female students, respectively, in the sample of medical school applicants only (N^m observations). These values are plotted as x-points in Figure 3. The figure shows that most data points lie below the 45-degree line, indicating that the average distance for males is greater than that for females. Additionally, these points are mostly distributed closer to the origin compared to the circle and rectangle points, suggesting that the ex-post average distances are smaller than the ex-ante ones. This implies that both males and females tend to choose schools closer to their residence.

Enrollment cost: We define the enrollment cost as the sum of the enrollment fee and the first-year tuition. For the study period, these fees and tuition rates were determined by national or local governments rather than by the universities themselves. While these

Figure 3: Average distance by gender



Note: This figure plots the average distance (in km) for males and females to each medical school. Circle points represent ex-ante distances, computed based on Equation 15, which considers all students regardless of application decisions. Rectangle points show ex-ante distances for medical school applicants only. Ex-post distances, calculated using Equation 16 for applicants' chosen schools, are plotted as x-points.

were identical across national universities due to the national government's uniform pricing scheme, they varied between public universities where local governments set the fees and the tuition rates. Additionally, prefectural and city universities often charged different rates for in-prefecture (or in-city) and out-of-prefecture (or out-of-city) students, typically offering favorable rates to local students. Therefore, the enrollment cost is as follows:

$$Cost_{nj} = I(l_n, l_j)c_j^{in} + (1 - I(l_n, l_j))c_j^{out},$$

where $I(l_n, l_j)$ is an indicator function that takes the value 1 if l_n and l_j belong to the same prefecture, and c_j^{in} (c_j^{out}) represents the enrollment cost of in-prefecture (out-of-prefecture) students for school j.

Table 4 presents the summary statistics for the enrollment costs of out-of-prefecture and in-prefecture students. The average costs are higher for out-of-prefecture students. The standard deviation for in-prefecture students is minimal, whereas that for out-of-prefecture students is larger due to the significantly higher entrance fees charged by local governments to out-of-prefecture students.

Table 4: Summary statistics of school-level variables

Variable		Mean	SD	Min	Max
Enrollment cost (¥1000): $Cost_{nj}$	In-prefecture students	813.4	18.0	714.0	817.8
	Out-of-prefecture students	856.8	126.7	817.8	1381.8
Median Total score of admittees: $\bar{S}_j$		561.4	16.9	524.5	606.0
Number of articles: $Article_j$		491.3	370.8	170.0	2035.0

Note: This table presents the summary statistics of school level variables. We define the enrollment cost as the sum of the enrollment fee and the first-year tuition. The total scores are the sums of English (250), Japanese (200), and Mathematics (200), with the maximum score for each subject shown in parentheses. "Number of articles" is the number of articles published in peer reviewed journals by faculty members at each school.

Median score: As a measure of school quality, we use the median scores of admitted students at each school, $\bar{S}_j$, derived from our dataset. The top five medical schools include the University of Tokyo, Kyoto University, Nagoya University, Osaka University, and Chiba University. As shown in Table 4, the average $\bar{S}_j$ is 561.4, with the highest median score of 606.0 for the University of Tokyo.

Number of articles: Academic outcomes for each school may affect application decisions, particularly among high-ability students. Therefore, we collect the number of articles published in peer reviewed journals by faculty members at each school; $Article_j$ as a measure of medical school quality. As shown in Table 4, the average number of articles published by faculty members is 491.3. The highest number of publications is 2,035 at the University of Tokyo.

4.3.2 Specification of $b_j(\cdot)$

Given the aforementioned variables, we specify the student-specific preference for each school, $b_j(\mathbf{x}_n^o, \nu_n; \boldsymbol{\beta})$. The observed individual characteristics for student n include their location, score, gender, and z-score: $\mathbf{x}_n^o = (l_n, S_n, Female_n, \mathbf{z}_n)$, where $Female_n$ takes 1 if student n is female and 0 otherwise. $\mathbf{z}_n$ is the $J \times 1$ vector of z-score for student n, where the j-th element is $z_j(\mathbf{y}^1)$. $\mathbf{z}_n$ is relevant only to the admission probability and is not included in $b_j(\cdot)$.

Then, for each school j, $b_j(\cdot)$ is specified as follows:

$$b_j(\mathbf{x}_n^o, \nu_n; \boldsymbol{\beta}) = \mathbf{X}_{nj}\bar{\boldsymbol{\beta}} + \left(Female_n \times \mathbf{X}_{nj}^F\right)\boldsymbol{\beta}^F + \beta_1^0 S_n + \beta_2^0 Female_n + \beta_3^0 \nu_n, \tag{17}$$

where

$$\mathbf{X}_{nj} = \left(Cost_{nj}, D_{nj}, D_{nj}^2, \left(S_n - \bar{S}_j\right)_+^2, \left(S_n - \bar{S}_j\right)_-^2, S_n \times Article_j, S_n \times Article_j^2\right). \tag{18}$$

$\bar{\boldsymbol{\beta}}$ is the vector of parameters capturing the male's preference, $\boldsymbol{\beta}^F$ is the vector of parameters capturing the heterogeneity in preference between genders. To allow for the possibility that their effect may either be increasing or decreasing, distances (D_{nj}) and the academic outcomes ($Article_j$) have quadratic terms, as shown in the variables included in $\mathbf{X}_{nj}$. $Article_j$ is interacted with the student's ability (S_n) to consider the heterogeneity in preferences for the academic outcomes across different ability levels. Following the previous studies (e.g., Fu et al, 2022), we include the variables to measure the preference for under-match and over-match: $\left(S_n - \bar{S}_j\right)_+ = \max\left\{S_n - \bar{S}_j, 0\right\}$ and $\left(S_n - \bar{S}_j\right)_- = \min\left\{S_n - \bar{S}_j, 0\right\}$, respectively. These variables capture the degree to which a student's ability (S_n) deviates above (over-match) or below (under-match) the median ability of admitted students at school j ($\bar{S}_j$). The vector of variables interacted with the female dummy, $\mathbf{X}_{nj}^F$, is a subset of $\mathbf{X}_{nj}$ (i.e., $\mathbf{X}_{nj}^F \subseteq \mathbf{X}_{nj}$). In our main specification, we focus on the case of $\mathbf{X}_{nj}^F = \mathbf{X}_{nj}$.

The preference for the outside option can differ by student ability (S_n) and gender ($Female_n$). Additionally, the unobserved heterogeneity is considered by including ν_n that follows a standard normal distribution. The preferences associated with S_n, $Female_n$, and ν_n are measured by parameters β_1^0, β_2^0, and β_3^0, respectively.

4.4 Estimation results

Estimation results are reported in Table 5. We conduct the estimation based on the two specifications on $b_j(\cdot)$: the subset of the variables $\mathbf{X}_{nj}$ interacted with female dummy variables $Female_n$, thereby $\mathbf{X}_{nj}^F \subset \mathbf{X}_{nj}$; and the full specification of $\mathbf{X}_{nj}^F = \mathbf{X}_{nj}$. These estimation results are shown in Tables 5 (i) and (ii), respectively.

The estimates of the scale parameter λ, namely the coefficient of admission probability $\ln q_{nj}$, are similar for both specifications and statistically significant. The coefficient of monetary costs, $Cost$ is negative and statistically significant. Additionally, the positive coefficients of $Female \times Cost$ indicate that females are price insensitive compared to males; however, it is not statistically significant for the full specification of (ii).

The estimates for the cost of distance are similar across specifications, suggesting that the results are robust to the choice of variables. Specifically, as the coefficient of the linear term is negative and that of the quadratic term is positive, the utility cost of distance follows a convex function with respect to the distance and varies by gender. Figure 4 shows the function for males and females that are constructed using the estimates of full specification (i.e., Table 5(ii)), within the range of distance observed in our dataset and with a maximum of 2,350km, as shown in Table 3. The results indicate that the cost decreases until approximately 1,350 km, after which it starts increasing. Within this range, females encounter higher costs than males, and the gap continues to widen up to this point. As the average cost of distance is 513km with a standard deviation of 368km, as shown in Table 3, most observations fall within the range up to 1,350km. Therefore, the cost mostly decreases within the observed range, and the difference between genders widens as distance increases. Thus, the cost generally

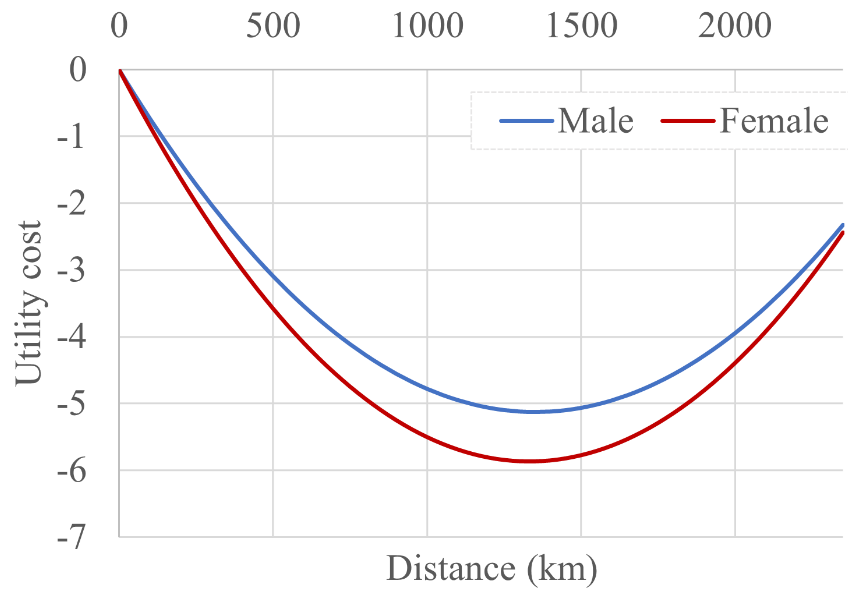
Table 5: Estimation results

Variables	(i) Est.	(i) S.E.	(ii) Est.	(ii) S.E.
(1) Scale parameter				
$\ln q_{nj}$	0.639	0.020	0.630	0.013
(2) Enrollment cost				
$Cost_{nj}$	-4.073	0.218	-4.023	0.330
$Female_n \times Cost_{nj}$	0.451	0.153	0.187	0.123
(3) Cost of distance				
D_{nj}	-7.633	0.102	-7.589	0.099
D_{nj}^2	2.828	0.056	2.809	0.055
$Female_n \times D_{nj}$	-1.041	0.070	-1.218	0.127
$Female_n \times D_{nj}^2$	0.421	0.052	0.498	0.077
(4) Preference for under-/over-match				
$(S_n - \bar{S}_j)_+^2$	-15.133	0.537	-17.804	0.610
$(S_n - \bar{S}_j)_-^2$	0.796	0.043	0.807	0.028
$Female_n \times (S_n - \bar{S}_j)_+^2$	-	-	5.804	0.366
$Female_n \times (S_n - \bar{S}_j)_-^2$	-	-	-0.024	0.022
(5) Preference for academic outcomes				
$S_n \times Article_j$	2.940	0.261	3.165	0.130
$S_n \times Article_j^2$	-1.250	0.135	-1.284	0.066
$Female_n \times (S_n \times Article_j)$	-	-	-0.089	0.038
$Female_n \times (S_n \times Article_j^2)$	-	-	-0.007	0.021
(6) Preference for outside option				
$Female_n$	-0.004	0.137	0.433	0.090
S_n	10.671	0.995	10.195	0.557
ν_n	2.666	0.068	2.666	0.058
Log-likelihood	-44265.757		-44211.281	

Note: The variable $Cost_{nj}$ is the sum of the enrollment fee and the first-year tuition, D_{nj} is calculated as the distance from the address of each municipal office in the student's high school's prefecture to the university's address and then taking the median of these distances, $Female_n$ is the female dummy, S_n is the sum of English (250), Japanese (200), and Mathematics (200), with the maximum score for each subject shown in parentheses, $\left(S_n - \bar{S}_j\right)_+ = \max\left\{S_n - \bar{S}_j, 0\right\}$ and $\left(S_n - \bar{S}_j\right)_- = \min\left\{S_n - \bar{S}_j, 0\right\}$ where $\bar{S}_j$ is the median of S_n in the jth school, $Article_j$ is the number of articles published in peer reviewed journals by faculty members at each school and ν_n is unobserved heterogeneity. Enrollment cost ($Cost_{nj}$), distance (D_{nj}), total score S_n, and number of articiles ($Article_j$) are measured in million yen, 1,000km, 100-point, and 1,000 article units, respectively.

declines within the observed range, with the gender gap expanding as distance increases.[16]

Figure 4: Utility cost of distance



Note: This figure shows the utility cost of distance (y-axis) as a function of distance in kilometers (x-axis). The blue line represents male students, whereas the red line represents female students. The cost estimates are based on Table 5, Column (ii).

For both specifications, the preference for under-match (i.e., the coefficient of $(S_n - \bar{S}_j)^2_+$) is estimated to be negative and statistically significant, while the preference for over-match (i.e., the coefficient of $(S_n - \bar{S}_j)^2_-$) is positive and significant. The estimates of under-match and over-match are highly asymmetric; in particular, students strongly disfavor universities where the majority of students have a lower academic performance than themselves. However, in the context of the medical schools, the median scores of admitted students are relatively high, 561.4 on average, as shown in Table 4, compared to the average scores of all students, 360.1, as shown in Table 2. Consequently, majority of students face over-match across all medical schools, meaning that the asymmetric preference is identified from a small fraction of elite students with high scores when selecting among top-tier institutions.

[16]Although the difference in the cost between genders get closer over 2,000km distance, such long distances are relevant only when students from the northern island, Hokkaido prefecture, choose a university in the southern island, Okinawa prefecture, or vice versa.

Nonetheless, this result is consistent with those of previous studies that examine the college application choice (e.g., Fu et al. (2022)).

Additionally, the result of the full specification indicates that $Female_n \times (S_n - \bar{S}_j)_+^2$ is significantly positive, suggesting that females are more tolerant of under-match. This implies that conditional to their abilities, females tend to choose less competitive schools, which is consistent with findings in the literature on the gender differences in competitiveness (e.g., Buser et al. (2014)).

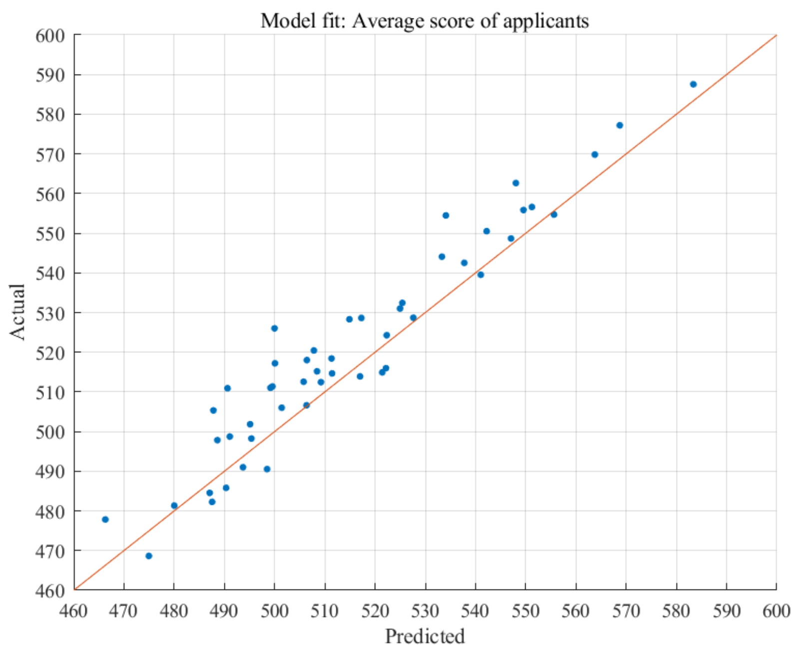
For both specifications, the estimates regarding the academic performance variables interacted with the student's score, $S_n \times Article_j$ and $S_n \times Article_j^2$, are both statistically significant. Using the estimates from Table 5(ii), the marginal effect for the school j can be calculated as $S_n \times (3.165 - 2 \times 1.284 Article_j)$, which is positive for most schools except for the top-three institutions, the University of Tokyo, Osaka University, and Kyoto University with 2,035, 1,451, and 1,397 articles, respectively. Thus, the utility function is increasing over most of the observed data range, indicating that high-scoring students tend to prefer schools with high academic performance. However, high-scoring females exhibit a weaker preference for academic performance, as evidenced by the negative and significant coefficient of $Female_n \times (S_n \times Article_j)$. This indicates that, compared to males, females are less likely to choose top-tier schools, which aligns with findings in the literature on the gender difference in competitiveness.

Finally, we report the estimates representing the preference between inside and outside options. The coefficients of $Female_n$ differ between specifications, which is attributable to the flexibility of preference structure by gender between them. In our main specification shown in Table 5(ii), the estimate is positive and significant, implying that females have stronger preference for medical schools. High-scoring students have stronger preference for the inside options, as indicated by the positive and significant coefficient of S_n. The coefficient of the unobserved taste ν_n is significantly estimated to be 2.666. This indicates that the unobserved preferences for medical schools across students, $\beta_3^o \nu_n$, has a standard deviation of 2.666.

4.5 Model Fit

To examine the validity of the model, Figures 5, 6, and 7 compare the model's predictions with the actual data. In each figure, the vertical line represents the actual data, horizontal line represents the model's predictions, blue points represent the average values by each medical school, and red line indicates the 45-degree line. Thus, if the blue points in the figures are located close to the red line, the model's predictions closely align with the actual data.

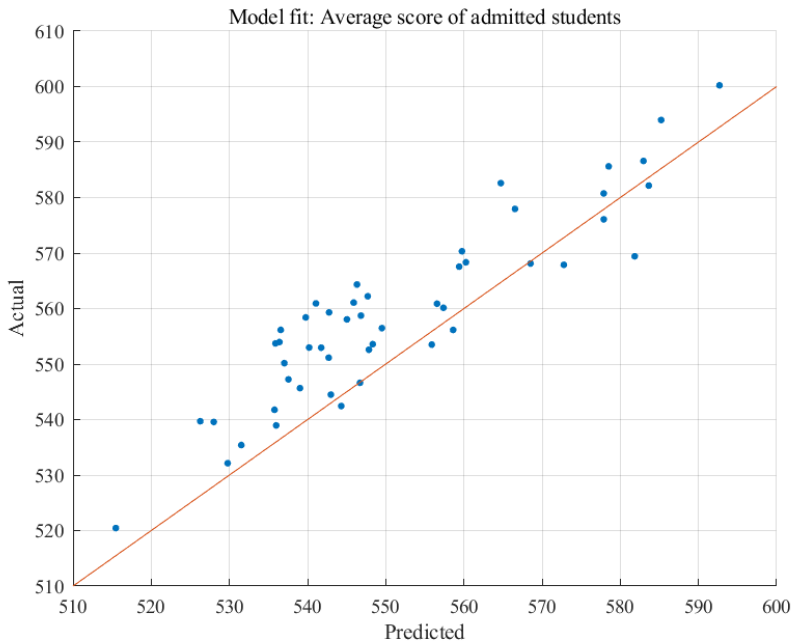
Figure 5: Model fit: Average score of application



Note: The x-axis represents predicted scores, while the y-axis represents actual scores. Each blue point corresponds to a medical school's average score. The red 45-degree line indicates perfect prediction, allowing for a visual assessment of model fit.

Figure 5 compares the average total predicted scores of applicants with the actual data, based on estimates from Table 5, Column (ii). It shows that most of the blue points are near the red line, indicating that the model successfully predicts the average total scores of applicants to the medical schools observed in the data. Similarly, Figure 6 shows that the average scores of admitted students predicted by the model closely matches the data. These results suggest that the model can successfully predict the academic abilities of students in all medical schools.

Figure 6: Model fit: Average score of admitted students

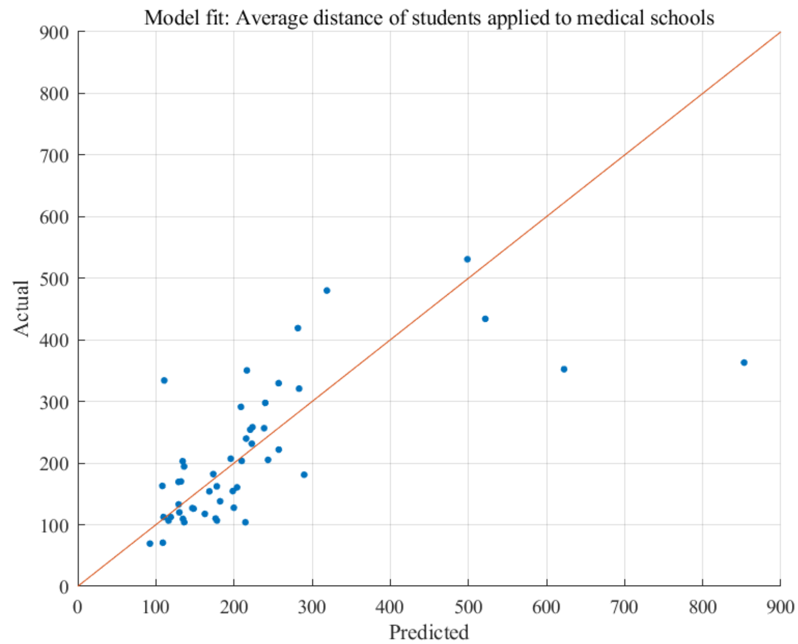


Note: This figure compares the model's predicted and actual average scores of admitted students by medical school, based on estimates from Table 5, Column (ii). The x-axis represents predicted scores, while the y-axis represents actual scores. Each blue point corresponds to the medical school's average score. The red 45-degree line indicates perfect prediction, allowing for a visual assessment of model fit.

Figure 7 compares the average predicted distance of students with the actual data, based on estimates from Table 5, Column (ii). Compared to Figures 5 and 6, the model's predictions are less accurate in this case. However, except for one outlier—Ryukyu University, located in Okinawa Prefecture—we consider the predicted distances for students to be reasonably accurate. Overall, our model can successfully predict the average distance for students in most medical schools.

In summary, we find that the estimated values of our results are reasonable, and the

Figure 7: Model fit: Average distance of students applied to medical schools



Note: This figure compares the model's predicted and actual average distance of students to medical schools, based on estimates from Table 5, column (ii). The x-axis represents the predicted distance, while the y-axis represents the actual distance, both measured in kilometers. Each blue point corresponds to a medical school's average distance. The red 45-degree line represents perfect prediction, providing a visual assessment of the model's fit.

model's predictions align well with the actual data. With these results, we are now confident in proceeding with counterfactual policy experiments in the next section.

5 Counterfactual Simulations

In this section, we conduct counterfactual simulations. We consider policy objectives that address two different disadvantages related to distance. First, the cost associated with the distance to a medical school is disadvantageous for applicants if they do not have a desirable medical school nearby, regardless of their gender. Second, assuming that the higher cost of distance for female applicants reflects social constraints on women, we interpret this as an additional disadvantage for female applicants. We examine how different policies designed to compensate for these disadvantages influence the admission of male and female applicants.

First, we examine how a subsidy that offsets distance-related costs affects the number of applicants and admissions. Given that female applicants grapple with higher distance-related costs, this policy not only supports students who do not have access to a desirable medical school nearby but also help to reduce the gender gap in admissions.

Specifically, we consider the impacts of the following financial aid for all admitted students:

$$\begin{aligned}\text{Aid}_{nj} = \frac{1}{\beta_c + \beta_c^F Female_n} \big[& \beta_d D_{nj} + \beta_{d2} D_{nj}^2 \\ & + Female_n \times \left(\beta_d^F D_{nj} + \beta_{d2}^F D_{nj}^2 \right) \big]\end{aligned} \tag{19}$$

where Aid_{nj} represents the subsidy for the nth admitted student to the jth university, D_{nj} denotes the distance between the high school of the nth admitted student and the jth university, and $Female_n$ is a female dummy variable. The parameters β_c and β_c^F are the estimated coefficients for enrollment cost and its interaction with the female dummy, respectively, as shown in Row (2) and Column (ii) of Table 5. The parameters β_d, β_{d2}, β_d^F, and β_{d2}^F are the estimated coefficients for distance, its square, and their interactions with the female dummy, respectively, as shown in Row (3) and Column (ii) of Table 5. This equation indicates that Aid_{nj} represents the monetary cost of distance that the nth student must bear if admitted to the jth university.

Table 6 presents the results of this policy. It shows that the total number of applicants to medical schools more than doubles. As expected, the policy also increases the number of female applicants more than that of male applicants: the number of female applicants increases by 130%, compared to that of male applicants by 98%. From this table, we calculate how the share of female applicants changes: the female share of applicants increases from $0.33 \approx 6219/18763$ to $0.37 \approx 14308/39084$. Therefore, this policy increases the share of female applicants. This increase in the total number of applicants indicates that the subsidy is a motivator for applying to medical school, especially for females, as it provides applicants

Table 6: The Impacts of the Subsidy that offsets Distance-related Costs

	#Applicants			#Admissions		
	Male	Female	Total	Male	Female	Total
(I) Actual	12544	6219	18763	2789	813	3602
(II) Counterfactual	24776	14308	39084	2839	763	3602
Difference: (II) - (I)	12232	8089	20321	50	-50	0
Rate of Change (%)	97.51	130.08	108.30	1.78	-6.09	0.00

Note: "(I) Actual" and "(II) Counterfactual" represent the prediction of the model without the policy and with the policy, respectively. "Difference" and "Rate of Change" refer to (II) - (I) and ((II)-(I))/(I), respectively.

with more options for applying to distant medical schools.

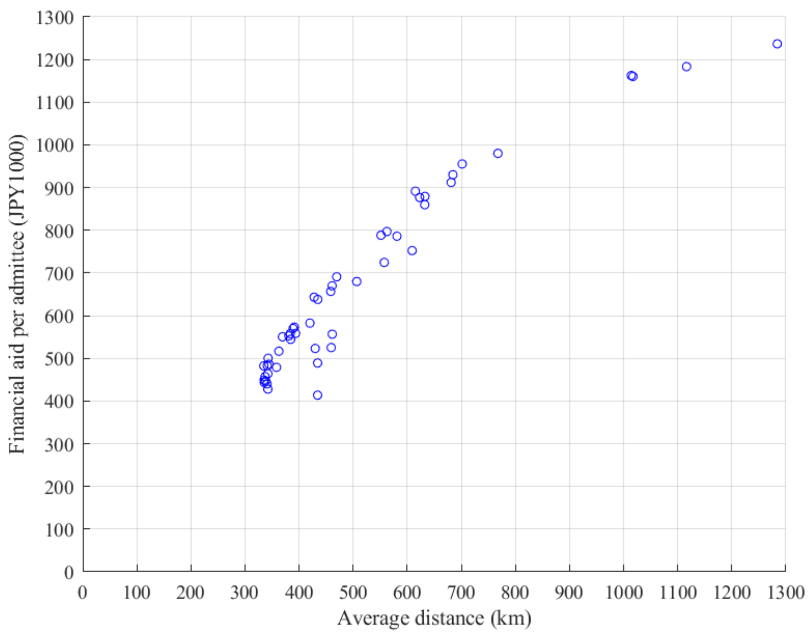
However, the number of admissions presents a different picture. While the policy increases the number of admitted males by 50, it reduces the number of admitted females by the same amount. It reduces the share of admitted females from $0.23 \approx 813/3602$ to $0.21 \approx 763/3602$. Because the total capacity of medical schools remains unchanged, the overall number of admissions do not increase. Instead, the increase in the total number of applicants intensifies competition for admission. This increased competition appears to crowd out female applicants. In other words, this policy fails to reduce the gender gap in admissions.

Figure 8 illustrates the cost of implementing this subsidy policy that offsets distance-related disadvantages in medical school admissions. The average financial aid per admitted students at each university ranges approximately between 400,000 yen and 1,250,000 yen, depending on the average distance from students' home prefectures to the university. This figure highlights that implementing this policy entails a significant financial burden.

This failure to reduce the gender gap in admissions leads us to examine the economic impact of a second policy: an affirmative action program for female students. Specifically, we analyze the following subsidy for all admitted female students:

$$\text{Aid}^F_{nj} = \frac{1}{\beta_c + \beta^F_c}\left(\beta^F_d D_{nj} + \beta^F_{d2} D^2_{nj}\right), \tag{20}$$

Figure 8: The Financial Costs of the Subsidy that Offsets Distance-related Costs



Note: This figure illustrates the financial costs associated with implementing the subsidy that offsets distance-related disadvantages in medical school admissions. The vertical axis represents the financial aid per admitted student (in thousand JPY), while the horizontal axis denotes the average distance to a medical school (in kilometers). The cost is calculated using Equation 19, with parameters derived from the estimated coefficients as reported in Row (3), Column (ii) of Table 5. These costs reflect the impact of financial aid provided to all admitted students, mitigating the disadvantage faced by applicants who do not have a desirable medical school nearby, regardless of gender.

where Aid_{nj}^{F} represents the subsidy for the nth admitted female student to the jth university, and D_{nj} denotes the distance between the high school of the nth admitted female student and the jth university. The parameters β_c and β_c^F are the estimated coefficients for the enrollment cost and its interaction with the female dummy, respectively, as shown in Row (2) and Column (ii) of Table 5. The parameters β_d^F and β_{d2}^F are the estimated coefficients for the interaction of the female dummy with distance and its square, respectively, as shown in Row (3) and Column (ii) of Table 5. This equation indicates that Aid_{nj}^{F} represents the additional monetary cost of distance, relative to male students, that the nth female student must bear if admitted to the jth university.

Table 7: The Impacts of an Affirmative Action Program for Female Students

	#Applicants			#Admissions		
	Male	Female	Total	Male	Female	Total
(I) Actual	12544	6219	18763	2789	813	3602
(II) Counterfactual	12442	6870	19312	2738	864	3602
Difference: (II) - (I)	-102	651	549	-52	52	0
Rate of Change (%)	-0.82	10.47	2.92	-1.86	6.38	0.00

Note: "(I) Actual" and "(II) Counterfactual" represent the prediction of the model without the policy and with the policy, respectively. "Difference" and "Rate of Change" refer to (II) - (I) and ((II)-(I))/(I), respectively.

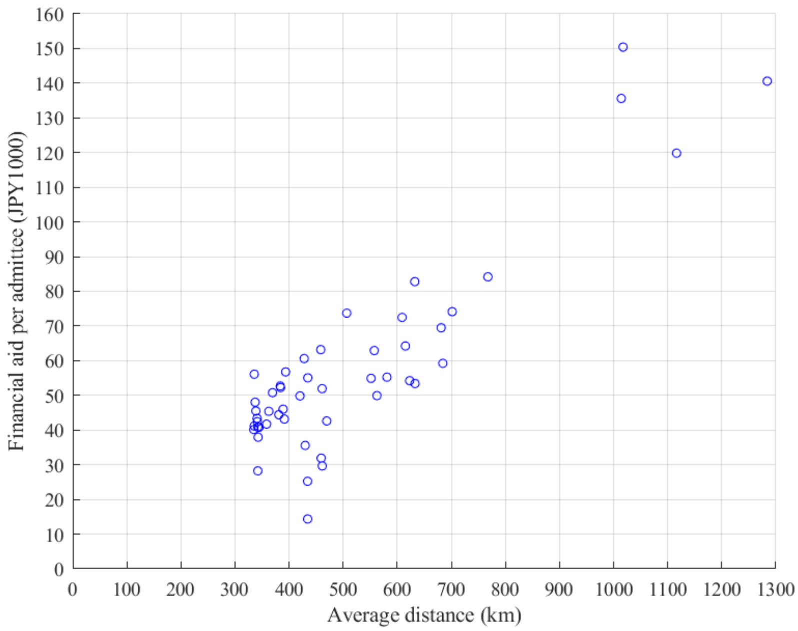
We implicitly assume that gender differences in preferences regarding the distance from home reflect social constraints on female students. If this assumption holds, the affirmative action policy can be considered a measure that offsets the disadvantage faced by female students who do not have access to a desirable public medical school nearby.

It should be noted that, unlike the proposal to introduce a gender quota as an affirmative action policy for female students, our proposed affirmative action policy allows female students to compete under the same conditions as male students.

Table 7 presents the results of this affirmative action policy in which the government provides financial aid exclusively to females to offset gender differences in the cost of distance. According to the table, the policy increases the number of female applicants by 10% while decreasing the number of male applicants by 0.8%. It also increases the number of female admissions by 6% and decreases the number of male admissions by 2%. Consequently, it increases the share of admitted female students from $0.23 \approx 813/3602$ to $0.28 \approx 1026/3602$. Therefore, the affirmative action program for female students helps to reduce the gender gap in admissions.

This policy will not be feasible if it is not cost effective. Hence, understanding the financial costs of implementing the affirmative action program is crucial. Figure 9 illustrates the cost of implementing the affirmative action policy that offsets distance-related disadvantages in medical school admissions. The average financial aid per admitted female students in each

Figure 9: The Financial Costs of the Affirmative Action Program for Female Students



Note: This figure illustrates the financial costs associated with implementing the affirmative action policy that offsets distance-related disadvantages in medical school admissions. The vertical axis represents the financial aid per admitted student (in thousand JPY), while the horizontal axis denotes the average distance to a medical school (in kilometers). The cost is calculated using Equation 20, with parameters derived from the estimated coefficients as reported in Row (3), Column (ii) of Table 5.

university ranges between 10,000 yen and 150,000 yen, depending on the average distance from students' home prefectures to the university. This amount is significantly lower than the subsidy required to offset distance-related costs. In other words, the figure suggests that implementing this affirmative action program could be a financially feasible policy option.

6 Conclusion

This study examines the geography of public medical school opportunities by constructing an equilibrium model of the medical school market. Using this model, we estimate gender differences in preferences related to distance from home and analyze how these differences affect gender disparities in medical school admissions in Japan.

Our results suggest that distance-associated costs for females are higher than those for males. Based on the estimated model, we conduct two counterfactual simulations. The findings show that while financial aid to offset distance-related costs can increase the proportion of female applicants to medical schools, it does not lead to a corresponding increase in female admissions due to the effects of competition.

Assuming that gender differences in preferences regarding the distance from home reflect social constraints on female students, we propose an alternative affirmative action policy in which the government provides financial aid exclusively to female students to offset gender differences in distance-related costs. We find that this policy not only reduces the gender gap in admissions but is also financially feasible. The evaluation of a policy depends on the underlying goals; however, it is considered a potential candidate if reducing the gender gap in admissions is a primary objective. We believe that this study contributes to a constructive policy discussion on this issue.

A Appendix

The Utility Function and Budget Constraint Explicitly Including Composite Goods: If we explicitly indicate the utility from composite goods and the budget constraint, $U_j(\varepsilon_j)$, U_f, and $U_0^e(\varepsilon_0)$ can be expressed as follows.

$$U_j(\varepsilon_j) = \tilde{U}_j(m_j - m_f)\exp\frac{\varepsilon_j}{\lambda} + U_f(m_f),$$
$$U_f = U_f(m_f),$$
$$U_0^e(\varepsilon_0) = \tilde{U}_0^e(m_0 - m_f)\exp\frac{\varepsilon_0}{\lambda} + U_f(m_f),$$

subject to

$$W + \Delta W_j = c_j + m_j, W + \Delta W_f^e = c_f + m_f,\ W + \Delta W_0^e = c_0^e + m_0,$$

where m_j, m_f, and m_0 are the utility derived from composite goods when the applicant enters the jth university, fails, or applies to another department, respectively. The variable W is the current total wealth of the applicant; ΔW_j, ΔW_f^e, and ΔW_0^e are the expected wealth increases when entering the jth university, failing, or applying to another department, respectively. c_j, c_f, and c_0^e are the applicant's payments to the jth university, cost of preparing for the examination next year, and expected tuition fee for applying to another department, respectively.

Derivation of equation (4): Substituting Equations (2) and (3), we can show that

$$\begin{aligned} & \arg\max \left\{ \begin{array}{c} \max_{j \in \{1,\dots,J\}} \left\{ q_j \left(s_j^m; \mathbf{y}^1 \right) U_j \left(\varepsilon_j \right) + \left[1 - q_j \left(s_j^m; \mathbf{y}^1 \right) \right] U_f \right\}, \\ U_0^e \left(\varepsilon_0 \right) \end{array} \right\} \\ = \; & \arg\max_j \left\{ EU_j \exp \frac{\varepsilon_j}{\lambda} \right\}, \end{aligned}$$

where $EU_j = q_j \left(s_j^m; \mathbf{y}^1 \right) \frac{\tilde{U}_j}{\tilde{U}_0^e} I \left(j \neq 0 \right) + \left[1 - I \left(j \neq 0 \right) \right]$. Hence, as $\lambda > 0$, the probability of applying to the jth university can be expressed as

$$\begin{aligned} & \Pr \left(EU_j \exp \frac{\tilde{\varepsilon}_j}{\lambda} \geq EU_{j'} \exp \frac{\tilde{\varepsilon}_{j'}}{\lambda} \right), \ \forall j', \\ = \; & \Pr \left(\lambda \ln EU_j + \tilde{\varepsilon}_j \geq \lambda \ln EU_{j'} + \tilde{\varepsilon}_{j'} \right), \ \forall j'. \end{aligned}$$

As ε_j follows the distribution $\exp - \left[\exp - \left(\varepsilon_j + \gamma \right) \right]$, and $\ln \frac{\tilde{U}_j}{\tilde{U}_0^e} = \frac{\delta_j + b_j \left(\mathbf{y}^1, \mathbf{x} \right)}{\lambda}$, the desired result follows directly from the standard random utility model.

Proof of the existence of $\left\{ \underline{s}_j \right\}$ and $\left\{ \bar{s}_j \right\}$: We show that we can find $\left\{ \underline{s}_j \right\}$ and $\left\{ \bar{s}_j \right\}$ for any $M_j \in \left[\underline{M}, \bar{M} \right]$ such that if there exists s_j^m that satisfies the equation (5), $s_j^m \in \left[\underline{s}_j, \bar{s}_j \right]$ for all j.

We define $\underline{p}_j\left(s,\delta;\mathbf{y}^1,\mathbf{x}\right)$ as follows:

$$\underline{p}_j\left(s,\delta;\mathbf{y}^1,\mathbf{x}\right)=\frac{\exp\left\{\lambda q_j\left(s;\mathbf{y}^1\right)+\delta_j+b_j\left(\mathbf{y}^1,\mathbf{x}\right)\right\}}{1+\sum_{i\neq 0,j}\exp\left\{\lambda+\delta_i+b_i\left(\mathbf{y}^1,\mathbf{x}\right)\right\}+\exp\left\{\lambda q_j\left(s;\mathbf{y}^1\right)+\delta_j+b_j\left(\mathbf{y}^1,\mathbf{x}\right)\right\}}.$$

Note that the admission probability in $\underline{p}_j\left(s,\delta;\mathbf{y}^1,\mathbf{x}\right)$ for schools other than the jth school is 1. Hence, this represents the lowest application probability to the jth school when the minimum score of the jth school is s.

Note that $\lim_{s\to-\infty}\int q_j\left(s;\mathbf{y}^1\right)\underline{p}_j\left(s,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)=\int p_j^*\left(\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)$. Additionally, $\min_j\int p_j^*\left(\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)>\frac{\bar{M}}{N}=\max\left\{\frac{M_i}{N}\right\}_i$ and $0<\frac{\underline{M}}{N}=\min\left\{\frac{M_i}{N}\right\}_i$. Because $\lim_{s\to\infty}q_j\left(s;\mathbf{y}^1\right)=0$, $\lim_{s\to-\infty}q_j\left(s;\mathbf{y}^1\right)=1$ and $\frac{\partial q_j\left(s;\mathbf{y}^1\right)}{\partial s}<0$, it is evident that there exists unique $\left\{\underline{s}_j\right\}$ and $\left\{\bar{s}_j\right\}$ for any $M_j\in\left[\underline{M},\bar{M}\right]$ such that, for all j

$$\begin{aligned}\frac{M_j}{N}&=\int q_j\left(\bar{s}_j;\mathbf{y}^1\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)>0,\\ \frac{M_j}{N}&=\int q_j\left(\underline{s}_j;\mathbf{y}^1\right)\underline{p}_j\left(\underline{s}_j,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)<\int p_j^*\left(\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right).\end{aligned}$$

Note that

$$\begin{aligned}&\int q_j\left(\bar{s}_j;\mathbf{y}^1\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)\\ =&\int q_j\left(s_j^m;\mathbf{y}^1\right)p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)\\ <&\int q_j\left(s_j^m;\mathbf{y}^1\right)dG\left(\mathbf{y}^1,\mathbf{x}\right),\ \forall j\end{aligned}$$

and

$$\begin{aligned}&\int q_j\left(\underline{s}_j;\mathbf{y}^1\right)\underline{p}_j\left(\underline{s}_j,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right),\\ =&\int q_j\left(s_j^m;\mathbf{y}^1\right)p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)\\ >&\int q_j\left(s_j^m;\mathbf{y}^1\right)\underline{p}_j\left(\underline{s}_j,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right),\forall j\end{aligned}$$

Hence, if there exists s_j^m that satisfies the equation (5), $s_j^m \in \left[\underline{s}_j, \bar{s}_j\right]$ for all j.

Rigorous statement of Theorem 2: Suppose that $\mathbf{s}^m \in \mathbf{S}^m$ and that the scale parameter $\lambda > 0$ is sufficiently small such that the following condition holds for all j:

$$\begin{aligned}
&(\lambda+1)\int \frac{\frac{\partial q_j\left(s_j^m;\mathbf{y}^1\right)}{\partial s_j^m}}{q_j\left(s_j^m;\mathbf{y}^1\right)}\hat{\omega}_j\left(\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right) && (21)\\
<\;\;&\lambda\int\left[\sum_{k=1}^{K}\frac{\frac{\partial q_k\left(s_k^m;\mathbf{y}^1\right)}{\partial s_k^m}}{q_k\left(s_k^m;\mathbf{y}^1\right)}\breve{\omega}_k\left(\mathbf{y}^1,\mathbf{x}\right)\right]\hat{\omega}_j\left(\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)
\end{aligned}$$

where $\breve{\omega}_k\left(\mathbf{y}^1,\mathbf{x}\right) = p_k\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)$, and $\hat{\omega}_j\left(\mathbf{y}^1,\mathbf{x}\right) = q_j\left(s_j^m;\mathbf{y}^1\right)p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)$. Then, there exists a unique $\left(\{p_i\}_i,\ \mathbf{s}^m\right)$ that satisfies the market equilibrium for medical school admission.

proof Define $\Gamma\left(\mathbf{s}^m\right):\mathbf{S}^m \to \mathbf{S}^m$ such that $\Gamma\left(\mathbf{s}^m\right) = \left(\Gamma_1\left(\mathbf{s}^m\right),\ldots,\Gamma_J\left(\mathbf{s}^m\right)\right)$, where for $\psi > 0$,

$$\Gamma_j\left(\mathbf{s}^m\right) \equiv s_j^m - \psi\left[\frac{M_j}{N} - \int q_j\left(s_j^m;\mathbf{y}^1\right)p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)\right],\ \forall j$$

with Equations (4) and (1).

If we find a unique $\mathbf{s}^m \in \mathbf{S}^m$ that satisfies $\Gamma\left(\mathbf{s}^m\right) = \mathbf{s}^m$, then

$$\frac{M_j}{N} = \int q_j\left(s_j^m;\mathbf{y}^1\right)p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right),\ \forall j.$$

Hence, this $\mathbf{s}^m$ solves Equation (5) along with Equations (4) and (1). Therefore, this $\mathbf{s}^m$ satisfies the market equilibrium for higher education.

Because $\mathbf{S}^m = \mathbf{\Pi}_j\left[\underline{s}_j, \bar{s}_j\right]$ is compact, it is a complete metric space. Hence, all Cauchy sequences $\left\{\mathbf{s}^{m,\tau}\right\}$ in $\mathbf{S}^m$ converge within $\mathbf{S}^m$. Thus, if $\Gamma\left(\mathbf{s}^m\right)$ is a contraction mapping for some $\psi > 0$, there exists a unique $\mathbf{s}^m$ in $\mathbf{S}^m$ that satisfies $\Gamma\left(\mathbf{s}^m\right) = \mathbf{s}^m$. To prove $\Gamma\left(\mathbf{s}^m\right)$ is a contraction mapping, we use the following lemma.

Lemma 3 *Suppose that* $\mathbf{D} \in \mathbf{R}^J$ *is a compact set where* $\delta \in \mathbf{D}$ *with a metric* $\left\|\hat{\delta} - \tilde{\delta}\right\| =$

$\max_i \left|\hat{\delta}_i - \tilde{\delta}_i\right|$ *for any* $\hat{\delta}$ *and* $\tilde{\delta} \in \mathbf{D}$. *Consider a continuously differentiable function* Γ : $\mathbf{D} \to \mathbf{D}$. *Suppose that*

$$\max_j \left\{ \sum_{k=1}^{J} \left| \frac{\partial \Gamma_j(\delta)}{\partial \delta_k} \right| \right\} < 1, \ \forall \delta \in \mathbf{D}.$$

Then, for any $\hat{\delta}, \tilde{\delta} \in \mathbf{D}$, *there exists* $\beta \in (0,1)$ *such that*

$$\left\| \Gamma\left(\hat{\delta}\right) - \Gamma\left(\tilde{\delta}\right) \right\| \leq \beta \left\| \hat{\delta} - \tilde{\delta} \right\|.$$

Proof. *Take* $\hat{\delta}, \tilde{\delta} \in \mathbf{D}$. *By the mean value theorem, there exists* $h \in (0,1)$ *such that*

$$\Gamma\left(\hat{\delta}\right) - \Gamma\left(\tilde{\delta}\right) = \frac{\Delta \Gamma(\delta)}{\Delta \delta} |_{\delta = h\left(\hat{\delta} - \tilde{\delta}\right) + \tilde{\delta}} \left(\hat{\delta} - \tilde{\delta}\right).$$

Now,

$$\begin{aligned} \left\| \Gamma\left(\hat{\delta}\right) - \Gamma\left(\tilde{\delta}\right) \right\| &= \max_j \left| \sum_{k=1}^{J} \frac{\partial \Gamma_j(\delta)}{\partial \delta_k} |_{\delta = h\left(\hat{\delta}_k - \tilde{\delta}_k\right) + \tilde{\delta}_k} \left(\hat{\delta}_k - \tilde{\delta}_k\right) \right| \\ &= \max_j \left\{ \sum_{k=1}^{J} \left| \frac{\partial \Gamma_j(\delta)}{\partial \delta_k} |_{\delta = h\left(\hat{\delta}_k - \tilde{\delta}_k\right) + \tilde{\delta}_k} \right| \right\} \max_k \left| \hat{\delta}_k - \tilde{\delta}_k \right| \\ &= \max_j \left\{ \sum_{k=1}^{J} \left| \frac{\partial \Gamma_j(\delta)}{\partial \delta_k} |_{\delta = h\left(\hat{\delta}_k - \tilde{\delta}_k\right) + \tilde{\delta}_k} \right| \right\} \left\| \hat{\delta} - \tilde{\delta} \right\|. \end{aligned}$$

If $\max_j \left\{ \sum_{k=1}^{J} \left| \frac{\partial \Gamma_j(\delta)}{\partial \delta_k} \right| \right\} < 1, \ \forall \delta \in \mathbf{D}$, *we can set* $\beta \in (0,1)$ *such that*

$$\beta = \max_j \left\{ \sum_{k=1}^{J} \left| \frac{\partial \Gamma_j(\delta)}{\partial \delta_k} \right| \right\} < 1.$$

The desired result follows immediately. ■

Following the lemma 3, it suffices to show that

$$\max_j \left\{ \sum_{k=0}^{J} \left| \frac{\partial \Gamma_j(\delta)}{\partial \delta_k} \right| \right\} < 1.$$

Note that Equation (4) implies

$$\begin{aligned}
\frac{\partial p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)}{\partial s_j^m} &= \lambda\frac{\frac{\partial q_j\left(s_j^m;\mathbf{y}^1\right)}{\partial s_j^m}}{q_j\left(s_j^m;\mathbf{y}^1\right)}p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\left[1-p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\right], \\
\frac{\partial p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)}{\partial s^m}|_{k\neq j} &= -\lambda\frac{\frac{\partial q_k\left(s_k^m;\mathbf{y}^1\right)}{\partial s_k^m}}{q_k\left(s_k^m;\mathbf{y}^1\right)}p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)p_k\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right).
\end{aligned}$$

Hence,

$$\begin{aligned}
\left|\frac{d\Gamma_j\left(\mathbf{s}^m\right)}{ds_j^m}\right| &= \left|1+\psi\int\left[\begin{array}{c}\frac{\partial q_j\left(s_j^m;\mathbf{y}^1\right)}{\partial s_j^m}p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\\ +q_j\left(s_j^m;\mathbf{y}^1\right)\frac{\partial p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)}{\partial s_j^m}\end{array}\right]dG\left(\mathbf{y}^1,\mathbf{x}\right)\right| \\
&= \left|1+\psi\int\frac{\partial q_j\left(s_j^m;\mathbf{y}^1\right)}{\partial s_j^m}p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\left[1+\lambda\left(1-p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\right)\right]dG\left(\mathbf{y}^1,\mathbf{x}\right)\right| \\
&= 1+\psi\int\frac{\partial q_j\left(s_j^m;\mathbf{y}^1\right)}{\partial s_j^m}p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\left[1+\lambda\left(1-p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)\right]
\end{aligned}$$

for small $\psi > 0$ and for $k \neq j$

$$\begin{aligned}
\left|\frac{d\Gamma_j\left(\mathbf{s}^m\right)}{ds_k^m}\right| &= \left|\psi\int q_j\left(s_j^m;\mathbf{y}^1\right)\frac{\partial p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)}{\partial s_k^m}dG\left(\mathbf{y}^1,\mathbf{x}\right)\right| \\
&= \left|-\psi\int q_j\left(s_j^m;\mathbf{y}^1\right)\lambda\frac{\frac{\partial q_k\left(s_k^m;\mathbf{y}^1\right)}{\partial s_k^m}}{q_k\left(s_k^m;\mathbf{y}^1\right)}p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)p_k\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)\right| \\
&= -\psi\int q_j\left(s_j^m;\mathbf{y}^1\right)\lambda\frac{\frac{\partial q_k\left(s_k^m;\mathbf{y}^1\right)}{\partial s_k^m}}{q_k\left(s_k^m;\mathbf{y}^1\right)}p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)p_k\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right)
\end{aligned}$$

for all $\psi > 0$. Assume that our Γ function is endowed with this small $\psi > 0$ that satisfies the equations above. Then,

$$
\begin{aligned}
&\sum_{k}^{K}\left|\frac{\partial\Gamma_j(\mathbf{s}^m)}{\partial s_k^m}\right| \\
= \;& \left|\frac{\partial\Gamma_j(\mathbf{s}^m)}{\partial s_j^m}\right| + \sum_{k\neq j}^{K}\left|\frac{\partial\Gamma_j(\mathbf{s}^m)}{\partial s_k^m}\right| \\
= \;& 1+\psi\int\frac{\partial q_j\left(s_j^m;\mathbf{y}^1\right)}{\partial s_j^m}p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\left[1+\lambda\left(1-p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\right)\right]dG\left(\mathbf{y}^1,\mathbf{x}\right) \\
& -\psi\sum_{k\neq j}^{K}\int q_j\left(s_j^m;\mathbf{y}^1\right)\lambda\frac{\frac{\partial q_k\left(s_k^m;\mathbf{y}^1\right)}{\partial s_k^m}}{q_k\left(s_k^m;\mathbf{y}^1\right)}p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)p_k\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right) \\
= \;& 1+\psi\int q_j\left(s_j^m;\mathbf{y}^1\right)p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\left\{\left[\begin{array}{c}(\lambda+1)\frac{\frac{\partial q_j\left(s_j^m;\mathbf{y}^1\right)}{\partial s_j^m}}{q_j\left(s_j^m;\mathbf{y}^1\right)} \\ -\lambda\sum_k^K\frac{\frac{\partial q_k\left(s_k^m;\mathbf{y}^1\right)}{\partial s_k^m}}{q_k\left(s_k^m;\mathbf{y}^1\right)}p_k\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\end{array}\right]\right\}dG\left(\mathbf{y}^1,\mathbf{x}\right)
\end{aligned}
$$

This means that if

$$
\begin{aligned}
&(\lambda+1)\int\frac{\frac{\partial q_j\left(s_j^m;\mathbf{y}^1\right)}{\partial s_j^m}}{q_j\left(s_j^m;\mathbf{y}^1\right)}q_j\left(s_j^m;\mathbf{y}^1\right)p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right) \\
< \;& \lambda\int\left[\sum_k^K\frac{\frac{\partial q_k\left(s_k^m;\mathbf{y}^1\right)}{\partial s_k^m}}{q_k\left(s_k^m;\mathbf{y}^1\right)}p_k\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)\right]q_j\left(s_j^m;\mathbf{y}^1\right)p_j\left(\mathbf{s}^m,\delta;\mathbf{y}^1,\mathbf{x}\right)dG\left(\mathbf{y}^1,\mathbf{x}\right),
\end{aligned}
$$

then $\sum_k^K\left|\frac{\partial\Gamma_j(\mathbf{s}^m)}{\partial s_k^m}\right|<1$ for all j. **Q.E.D.**

B Estimation algorithm

Our estimation algorithm follows previous studies (e.g., Berry et al., 2004; Goolsbee and Petrin, 2004; Train and Whinston, 2007) in which both individual-level (micro) and market-level (macro) data are utilized in the estimation of a consumer choice model. Specifically, we incorporate the individual-level data on medical school choice alongside the market-level data on applications and admissions by medical school. A key distinction from the previous studies is that the market-level data comprise two elements. Specifically, we utilize not only quantity chosen by consumers (i.e., number of applications) but also their admissions.

As outlined in Section 4, the estimation is performed by searching for the value of $\boldsymbol{\theta}$ that maximize the likelihood function in Equation (11). In the process of the maximization, the equality constraints on the market-level application shares and admission rates, specified in Equations (13) and (14), respectively, are used to compute the common parts of utility, $\boldsymbol{\delta}$, and the modified minimum scores, $\boldsymbol{\mu}$, for any values of $\boldsymbol{\theta}$. Drawing from Berry et al. (1995), we adopt a contraction mapping procedure to compute $(\boldsymbol{\delta}, \boldsymbol{\mu})$. Given that we have two equality constraints for the two school-specific vectors, the contraction mapping procedure also has two stages. The detailed procedure is as follows.

Contraction mapping to compute $(\boldsymbol{\delta}, \boldsymbol{\mu})$ from market-level data: First, we consider the computation of $\boldsymbol{\delta}$ given the value of $(\boldsymbol{\mu}, \boldsymbol{\theta})$. In this case, the contraction mapping procedure proposed by Berry et al. (1995) can be directly applied. Specifically, for any given values of $(\boldsymbol{\mu}, \boldsymbol{\theta})$, $\boldsymbol{\delta}$ that satisfies the equality constraint of Equation (13) can be computed numerically using the following series of iterations:

$$\boldsymbol{\delta}^{h+1} = \boldsymbol{\delta}^{h} + \left[\log\left(\frac{\mathbf{A}}{N}\right) - \log\left(\mathbf{P}(\boldsymbol{\delta}^{h}; \boldsymbol{\mu}, \boldsymbol{\theta})\right)\right], \tag{22}$$

where h denotes the number of iterations. $\mathbf{A}/N$ is the vector of application shares observed in the market-level data, where the j-th element is A_j/N, the application share for university j. $\mathbf{P}(\cdot)$ denotes the vector of the application shares predicted from our model, where the j-th element is $P_j(\cdot)$, the application share function in Equation (8). For notational convenience, $P_j(\cdot)$ is denoted here as a function of $\boldsymbol{\delta}$ with parameters $(\boldsymbol{\mu}, \boldsymbol{\theta})$. The iteration converges at $h = h^*$ where $||\boldsymbol{\delta}^{h^*+1} - \boldsymbol{\delta}^{h^*}||$ become smaller than some tolerance level. We denote $\boldsymbol{\delta}^{h^*}$ as a function of $\boldsymbol{\mu}$ with a parameter $\boldsymbol{\theta}$, namely $\boldsymbol{\delta}^{h^*} = \boldsymbol{\delta}^*(\boldsymbol{\mu}; \boldsymbol{\theta})$.

Next, following that $\boldsymbol{\delta}$ can be denoted as a function of $\boldsymbol{\mu}$, we consider the computation of $\boldsymbol{\mu}$ given the value of $\boldsymbol{\theta}$. Specifically, based on the equality constraint in Equation (14), the modified minimum score vector $\boldsymbol{\mu}$ is computed by the following series of iterations:

$$\boldsymbol{\mu}_j^{k+1} = \boldsymbol{\mu}_j^k - \left[\log\left(\frac{\mathbf{M}}{\mathbf{A}}\right) - \log\left(\frac{\mathbf{Q}\left(\boldsymbol{\mu}^k, \boldsymbol{\delta}^*(\boldsymbol{\mu}^k; \boldsymbol{\theta}); \boldsymbol{\theta}\right)}{\mathbf{P}\left(\boldsymbol{\mu}^k, \boldsymbol{\delta}^*(\boldsymbol{\mu}^k; \boldsymbol{\theta}); \boldsymbol{\theta}\right)}\right)\right], \tag{23}$$

where k denotes the number of iterations. $\mathbf{M}/\mathbf{A}$ denotes the vector of admission rates observed in the market-level data, where the j-th element represents M_j/A_j, the admission rate for university j. $\mathbf{Q}(\cdot)/\mathbf{P}(\cdot)$ denotes the vector of admission rates predicted from the model, where the j-th element represents $Q_j(\cdot)/P_j(\cdot)$. $Q_j(\cdot)$ is the admission share function in Equation (9). The iteration converges at $k = k^*$ where $||\boldsymbol{\mu}^{k^*+1} - \boldsymbol{\mu}^{k^*}||$ becomes smaller than some tolerance level.

This iteration indicates that the minimum score for school j is adjusted downward (upward) if its actual admission rate is higher (lower) than the predicted ones. While it is known that the iteration for $\boldsymbol{\delta}_j$ in Equation (22) is a contraction mapping, it is not clear whether this iteration also possesses the contraction mapping property. However, we verify that this iteration consistently converges for any values of $\boldsymbol{\theta}$ used in our estimation process.

Given the validity of the contraction mapping procedures above, we can express $\boldsymbol{\delta}$ and $\boldsymbol{\mu}$ as a function of $\boldsymbol{\theta}$, denoted as $\boldsymbol{\delta}(\boldsymbol{\theta})$ and $\boldsymbol{\mu}(\boldsymbol{\theta})$. Consequently, the individual likelihood function in Equation (11) can be denoted as a function of $\boldsymbol{\theta}$ alone, denoted as $L_n(\boldsymbol{\theta})$, allowing for the maximum likelihood estimation over the space of $\boldsymbol{\theta}$.

To conduct the estimation including the contraction mapping procedure, we need to approximate the integrals found in the individual choice probability in Equation (12) and the market-level application and admission share functions in Equations (8) and (9). The procedure for this approximation is outlined below.

Approximation of the model: First, to approximate the individual choice probability in Equation (12), we simulate $\tilde{N}_1 = 100$ draws of ν_n, denoted as $\tilde{\boldsymbol{\nu}}_n^1 = \{\tilde{\nu}_{ni}^1\}_{i=1}^{\tilde{N}_1}$, from the standard normal distribution for N_m students in the individual data. Then, the individual choice probability function is rewritten as:

$$\bar{p}_j\left(\boldsymbol{\mu},\boldsymbol{\delta},\mathbf{x}_n^o;\boldsymbol{\theta}\right)\approx\frac{1}{\tilde{N}_1}\sum_{i=1}^{\tilde{N}_1}p_j\left(\boldsymbol{\mu},\boldsymbol{\delta},\mathbf{x}_n^o,\tilde{\nu}_{ni}^1;\boldsymbol{\theta}\right),\forall j. \tag{24}$$

We replace the individual choice probability in the likelihood function for student n of Equation (11) with this approximation and denote this likelihood as $\tilde{L}_n(\boldsymbol{\mu},\boldsymbol{\delta};\boldsymbol{\theta})$.

Next, we discuss the approximation of the market-level applications and admission share functions in Equations (8) and (9). These approximations are based on simulation draws from the empirical distribution of the observed student characteristics, $\mathbf{x}_n^o=(l_n,S_n,Female_n,\mathbf{z}_n)$, and the standard normal distribution of the unobserved heterogeneity, ν_n. We set the number of simulation draws as $\tilde{N}_2=5000$ and denote the sets of draws for the observed characteristics and the unobserved heterogeneity as $\tilde{\mathbf{x}}_n^o=\{\tilde{\mathbf{x}}_{ni}^o\}_{i=1}^{\tilde{N}_2}$ and $\tilde{\boldsymbol{\nu}}_n^2=\{\tilde{\nu}_{ni}^2\}_{i=1}^{\tilde{N}_2}$, respectively.[17]

Given the sets of draws, we can approximate application and admission share functions in Equations (8) and (9) as follows:

$$\tilde{P}_j\left(\boldsymbol{\mu},\boldsymbol{\delta};\boldsymbol{\theta}\right)=\frac{1}{\tilde{N}_2}\sum_{i=1}^{\tilde{N}_2}p_j\left(\boldsymbol{\mu},\boldsymbol{\delta},\tilde{\mathbf{x}}_{ni}^o,\tilde{\nu}_{ni}^2;\boldsymbol{\theta}\right),\forall j, \tag{25}$$

and

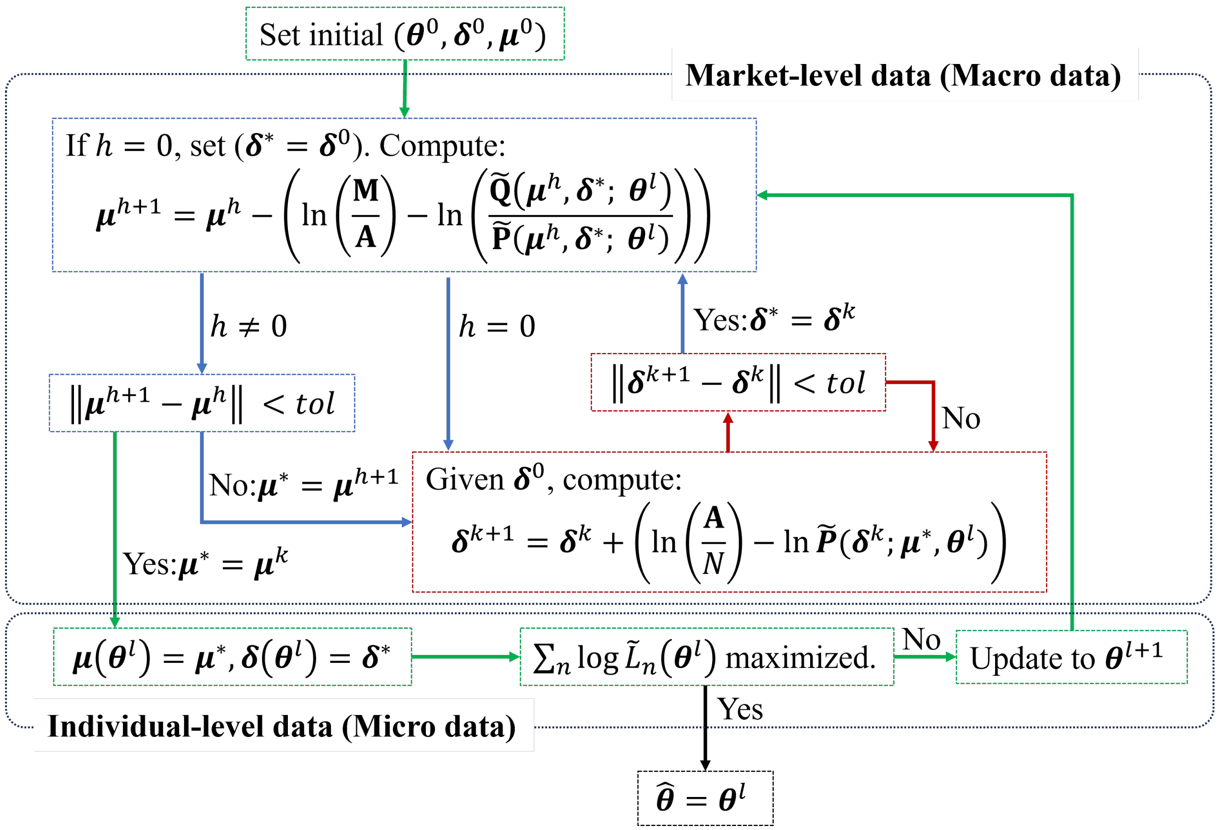
$$\tilde{Q}_j\left(\boldsymbol{\mu},\boldsymbol{\delta};\boldsymbol{\theta}\right)=\frac{1}{\tilde{N}_2}\sum_{i=1}^{\tilde{N}_2}q_j\left(\mu_j,\tilde{\mathbf{x}}_{ni}^o;\alpha_j\right)p_j\left(\boldsymbol{\mu},\boldsymbol{\delta},\tilde{\mathbf{x}}_{ni}^o,\tilde{\nu}_{ni}^2;\boldsymbol{\theta}\right),\forall j. \tag{26}$$

Summary of the estimation procedure: Given the formulation described above, we summarize the estimation procedure in Figure 10. The estimation begins by setting $(\boldsymbol{\theta}_0,\boldsymbol{\delta}_0,\boldsymbol{\mu}_0)$. The j-th elements of $\tilde{\mathbf{P}}(\cdot)$ and $\tilde{\mathbf{Q}}(\cdot)/\tilde{\mathbf{P}}(\cdot)$ represent $\tilde{P}_j(\cdot)$, the approximated application share for university j, and $\tilde{Q}_j(\cdot)/\tilde{P}_j(\cdot)$,the approximated admission rate for university j, respectively.

The upper part of this figure shows the contraction mapping procedure based on the

[17] The simulation draws for the unobserved heterogeneity ν_n differ between the approximation of individual-level data (i.e., $\tilde{\nu}_n^1$) and that of market-level data (i.e.$\tilde{\nu}_n^2$).

Figure 10: Estimation algorithm



market-level (macro) data, whereas the lower part indicates the maximum likelihood estimation based on the individual-level (micro) data of medical school choice. Given the starting value $\boldsymbol{\theta}_0$, the values of $\boldsymbol{\mu}$ and $\boldsymbol{\delta}$ under the value of $\boldsymbol{\theta}_0$ are derived from the contraction mapping from the initial their values, namely $(\boldsymbol{\mu}_0, \boldsymbol{\delta}_0)$. If the log-likelihood is not maximized, $\boldsymbol{\theta}_0$ is updated to $\boldsymbol{\theta}_1$. $\boldsymbol{\theta}_l$ indicates the values of $\boldsymbol{\theta}$ after l steps from the starting value. Consequently, the parameter estimate $\hat{\boldsymbol{\theta}}$ is chosen at the value that maximizes the likelihood function.

C Counterfactual simulation

This appendix provides details on the counterfactual simulations discussed in Section 5. Throughout our counterfactual exercises, the common part of utility $(\boldsymbol{\delta})$ and admission capacity ($\mathbf{M}$) remain unchanged from the original ones across alternative scenarios. The common part of utility used in the counterfactual simulations is evaluated at $\hat{\boldsymbol{\theta}}$, which we denote as $\hat{\boldsymbol{\delta}} = \boldsymbol{\delta}(\hat{\theta})$. A key parameter varying across counterfactual environments is the modified minimum score $\boldsymbol{\mu}$, which is obtained by using the contraction mapping procedure explained below.

To describe the counterfactual environments, a set of notations is introduced. First, we denote student n's specific preference for school j as $b_{nj} \equiv b_j(\mathbf{x}_n^o, \nu_n; \boldsymbol{\beta})$ and represent its J-dimensional vector as $\mathbf{b}_n$. In our counterfactual simulation, we derive the equilibrium where $\mathbf{b}_n$ is replaced by a counterfactual vector $\mathbf{b}_n^c$ (e.g., the student n's specific preference in the presence of the financial aid to offset the negative utility associated with the distance). Next, given $\hat{\boldsymbol{\delta}}$ and $\hat{\boldsymbol{\theta}}$, we denote the admission share function evaluated at $\mathbf{b}_n^c$ as $Q_j^c(\boldsymbol{\mu}; \hat{\boldsymbol{\delta}}, \hat{\boldsymbol{\theta}})$. Q_j^c is approximated as in Equation (26); specifically, given the parameter estimate $\hat{\boldsymbol{\theta}}$, the approximated admission probability at $\mathbf{b}_n^c$, $\tilde{Q}_j^c$, is denoted as follows.

$$\tilde{Q}_j^c\left(\boldsymbol{\mu}, \boldsymbol{\delta}; \hat{\boldsymbol{\theta}}\right) = \frac{1}{\tilde{N}_2} \sum_{i=1}^{\tilde{N}_2} q_j\left(\mu_j, \tilde{\mathbf{x}}_{ni}^o; \hat{\alpha}_j\right) p_j^c\left(\boldsymbol{\mu}, \boldsymbol{\delta}, \tilde{\mathbf{x}}_{ni}^o, \tilde{\nu}_{ni}^2; \hat{\boldsymbol{\theta}}\right), \forall j, \tag{27}$$

where $p_j^c(\cdot)$ is the application probability in Equation (7) evaluated at b_{nj}^c. Recall that $\alpha_j = \frac{1}{(1-\omega_j)\sigma_j}$, where ω_j is the weight of first exam and σ_j is a parameter in the variance of u_j. As these two parameters are the primitive of the model, the estimate of α_j (i.e., $\hat{\alpha}_j$) remains unchanged under the counterfactual environments.

Given J-dimensional vector of $\tilde{Q}_j^c$, denoted as $\tilde{\mathbf{Q}}^c$, the counterfactual modified minimum score, $\boldsymbol{\mu}^c$, can be obtained using the following contraction mapping procedure.

$$\boldsymbol{\mu}_j^{h+1} = \boldsymbol{\mu}_j^h - \left[\ln\left(\frac{\mathbf{M}}{N}\right) - \ln\left(\tilde{\mathbf{Q}}^c\left(\boldsymbol{\mu}^h; \hat{\boldsymbol{\delta}}, \hat{\boldsymbol{\theta}}\right)\right)\right], \tag{28}$$

where h denotes the number of iterations. The iteration converges at $h = h^*$, when $||\boldsymbol{\mu}^{h^*+1} - \boldsymbol{\mu}^{h^*}||$ becomes smaller than a specified tolerance level, thereby yielding $\boldsymbol{\mu}^c = \boldsymbol{\mu}^{h^*}$.

Notably, the contraction mapping procedure has only one-stage, contrary to the two-stage process in the estimation algorithm, because $\boldsymbol{\delta}$ is fixed at $\hat{\boldsymbol{\delta}}$. Additionally, we do not use the admission rate (i.e., $\mathbf{M}/\mathbf{A}$) when updating the value of $\boldsymbol{\mu}$ in the contraction mapping procedure as in Equation (26). This is because the application numbers change under the counterfactual scenario, while the admission capacities remain unchanged.

The counterfactual number of applications A_j^c, applications by gender, and admissions by gender are derived under the counterfactual minimum score $\boldsymbol{\mu}^c$.

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