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ABSTRACT

Using data on the universe of students who graduated from U.S. medical schools between 1996 and 1998, we examine whether the abilities and specialty preferences of a medical school class affect a student's academic achievement in medical school and his choice of specialty. We mitigate the selection problem by including school-specific fixed effects, and show that this method yields an upper bound on peer effects for our data. We estimate positive peer effects that disappear when school-specific fixed effects are added to control for the endogeneity of a peer group. We find no evidence that peer effects are stronger for blacks, that peer groups are formed along racial lines, or that students with relatively low ability benefit more from their peers than students with relatively high ability. However, we do find some evidence that peer groups form along gender lines.

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1 Introduction

The belief that peer groups in schools influence the behavior and outcomes of their members has been important in shaping public policy. The Coleman report (Coleman et al., 1966) concluded that peer effects in public schools contributed to differences in the achievement of black and white students. Busing was implemented in many school districts due in part to this finding. Moreover, one of the principal arguments against school vouchers is that the best students will leave the public school system, and thereby impair the performance of the students who remain behind. Several recent theoretical papers on the impact of school vouchers assume that student achievement is influenced by the characteristics, achievement, or behavior of a person's classmates (Nechyba, 2000; Caucutt, 2000; Epple and Romano, 1998).

There is a substantial empirical literature examining how peer groups affect teenagers' criminal behavior (Glaeser, Sacerdote, and Scheinkman, 1996), the likelihood that teenagers will become pregnant and complete high school (Evans, Oates, and Schwab, 1992), grade school childrens' achievement (Hoxby, 2000; Ding and Lehrer, 2001), college students' grades, choice of major, and fraternity choices (Sacerdote, 2001; Arcidiacono, 1999), and high school students' drug and alcohol use, cigarette smoking, church attendance, and the likelihood of completing high school (Gaviria and Raphael, 2001). However, many economists remain skeptical of estimates of social interactions due, in part, to the difficulty of separately measuring the effect of a peer group, the effect of unobserved characteristics shared by members of the peer group, and the effect of the environment (e.g., a school) in which the members of the peer group operate (Manski, 2000).

Most existing studies of peer groups focus on adolescents and grade school children. The influence of peer groups on medical students' specialty choices may have important policy implications because many policy makers believe the U.S. has a shortage of physicians in the primary care specialties (pediatrics, family practice, and general internal medicine), which contributes to high health care expenditures and inadequate access to medical care (Physician Payment Review Commission, 1995). The federal government provides a higher subsidy to teaching hospitals for training primary care rather than non-primary care residents, and a majority of state governments passed bills in the 1990s to provide loans and scholarships to medical students who enter primary care specialties (Nicholson, 2001).

Physicians in primary care specialties generally earn much less than physicians in non-primary care specialties. In 1997, for example, the mean annual income exceeded $200,000 in 11 non-primary care specialties (e.g., orthopedic surgery, radiology, cardiology), while the mean income in the three primary care specialties were all under $150,000. Women and blacks are much more likely than men and whites to choose the relatively low-paying primary care specialties. Forty-two percent of female physicians were in a primary specialty in 2000 versus 29 percent of male physicians, and 46 percent of black physicians were in a primary care specialty versus 33 percent of white physicians. Occupational segregation is more striking in certain high-paying specialties. Women represented 25 percent of doctors in 2000 but accounted for only 3.5 percent of orthopedic surgeons, the specialty with the highest mean income. If peer groups influence students' specialty choices, medical schools may be able to encourage more students to enter primary care and promote greater gender and racial balance across specialties by altering their admission policies to change the characteristics of their matriculating students.

In order to examine the influence of medical school peer groups, we have obtained access to a data set on the universe of students who graduated from a U.S. medical school between 1996 and 1998. Medical students take a standardized exam, the Medical College Admissions Test (MCAT), before entering medical school. The MCAT score provides us with a uniform measure of each student's ability before they join their peer group – their medical school class. Medical students spend their first and second year together in the same classes, so a medical school class (e.g., students matriculating at Harvard Medical School in 1993) is arguably the relevant peer group – the unit in which students interact. Performing well in medical school is important because residency positions in high-income specialties such as orthopedic surgery and dermatology are rationed (Nicholson, 2001). As a result, students who receive high scores on the National Board of Medical Examiners test (commonly referred to as the board exam), which is taken between the second and third years of medical school, will have a relatively high probability of entering a high-income specialty when they complete medical school. We also observe each student's preferred specialty at the beginning and end of medical school, so we can identify people who switch specialties after their peer group has been formed. In the market that we study, therefore, members of a peer group can affect a medical student's future earnings by improving a student's accumulation of human capital, and thereby increasing the student's likelihood of being admitted into a high-income specialty, and by influencing a student's specialty preference directly.

Manski (1993) highlights three empirical challenges when measuring peer effects. First, peer groups are endogenous. Students who choose to attend the same school probably share similar observed as well as unobserved characteristics. Therefore, an association between the observed characteristics of a peer group and the outcomes of individual members of the group may not imply a causal relationship if outcomes are affected by an unobserved characteristic (e.g., motivation). Second, by definition members of a peer group operate in the same environment and are exposed to the same set of policies. In our context, students at a medical school take the same courses from the same faculty, which makes it difficult to isolate the impact of a peer group from the impact of the school itself. Third, if behavior by two members of a peer group affect each other simultaneously, it is difficult to measure the causal effect of any single member on another member's behavior. This reflection problem is less relevant in our study because we focus on whether the characteristics of peer group members before the observation period (medical school) affect the behavior of other members during the observation period.

Unlike Hoxby (2000) and Sacerdote (2001), [1] our peer groups are not random; prospective medical students choose where to apply. The richness of our data, however, does allow us to address the endogenous nature of a peer group. We include school-specific fixed effects to control for unobserved characteristics that are shared by students who attend the same medical school, and to control for the influence of the school itself on the outcomes and behavior of its students. The peer effect variables are identified by variation within a school over time in the entering students' abilities and specialty preferences. In Manski's (1993) framework, the school fixed effects allow us to separately identify the correlated effects (common unobserved characteristics of the constituents of the peer group and the common environment in which the group members operate) from the exogenous effects (characteristics and background of the students in the peer group).

Our approach yields an upper bound on peer effects if cohorts with high observed ability are also cohorts with high unobserved ability. We present evidence that the observed and unobserved abilities of medical school classes are positively correlated by examining how the average observed ability of an entering medical school class varies within a school over time as the size of the applicant pool varies, and as the percentage of entrants who are in-state residents varies. High observed ability is correlated with high applicant to entrant ratios and low percentages of in-state entrants, suggesting that cohorts with high observed ability also

[1] Sacerdote (2001) examines peer effects at the room and dormitory level at Dartmouth College, where freshmen are randomly assigned to rooms and dorms. He finds that peer groups defined at the dormitory level have no effect on an individual's grade point average and choice of major, but the grade point average of a person's roommate does have a positive effect on the person's own grade point average. Hoxby (2000) examines grade school children in Texas and assumes that gender, race, and ability variation across schools over time is random. She finds that students receive higher reading scores when their classmates have high reading scores relative to the particular school and grade.

have high unobserved ability.

One of the additional advantages of having data on the universe of medical students is that we can experiment with different definitions of a peer group. If students form peer groups based upon their race or gender, an analyst who only observes the characteristics of the entire student population may falsely conclude that there are no spillovers from a peer group to its members. We are also able to test whether a peer group exerts a stronger influence on men versus women, blacks versus non-blacks, and high versus (relatively) low ability students. By contrast, most existing studies of peer effects either have aggregated data on the characteristics of a peer group (e.g., proportion of each school's students with household income below the poverty line), or individual-specific data for a single school (e.g., grade point average for each student at a single college).

We find that the abilities and specialty preferences of a peer group have a significant effect on medical students' performance on the board exam and on students' specialty choices when we assume the characteristics of a person's peer group are exogenous. After controlling for the endeogeneity of peer groups using school-specific fixed effects, however, most of the peer effects disappear. Although a student's board score and ultimate specialty choice are influenced by the school they attend, the transmission mechanism does not appear to be the abilities and specialty preferences of the student's classmates. Using a variety of definitions of a peer group in the school-specific fixed effects model, we find no evidence that peer groups affect specialty choices or performance on the board exam for males or blacks. The only evidence of a peer effect is for female students. Females who attend schools where the other female students received relatively high scores on the verbal portion of the MCAT exam subsequently receive higher board scores themselves, although the magnitude of this effect is small. In all specifications, the effect of the specialty preferences of a student's peer group on his own specialty choice disappears after controlling for school fixed effects.

We also examine whether a peer group exerts a different influence on low- versus high-ability students. Redistributing students to different schools according to their ability will not improve overall student performance if peer effects are symmetric – if low-ability students benefit from high-ability students, and high-ability students are harmed in a equal manner by low-ability students. People opposed to tracking students according to ability, on the other hand, argue that low-ability students benefit from the presence of high-ability students, but the presence of low-ability students has few negative consequences for the high-ability students. We find no evidence of asymmetric peer group effects according to students' abilities, whether or not we include school fixed effects.

The paper is organized as follows. Section 2 describes the process by which medical students choose specialties. The data are described in Section 3. We present the model and the empirical approach in Section 4, discuss the results in Section 5, and conclude in Section 6.

2 How Medical Students Choose a Specialty

Physicians in the United States practice in more than 40 different specialties. There are substantial income differences between the specialties and substantial differences in non-monetary attributes such as the type of patients treated (e.g., children versus adult; chronically ill versus relatively healthy), the amount of face-to-face contact with patients, the length of residency training, and the probability of being sued for malpractice.

Medical students do not formally choose a specialty until the fourth year of medical school when students apply for a residency position in a particular specialty. In the first two years of school students take required courses such as anatomy and pharmacology that are general rather than specific to a specialty. Medical students begin their clinical training with a series of required clerkships or rotations in the third year, including internal medicine, surgery, pediatrics, psychiatry, obstetrics/gynecology, and family practice. In these rotations students treat patients under the supervision of residents and faculty. Fourth-year students take elective rotations in specialties such as plastic surgery, dermatology, and infectious diseases. Students are likely, therefore, to learn about the characteristics of specialties after taking the board exam.

Over 92 percent of U.S. medical students enter the National Resident Matching Program in the Spring of their fourth year. In the Match, as it is commonly referred to, students rank residency programs in descending order of preference and residency programs rank students in descending order of preference. A computer algorithm then assigns students to residency programs taking into consideration the preferences of both parties (Roth, 1984). All fourth-year medical students who are in good academic standing are technically qualified to apply to a residency program in any specialty. In many-high income specialties, however, there are more applicants than available positions (Nicholson, 2001). As a result, positions are rationed; students who perform well in medical school will be ranked relatively high by residency program directors and will therefore have a better chance of receiving a position in the Match.

Orthopedic surgery provides a good illustration of the rationing process. Practicing orthopedic surgeons had the highest mean income of any specialty ($313,000) in 1998. Between 1996 and 1998, the number of medical students who listed an orthopedic surgery residency program first in the Match exceeded the number of available positions by an average of 53 percent per year.

In Table I we report coefficient estimates from a probit regression for students whose preferred specialty in the fourth year of medical school was orthopedic surgery. The dependent variable takes on the value of one if a student was actually training in an orthopedic surgery residency program after graduating from medical school, and a zero otherwise. We use the score on the board exam, a uniform national exam that covers material from the first two years of medical school and is taken between the second and third years of school, to measure student performance in medical school. The board exam is important because it is one of three tests an individual must pass in order to be licensed to practice medicine in the United States and residency program directors often consider the score when evaluating applicants (Crane and Ferraro, 2000).

The coefficient on the board score in Table I is positive as expected. In the bottom panel of Table I we report the predicted probability that three different students would be able to receive a residency position in orthopedic surgery. A white male student who has the median board score among fourth-year students who prefer orthopedic surgery has a predicted probability of 0.89 of receiving a residency position in the specialty. Otherwise similar students with board scores at the 5th percentile and the 95th percentile have predicted probabilities of 0.70 and 0.96, respectively. In general, the probability of entering a specialty is inversely related to the average income of the specialty, and the board score has a stronger effect on entry probabilities in high-income than low-income specialties (Nicholson, 2001).

The entry probabilities in Table I most likely understate the importance of medical school performance on specialty choice for two reasons. First, a high board score probably helps the student match to a more prestigious residency program within a particular specialty and to a residency program in a relatively desirable location. Second, students are aware of the rationing process and probably self-select into specialties where they have a good chance of matching. Hence, a person with low unobserved ability will only enter the match in orthopedic surgery if he has a high unobservable preference for orthopedic surgery or high hidden information that he would be able to find a match. If the hidden information on matching is uncorrelated with board scores and unobservable preferences, the selection on the hidden information will bias the estimated effect of board scores downward. That is, those who have low board scores and still choose orthopedic surgery on average have higher values of the hidden information.

Although medical students might not be aware of the difficulty of entering high-income specialties when they first enter medical school, they are clearly aware of how competitive certain specialties are by the time they take the board exam. A book that many second-year medical students use to help prepare for the board exam advises students regarding how well they need to do on the board exam in order to have a good chance of entering each specialty. Students who would like to match in dermatology, ENT, orthopedic surgery, or opthalmology are advised in a recent edition to "ace the exam"; students interested in emergency medicine, ob/gyn, radiology and general surgery are advised to "beat the mean"; and students who plan to enter pediatrics, family practice, internal medicine, anesthesiology, and psychiatry need only "comfortably pass" the exam (Bhushan, Chu, and Hansen, 1998).

Manski (2000) outlines three ways that an action by one agent may affect the actions of other agents in the same peer group: expectations, constraints, and preferences. Each of these three channels appears to be important for medical students. First, as medical students acquire information on the monetary and non-monetary attributes of each specialty, the revealed expectations (e.g., starting salary) of one's fellow students may influence a person's own expectations. Second, if medical schools impose explicit or implicit quotas on the number of students they will support for residency training in each specialty, or if medical students perceive that schools behave in this manner, then when one student expresses a preference for a specialty it could reduce the probability that her peers will also choose that specialty. Alternatively, consider a student who matriculates at a medical school where the majority of first-year students plan to enter a high-income specialty. Since residency positions are rationed according to performance in medical school, the specialty preferences of the peer group might create a highly-competitive environment that makes it less costly for other students to study hard. Third, the revealed specialty preferences of a person's classmates might directly affect a person's own ordering of specialty alternatives.

3 Data

The sample for this paper is the universe of medical students (n=47,755) who graduated from a U.S. medical school in 1996, 1997, or 1998. Students were surveyed in the Fall of their first year and the Spring of their fourth year by the Association of American Medical Colleges (AAMC). On these surveys students were asked to indicate their preferred specialty or to indicate if they were undecided about a specialty. The AAMC survey response rates among the first-year and fourth-year students were 90.5 percent and 86.7 percent, respectively.

The Medical College Admission Test (MCAT) is our measure of students' initial ability. The MCAT has three sections that are separately graded: physical sciences, biological sciences, and verbal reasoning. Each of the three components of the MCAT exam has a maximum of 15 points. We use the board exam to measure student performance in medical school.

After consolidating the AAMC surveys with test score data and eliminating observations with missing values, we have complete data on MCAT scores, board scores, first- and fourth-year specialty preferences, and demographic information for 31,698 students across 124 U.S. medical schools. The three most common reasons why students were dropped from the sample were if they took the MCAT exam before 1991 when the format was slightly different (4,792 students dropped for this reason), if they failed to complete the first-year AAMC survey (3,703 students dropped for this reason), or if they failed to complete the fourth-year AAMC survey (4,632 students dropped for this reason). We also deleted 392 students who attended one of the three medical schools where a majority of the students are black because the racial mix, and probably the peer group structure, are so different at these three schools than at the other 124 schools. To analyze potential bias in our sample, we ran a probit regression where the dependent variable is one for students who were dropped from the analytic data set. Students with lower verbal reasoning and biology MCAT scores, blacks, males, first-year students who preferred a low-income specialty, and students who graduated in 1996 were more likely to be deleted from the sample.

Sample means are reported in Table II. Forty-three percent of the students are female and 5.4 percent are black. Two variables are created to capture the ability and specialty preferences of each student's peer group. For most of the analysis we define a person's peer group as all other students who graduate from his/her school in the same year (e.g., 1997 graduates of Jefferson Medical College), other than the student in question. In some cases we define the peer group more narrowly as all female or all black students who graduate from a particular school in a particular year. The ability peer effects are defined as the mean MCAT scores for each section by a student's classmates; the specialty peer effect is defined as the proportion of a student's classmates who indicated a preference for a high-income specialty in their first year of school.

The mean combined MCAT score for the 124 medical schools over all three years ranges from a low of 16.8 (out of a possible 45) at the lowest-scoring school to 34.0 at the highestscoring school, with a mean of 28.2. The proportion of first-year students interested in a high-income specialty ranges from 0.066 to 0.667 across schools, with a sample mean of 0.33.

For our analysis, we aggregate the specialties into high- and low-income categories. The following specialties had a mean income of $220,000 or more during the 1991 to 1997 time period and are classified as high-income specialties: surgery, medical sub-specialties, radiology, anesthesiology, pathology, and obstetrics.[2] Low-income specialties include internal medicine, emergency medicine, pediatrics, family practice, and psychiatry. Students undecided about a specialty constitute a third specialty category.

4 The Model and Empirical Approach

We examine the students' performances on the board exam as well as their speciality choices in the final year of medical school. First we present a base model, ignoring for the moment the endogeneity of a student's peer group. Next we describe how we control for the potential biases that may result because students choose their peer group, and we demonstrate why our method yields an upper bound on the effect of the peer group.

Finding the right definition of a peer group is one of the goals of this paper. In particular, the proper characterization of a student's peer group may be the medical class as a whole, or it may consist only of students of the same race or sex as the reference person. A second goal is to examine whether peer groups have stronger effects for particular groups of people. For example, Neal (1997) finds that blacks from low income families experience the largest test score improvements from attending Catholic schools. We experiment with many peer group definitions and allow peer groups to have different effects across racial and gender groups, and across ability levels.

4.1 The Base Model

The board score for individual i, B_i, is assumed to be a function of both the individual's and the peer group's abilities and preferences. An individual's scores on the three components of the MCAT exam represents his observed ability, A_{oi}. People may exert more or less effort in preparation for the board exam depending on the specialty they intend to pursue. We therefore control for differential effort by including an indicator variable for an individual's specialty preferences, d_{1i}. This indicator variable takes on a value of one if the individual expresses a

[2]Income data on practicing physicians are from the American Medical Association's annual Socioeconomic Monitoring Study, a stratified random sample of practicing physicians.

preference for a high-income specialty when they first matriculate in medical school.[3]

We allow both the abilities and the specialty preferences of a peer group to affect the board score of the peer group's constituents. The observed ability of the peer group is represented by the average score on each of the three sections of the MCAT exam, $\overline{A}_{oi}$. Students interested in a high-income specialty may work harder in medical school to improve their chances of entering these competitive specialties. When members of a person's peer group work hard, it may become less costly for that person to exert effort. The specialty preferences of the peer group are represented by the proportion of the peer group who prefer a high-income specialty at the beginning of medical school, $\overline{d}_{1i}$.

The estimating equation for a student's board score is expressed as follows:

$$B_i = \beta_0 + A_{oi}\beta_1 + d_{1i}\beta_2 + \overline{A}_{oi}\beta_3 + \overline{d}_{1i}\beta_4 + \epsilon_{Bi} \quad (1)$$

$$= Z_{Bi}\beta + \epsilon_{Bi} \quad (2)$$

where ϵ_{Bi} is unobserved and is assumed to be distributed $N(0,\sigma_B^2)$.

The specialty a student chooses in the fourth year of school is a function of demographic characteristics of the individual (X_i), the individual's board score (B_i), his initial specialty preference (d_{1i}), and the specialty preferences of his peer group ($\overline{d}_{1i}$). Note that a student's observed ability and the observed ability of their peer group affect specialty choice only through the board score.

An individual's latent utility of choosing a high-income or low-income specialty can be expressed as follows:

$$U_{Hi} = \alpha_{H0} + X_i\alpha_{H1} + B_i\alpha_{H2} + d_{1i}\alpha_{H3} + \overline{d}_{1i}\alpha_{H4} + \epsilon_{Hi} \quad (3)$$

$$U_{Li} = \alpha_{L0} + X_i\alpha_{L1} + B_i\alpha_{L2} + d_{1i}\alpha_{L3} + \overline{d}_{1i}\alpha_{L4} + \epsilon_{Li} \quad (4)$$

where ϵ_{Hi} and ϵ_{Li} represent the individual's unobserved specialty preferences.[4]

Subtracting the latter equation from the former yields the difference in utility from choosing a high- rather than a low-income specialty in the fourth year of medical school:

$$U_{Hi} - U_{Li} = \alpha_0 + X_i\alpha_1 + B_i\alpha_2 + d_{1i}\alpha_3 + \overline{d}_{1i}\alpha_4 + \epsilon_{Si} \quad (5)$$

$$= Z_{Si}\alpha + \epsilon_{Si} \quad (6)$$

[3] Although we do control for initial specialty preferences in both the board score and specialty choice equations, the qualitative results do not change substantially if d_{1i} is omitted. Further, there is virtually no sorting on initial specialty choice by MCAT scores, suggesting that this variable represents individuals' preferences.

[4] We use $d_{1i} = 1$ as opposed to $d_{1i} = 0$ in this latter equation so that the variables in the two equations are consistent. Since either $d_{1i} = 1$ or $d_{1i} = 0$, only the constant term is affected by this notation.

We observe whether this utility difference is positive or negative, where:

$$\begin{aligned} d_{2i} &= 1 \qquad \text{if } U_{Hi} - U_{Li} \geq 0 \\ &= 0 \qquad \text{if } U_{Hi} - U_{Li} < 0 \end{aligned} \tag{7}$$

Students who want to enter a high-income specialty need to receive a relatively high score on the board exam. A first- or second-year medical student who experiences a preference shock that increases the utility of a high-income specialty will work harder when preparing for the board exam. Therefore, we expect the unobserved component of the board score equation to be correlated with the unobserved component of specialty utilities. If one does not control for this correlation, the coefficient estimate on the board exam, α_2, will be biased, most likely upward. An upward bias in α_2 would cause us to overestimate the effect of a peer group's ability on a person's specialty choice, as transmitted through the person's board score. We assume instead that the unobservables in equation (7) and the unobservables in equation (1) have a bivariate normal distribution with the following covariance matrix:

$$\Sigma = \begin{bmatrix} \sigma_B^2 & \rho_{BS}\sigma_B \\ \rho_{BS}\sigma_B & 1 \end{bmatrix} \tag{8}$$

The joint density $f(\epsilon_B, \epsilon_S)$ can be expressed as:

$$f(\epsilon_B, \epsilon_S) = f(\epsilon_S|\epsilon_B)f(\epsilon_B) \tag{9}$$

With this factorization, Evans, Oates, and Schwab (1992) show that the log likelihood function for individual i can be written as the sum of two parts:[5]

$$L_{1i} = d_{2i} \ln \Phi(W_i) + (1 - d_{2i}) \ln[1 - \Phi(W_i)] \tag{10}$$

$$L_{2i} = -\ln(2\pi\sigma_B) - \left(\frac{B_i - Z_{Bi}\beta}{2\sigma_B}\right)^2 \tag{11}$$

where:

$$W_i = \frac{Z_{Si}\alpha + (B_i - Z_{Bi}\beta)\rho_{BS}\sigma_B}{(1 - \rho_{BS}^2)^{.5}} \tag{12}$$

and $\Phi(W)$ is the cumulative standard normal distribution.

If the correlation between ϵ_S and ϵ_B were zero, the first part of the log likelihood function would simplify to a probit specification. The key assumption needed to identify ρ is that at least one variable in Z_B is not in Z_S. We include initial ability measures (MCAT scores) in

[5]Evans, Oates, and Schwab (1992) use this method to control for the endogeneity of a student's peer group. We use this method to control for the effect of specialty preferences on the effort exerted by a student in preparation for the board exam.

Z_B but not in Z_S. That is, we assume that a student's initial ability affects their board score (which in turn affects specialty choice), but the MCAT score itself has no independent effect on their specialty choice. We believe this is an appropriate specification as the MCAT score had no significant effect on the probability of obtaining a residency position in the student's preferred specialty when the student's board score was also included in the model.

4.2 Endogenous Peer Groups

A natural criticism of the proposed specification is that students choose their medical school, so there may exist an unobserved ability variable A_u that is correlated with both the average observed ability and the observed first-year specialty choices of a school's students. Students who have high values of this unobserved ability measure may enroll at schools where the level of unobserved ability of their peers is also high. Not being able to directly control for unobserved ability may therefore bias upward the estimates of peer effects (both in estimating board scores and specialty choices) because the peer measure would capture some of the effect of an individual's own unobserved ability.

Similar to Dale and Krueger (2000), suppose that a medical school's admission officers actually observe a student's unobserved ability. School j admits student i if

$$A_{oi} + A_{ui} + \epsilon_{ij} > s_j, \tag{13}$$

where s_j is some threshold combination of observed and unobserved ability and ϵ_{ij} is noise that is uncorrelated with either ability measure. Schools that have higher thresholds will accept students with higher values of both A_o and A_u.

It is here that we take advantage of the panel aspect of our data set. In particular, we add school-specific fixed effects to control for the average ability of students, both observed and unobserved, at each school. When school fixed effects are included, the coefficients on the peer effect variables are identified by variations within schools over time in the average ability and specialty preferences of the medical school class. The question we examine, therefore, is whether a student's performance in school and chosen specialty change if he matriculates at a particular school with a high-ability cohort or a cohort that has a strong preference for high-income specialties.

Including school indicator variables allows us to separately identify the correlated effects from the exogenous peer effects in Manski's (1993) framework. Correlated effects exist if the school itself or a student's unobserved ability affects board scores and specialty choices;

exogenous peer effects exist when the characteristics of a group affect the decisions of its members.

Our method will yield an upper bound on the estimates of the peer effects if cohorts with high observed ability also have high unobserved ability. This will be the case when a school's admission standards change over time, due to a particularly strong and/or large applicant pool. Another possibility, however, is that the admission standards do not change over time, but instead medical schools admit classes with the same overall ability but with a different composition of observed and unobserved ability. School fixed effects would then fully capture the peer effect.[6] We examine the relationship between the size of the applicant pool and the observed ability of each medical school class and find evidence supporting the former hypothesis above; cohorts at medical schools that have relatively high observed ability are likely to also have relatively high unobserved ability.

To show this, we perform two tests using data from the *Medical School Admission Requirements* publication for 1992-1994, the years when the students in our sample enrolled in medical school. At some medical schools the number of applicants varied substantially between 1992 and 1994, due presumably to changes in the prestige, reputation, and relative tuition of a school, or to other idiosyncratic factors. For example, the number of applicants to George Washington's medical school increased from 8,496 for the 1992-93 school year to 12,074 for the 1994-95 school year, while Georgetown experienced a much smaller increase (from 9,100 to 11,894). During this time period, the number of entrants at the two schools, and at medical schools generally, was constant. Similarly, Columbia had fewer applicants (2,463) than Harvard (2,949) for the 1992-93 school year; by the 1994-95 school year, however, Columbia had more applicants (3,508 to Harvard's 3,424). Again, these changes in applicants occurred with virtually no change in the number of entering first-year students.

In our first test, we examine whether schools admit students with higher observed ability in years when they have a high applicant to entrant ratio. We regress the mean MCAT score of a school's entering students on school indicator variables, a time trend, and the school's applicant to entrant ratio. We include a time trend because applications to medical schools increased during this period. The mean MCAT score of an entering class was significantly higher, at the 90 percent level, in years when a school's applicant to entrant ratio was relatively high. Furthermore, this result is significant at the 95 percent level when we restrict the sample to

[6]Note that this is only an issue for the ability peer effects; no such argument could be made with the specialty preference peer effects.

private schools.[7] It seems reasonable to assume that if an increase in the number of applicants is associated with an increase in the observed ability of an entering class, then the same relationship would hold true for unobserved ability.

The second test examines the composition of the entering class. Public medical schools may be encouraged by state legislatures to admit a quota of in-state students. If so, we would expect out-of-state entrants to have higher observed and unobserved ability than in-state entrants at public medical schools. We examine how MCAT scores vary with the proportion of entrants who are residents of the same state where the medical school is located. We find that the mean MCAT score is significantly higher, at the 95 percent level, in years when the percentage of matriculating students who are state residents is lower than the mean percentage for that school. Since out-of-state applicants most likely have high observed and unobserved ability, this result suggests that high observed ability cohorts are also high unobserved ability cohorts. Both of these tests support the hypothesis that cohorts with high observed ability also have high unobserved ability cohorts, which implies that our method will yield an upper bound on the true peer effect.

One potential difficulty of using school-specific fixed effects is that there may not be enough variation in the mean abilities and specialty preferences of entering cohorts within a school over time to identify the peer effects. If this is the case, the standard errors will be so large that the point estimates become meaningless. This does not occur in our analysis. Furthermore, the two previous tests demonstrate that there are substantial differences in abilities between cohorts.[8]

5 Results

5.1 Estimates of the Board Score Equation

Although the parameters of the board score equation and specialty choice equations are estimated jointly, we present the estimation results separately for ease of interpretation. We discuss the fit of the model when reviewing the results on specialty choice. Throughout, the definition of the peer group is constant within a particular specification. For example, if peer

[7] The coefficient on the applicant to entrant ratio was insignificant when the sample was limited to state schools, which may be due to constraints that state schools face to admit a quota of state residents. An increase in the applicant to entrant ratio may produce higher ability in-state applicants, but these students might still be below average relative to the out-of-state accepted applicants. We address this issue with the second test.

[8] Although we did not analyze it formally above, the descriptive data indicate that there is even greater variation in specialty preferences than abilities between cohorts at a medical school.

groups are defined by gender in the board score equation, they are defined identically in the specialty choice equation.

In Table III we present the board score results when a peer group is defined to be a person's medical school class as a whole, excluding the person himself. The two columns report results of the same regression with and without school-specific fixed effects. Students with high initial ability, as measured by their scores on the three components of the MCAT exam, also perform well on the board exam. The score on the biological sciences component of the MCAT exam has an effect on the board score that is three times the magnitude of the verbal score. Students who preferred a high-income specialty or were undecided about their specialty in the first year of school received slightly higher board scores relative to students who initially preferred a low-income specialty. Although the magnitude of this effect is small, it does imply that students who plan to enter high-income specialties either have relatively high unobserved ability or work relatively hard to prepare for the board exam.

In column one the ability peer effect for the verbal MCAT score is positive and significant; students who attend schools where other first-year students have relatively high verbal MCAT scores also receive relatively high board scores themselves. The ability peer effects for biological and physical sciences are not significant. The specialty preferences of a person's peer group are also correlated with outcomes on the board exam. Students who attend medical schools where a relatively large proportion of first-year students are undecided or prefer a high-income specialty receive relatively high board scores.

In column two of Table III we report coefficient estimates from a specification that includes school fixed effects.[9] Although the coefficients on student characteristics do not change, the coefficients on the ability and specialty peer effect variables become much smaller and all are insignificant. Students who attend schools that have smart students perform relatively well on the board exam. This improvement appears to be caused by either characteristics of the school, such as the curriculum and the faculty, or the unobserved ability of the student, not the abilities of a student's peer group. The peer effect coefficients are now identified by changes within a school over time in the average MCAT score and specialty preferences of first-year students.

The coefficient estimates on the school indicator variables have a range of 21 points from the school with the smallest to the largest incremental effect on a student's board score. This 21 point range is about 1.2 standard deviations of the board score among the entire sample.

[9]The school indicator variables are jointly significant. The log likelihood of the model is reported in Table V.

These coefficients measure the incremental effect of a school on a student's accumulation of human capital and the effect of the unobserved ability that is common among the students but uncorrelated with observed ability.

The insignificance of the peer effect coefficients in the latter specification may occur because we mistakenly defined a peer group as a student's entire medical school cohort rather than the students within a person's class who are of the same race or sex. It is also possible that certain types of students benefit more from working with high ability students than others. We test these hypotheses in Table IV. The first column repeats the ability peer effect estimates from the base specification (Table III). As shown in the last three rows of the table, the definition of a peer group, with and without school fixed effects, has little impact on the coefficients on a student's own ability.

In the second set of estimates, the school-wide peer effect is interacted with the black indicator variable to see if blacks receive larger spillovers from their peers. The coefficients are large and negative for both the verbal and biology peer effect. However, none of the black interactions are statistically significant regardless of whether or not we control for school fixed effects. Apparently there is not enough variation in MCAT scores in this version of the peer group variable to precisely estimate the peer effect. In all other specifications there is sufficient variation to precisely estimate the peer effect.

In the third specification of Table IV, we define the peer group for non-black students to be the entire medical school class, as before. For black students, we define a second peer group that only includes the other black students in the class. This second peer effect, which is interacted with the black indicator variable, allows the abilities of black students in a cohort to affect the performance of other black students. The coefficients on the interactions are very small, both with and without school fixed effects. Unlike the previous set of estimates, here the standard errors are quite small. Once again, when school-specific fixed effects are included, none of the peer effect coefficients are significant.

Although none of the alternative peer group definitions yield significant peer effects for blacks, this is not the case for women. In the fourth set of estimates, we interact the female indicator variable with the school-wide peer effect variables. The coefficients on the biological science and physical science peer effects are small and insignificant. The coefficient on the verbal peer effect interacted with the female indicator is positive and significant when school fixed effects are included. However, the school-wide verbal peer effect is negative and larger than the female interaction. According to these results, men actually perform worse when their cohort has strong verbal skills and women are unaffected. This seems implausible, which suggests that the entire class may not be the correct peer group.

The final set of estimates uses same-sex peer groups within a medical school class. That is, males are assumed to be affected only by other males, and females only by other females. We also allow the effect of a peer group to vary by gender. The coefficient on the interaction of the female indicator with the verbal reasoning peer effect is positive and significant when we control for school fixed effects, while the coefficient for males is small and insignificant. The biology and physical science peer effects are both insignificant. It is interesting that peer effects appear to operate through the verbal score because the contribution of a student's own verbal reasoning MCAT score on his board score is substantially smaller than the contribution of his biological science and physical science MCAT scores. In fact, the verbal peer effect for a female student is similar in magnitude to the effect of her own verbal score. The verbal score may capture how well individuals communicate which, based upon the results from Table IV, may be more important for women than for men.[10]

We have also estimated models allowing the impact of peer groups to vary according to the initial ability of a student (e.g., MCAT score at the bottom quartile, the middle two quartiles, and the top quartile). If the mean ability of a peer group has the same impact on all members of the group, then reassigning high ability students to a different school will not affect total achievement. For peer effects not to be a zero sum game, some constituents must benefit more from a peer group than others. In the debate on tracking by ability in public schools, for example, some people argue that low ability students receive greater benefits from high ability students than do other high ability students. Using a variety of specifications, we find no evidence that peer groups exert a differential effect by ability.[11]

5.2 Specialty Choice Estimates

We report estimated coefficients from the specialty choice portion of the model in Table V. The dependent variable takes on a value of one if a student prefers a high-income specialty in his fourth year of medical school and a zero otherwise. The specification in the first column does not include school fixed effects while the specification in the second column does.

[10] This specification also has the highest log likelihood, as reported in Table VI.

[11] In fact, when there were differential effects, it was the high-ability individuals who received the greatest benefits from their peers. The mean biology MCAT score for a medical school class had a greater (and positive) effect on the board scores of students in the highest ability quartile than students in the bottom two quartiles. Although this result was often statistically significant, the performance differential was small. Results are available from the authors upon request.

The coefficient on a student's board score is positive as expected. Students who receive relatively high board scores are attracted to high-income specialties, even after conditioning on a student's first-year specialty preference. The estimated correlation between the error in the the board score equation and the error in the specialty choice equation is 0.11 and is significant (reported at the bottom of Table VI), which confirms that the board score is, to some extent, endogenous.

The coefficient on the female indicator is large and negative; women are more likely than men to switch into low-income specialties during medical school. In both specifications, the coefficients on a student's specialty preferences in the first year of school are positive and very large. Although a majority of students switch specialties during medical school, preferences are clearly correlated across time. The coefficient on the proportion of a student's peers who prefer a high-income specialty in the first year of medical school (the specialty preference peer effect) is positive and significant in the model without school fixed effects.

In column two we report the coefficient estimates when school fixed effects are included. The 123 school indicator variables, whose coefficients are not reported in Table V, are jointly significant. The only coefficient that changes substantially when school fixed effects are included is the specialty preference peer effect variable, which is now identified by variations within a school over time in the proportion of first-year students who prefer high-income specialties. The magnitude of the high-income peer effect falls substantially and is no longer statistically or economically significant. Although a student's ultimate specialty choice is influenced by the school they attend, the transmission mechanism does not appear to be the specialty preferences of a student's classmates, as was also the case with the board score analysis.

Corresponding to the board score results in Table IV, we report results with different peer group definitions and where the magnitude of the peer effect is allowed to vary by race and gender. This extended analysis is reported in Table VI. The peer groups are defined in the same manner as in Table IV. The first specification in Table VI represents the baseline case (with and without school fixed effects). In the second specification we interact the black indicator variable with the school-wide specialty preference peer effect. The third specification adds a second peer group variable that measures the proportion of blacks in a medical school class who preferred a high-income specialty in their first year of school. This race-specific peer effect variable is interacted with the black indicator variable. The fourth specification includes an interaction of the school-wide peer effect with the female indicator variable. The fifth specification defines peer groups by gender and interacts the female-specific peer effect with the female indicator variable.

Without school fixed effects, the coefficient on the interaction between the black indicator and the overall peer effect (in the third column of Table VI) has a similar magnitude as the coefficient on the overall peer effect variable. The coefficient on the black interaction term remains the same when school fixed effects are added, while the magnitude of the overall peer effect coefficient does decrease substantially (column 4 of Table VI). However, as in the board score regression, none of the interacted peer effects are statistically significant. All the coefficients on the black peer group variables in the third specification are small and insignificant.

In contrast to the board score analysis, where women had positive and significant ability peer group effects when peer groups were defined more narrowly, the specialty peer effects for women in Table VI are statistically insignificant and economically unimportant. This holds both for the case when female is interacted with the overall peer effect and also when peer groups are defined by gender.

Peers may influence each other at medical school in ways that we can not measure with our data. For example, we do not actually observe students at the study group level. However, we do observe many of the same characteristics that a medical school observes when making admission decisions. Unlike undergraduate education, where students can be randomly assigned across housing units (see Sacerdote 2001), medical schools can affect peer groups only through the admission of a medical school class. Medical schools cannot decide who the medical students can or cannot study with. Hence, we believe that our peer group measures are the most relevant ones for this study.

6 Conclusion

If peer groups influence students' specialty choices, medical schools may be able to encourage more students to enter primary care specialties by altering the characteristics of their matriculating classes. We use the universe of medical students who graduated from U.S. medical school schools between 1996 and 1998 to examine whether the abilities and preferences of a student's peer group affects his achievement in medical school and his choice of specialty. We take advantage of this rich data set to examine whether peer effects are stronger when the peer group is defined by gender and race within a particular medical school class, and whether the effect of a peer group is different across different types of people.

We find that the ability of a person's peer group does affect his board score when we do not control for the endogeneity of peer groups. When school fixed effects are included to control for the endogeneity of peer groups, however, the ability peer effects disappear in almost all specifications. We find no evidence that low-ability students receive a greater benefit from the presence of high-ability peers than do high ability students. The one positive peer effect that we find is for female students, who appear to benefit from attending medical schools that have other female students with relatively high scores on the verbal reasoning section of the MCAT exam.

In the models with school fixed effects, the peer effects are identified by variation in the average ability of students within schools over time. We provide evidence that our method yields an upper bound on the peer effect. In years where schools have relatively high applicant to entrant ratios, schools matriculate students with relatively high observed abilities. Furthermore, in years when public medical schools have a relatively large number of in-state entrants, observed ability is relatively low. This evidence suggests that cohorts with high observed ability also have high unobserved ability.

We also find positive peer effects with specialty preferences when we assume the characteristics of a student's classmates are exogenous. Attending a medical school with other students who plan on choosing a high-income specialty appears to increase a person's board score and the probability they will choose a high-income specialty at the conclusion of medical school. We find no evidence that specialty preference peer effects are stronger when the peer group is defined by race or gender rather than the entire medical school class, or that specialty preference peer effects have a stronger impact on blacks or women. As before, when we include school-specific fixed effects to control for the endogeneity of a peer group, the specialty preference peer effects become statistically and economically insignificant. Although a student's board score and ultimate specialty choice are influenced by the school they attend, the transmission mechanism does not appear to be the abilities and specialty preferences of the student's classmates.

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Table I

Coefficient Estimates: Determinants of Receiving an Orthopedic Surgery Residency Position

	Coefficient	Standard Error
Step 1 board score	0.0225*	0.0026
Female	-0.196	0.141
Black	-0.154	0.176
Graduated in 1997	0.0945	0.116
Graduated in 1998	-0.437*	0.105
Constant	-3.70*	0.569
Observations	1,375	
Log likelihood	-558.38	

Note: sample includes students who state a preference for orthopedic surgery in their fourth year of school. Dependent variable is 1 if they were actually in an orthopedic surgery residency position the year after graduating from medical school, and 0 otherwise.

*significantly different from zero at the five percent level

Predicted Probability of Entering Orthopedic Surgery For a White, Male Student Graduating in 1996

Board score among fourth-year students who prefer orthopedic surgery	
5^{th} percentile (187)	0.695
Median (220)	0.894
95^{th} percentile (243)	0.962

Table II

Sample means (n = 31,698)

	Mean	Standard Deviation
Female	0.425	0.494
Black	0.0544	0.227
Graduated in		
- 1996	0.279	0.449
- 1997	0.360	0.480
- 1998	0.361	0.480
MCAT score		
- biological sciences	9.54	1.76
- physical sciences	9.34	1.98
- verbal reasoning	9.41	1.76
Step 1 NBME board score	210.8	18.0
Ability peer effects:		
- biological sciences	9.52	0.763
- physical sciences	9.32	0.880
- verbal reasoning	9.38	0.673
Specialty preference peer effects		
- proportion of first-year classmates who choose a high-paying specialty	0.327	0.0749
- proportion of first-year classmates who are undecided	0.246	0.0646

Table III: Determinants of a Student's Board Store

Dependent variable is Step 1 board score (n = 31,698)
(standard errors in parenthesis)

	Coefficient Estimates Without School Effects	Coefficient Estimates With School Effects
Student's MCAT verbal reasoning	0.933*	0.903*
	(0.0558)	(0.055)
Student's MCAT biological sciences	3.20*	3.18*
	(0.0647)	(0.0638)
Student's MCAT physical sciences	1.85*	1.84*
	(0.0594)	(0.0588)
Student preferred high-income specialty in first year	0.680*	0.640*
	(0.196)	(0.193)
Student was undecided in first year	0.696*	0.648*
	(0.213)	(0.210)
<u>Peer Effects</u>:		
School avg verbal reasoning MCAT	1.35*	-1.12
	(0.239)	(0.613)
School avg biological sciences MCAT	0.104	0.378
	(0.471)	(0.730)
School avg physical sciences MCAT	-0.165	0.350
	(0.411)	(0.729)
Proportion of first-year classmates who preferred high-income specialty	5.13*	1.07
	(1.29)	(2.43)
Proportion of first-year classmates who were undecided	7.78*	2.91
	(1.42)	(2.26)
Graduated in 1997	1.08*	1.12*
	(0.218)	(0.240)
Graduated in 1998	2.99*	2.90*
	(0.230)	(0.303)
Constant	137*	154*
	(1.51)	(6.49)

Note: model also includes indicator variables for females and blacks.
*significantly different from zero at the five percent level

Table IV: Determinants of Step 1 Board Score Under Alternative Definitions of a Student's Peer Group (n=31,698)

	Peer Group: All Students		Peer Group: All Students		Race-specific peer effect for blacks		Peer Group: All Students		Peer Group: Same Gender	
Overall Peer Effect										
- MCAT verbal	**1.35**	-1.12	**1.34**	-1.06	**1.35**	-1.09	**0.975**	**-1.53**	**1.35**	-0.272
	(0.239)	(0.613)	**(0.244)**	(0.617)	**(0.239)**	(0.613)	**(0.315)**	**(0.646)**	**(0.297)**	(0.474)
- MCAT biological sci	0.104	0.378	0.211	0.496	0.1383	-0.387	0.104	0.285	0.474	0.468
	(0.471)	(0.730)	(0.482)	(0.737)	(0.472)	(0.730)	(0.611)	(0.824)	(0.522)	(0.625)
- MCAT physical sci	-0.165	0.350	-0.187	0.282	-0.150	0.373	-0.117	0.485	-0.566	0.095
	(0.411)	(0.729)	(0.420)	(0.735)	(0.412)	(0.730)	(0.535)	(0.803)	(0.457)	(0.574)
Black interactions										
- MCAT verbal			-1.23	-0.357	-0.513	-0.158				
			(1.29)	(1.29)	(0.504)	(0.500)				
- MCAT biological sci			-2.33	-2.32	-0.501	-0.300				
			(2.17)	(2.15)	(0.617)	(0.611)				
- MCAT physical sci			1.31	.986	-0.195	0.417				
			(1.92)	(1.91)	(0.614)	(0.609)				
Female interactions										
- MCAT verbal							0.814	0.918	0.202	**1.23**
							(0.469)	(0.464)	(0.424)	**(0.438)**
- MCAT biological sci							-0.014	0.213	-0.082	0.252
							(0.934)	(0.924)	(0.723)	(0.766)
- MCAT physical sci							-0.092	-0.332	0.199	-0.588
							(0.820)	(0.811)	(0.634)	(0.673)
Student's score										
- MCAT verbal	**0.933**	**0.903**	**0.936**	**0.908**	**0.938**	**0.908**	**0.931**	**0.902**	**0.930**	**0.903**
	(0.0558)	**(0.0551)**	**(0.0558)**	**(0.0550)**	**(0.0558)**	**(0.0551)**	**(0.0558)**	**(0.0551)**	**(0.0557)**	**(0.0551)**
- MCAT biological sci	**3.20**	**3.18**	**3.20**	**3.19**	**3.21**	**3.19**	**3.20**	**3.18**	**3.20**	**3.18**
	(0.0647)	**(0.0638)**	**(0.0647)**	**(0.0638)**	**(0.0647)**	**(0.0638)**	**(0.0647)**	**(0.0638)**	**(0.0646)**	**(0.0638)**
- MCAT physical sci	**1.85**	**1.84**	**1.84**	**1.84**	**1.84**	**1.84**	**1.85**	**1.85**	**1.85**	**1.85**
	(0.0594)	**(0.0588)**	**(0.0590)**	**(0.0588)**	**(0.0594)**	**(0.0588)**	**(0.0594)**	**(0.0588)**	**(0.0594)**	**(0.0587)**
School fixed effects?	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: model also includes female and black indicator variables, student's initial preferred specialty, specialty peer effects, and year indicators
Coefficients in bold are significant at the 95% level

Table V: Determinants of Specialty Choice

Utility Function Parameter Estimates for Choosing a High-Income Specialty (n = 31,698)
Dependent variable = 1 if chose high-income specialty in fourth year
(standard errors in parentheses)

	Without School Effects	With School Effects
Board Score	0.00350*	0.00349*
	(0.00085)	(0.00104)
Student chose high-income	1.53*	0.924*
in 1st year	(0.0292)	(0.0177)
Student undecided in first year	0.626*	0.372*
	(0.0322)	(0.0194)
Peer effects:		
Proportion of first-year classmates	0.933*	-0.0336
preferring high-income specialty	(0.188)	(0.221)
Proportion of first-year classmates	0.167	-0.0748
who were undecided	(0.206)	(0.207)
Female	-0.328*	-0.197*
	(0.0263)	(0.0162)
Black	0.0882	0.0533
	(0.0564)	(0.0384)
Graduated in 1997	0.0650*	0.0173
	(0.0324)	(0.0211)
Graduated in 1998	0.132*	0.0393
	(0.0345)	(0.0249)
Constant	- 2.86*	-2.43*
	(0.294)	(0.413)
Log likelihood	-149135	-148428

*significantly different from zero at the five percent level

Table VI: Determinants of Specialty Choice in Fourth Year of Medical School (n=31,698)

	Peer Group: All Students		Peer Group: All Students		Race-specific peer effect for blacks		Peer Group: All Students		Peer Group: Same Gender	
Overall Peer Effect										
% of first year students choosing high-income	**0.560** **(0.113)**	-0.034 (0.221)	**0.531** **(0.115)**	-0.065 (0.223)	**0.555** **(0.113)**	-0.039 (0.221)	**0.564** **(0.145)**	-0.044 (0.239)	**0.423** **(0.118)**	0.044 (0.154)
% of first year students undecided	0.102 (0.125)	-0.075 (0.207)	0.083 (0.128)	-0.101 (0.209)	0.106 (0.125)	-0.072 (0.207)	0.127 (0.161)	-0.063 (0.230)	0.204 (0.148)	-0.083 (0.186)
Black interactions										
% of first year students choosing high-income			0.573 (0.483)	0.525 (0.491)	0.110 (0.171)	0.065 (0.173)				
% of first year students undecided			0.418 (0.558)	0.441 (0.565)	-0.079 (0.208)	-0.097 (0.211)				
Female interactions										
% of first year students choosing high-income							-0.010 (0.211)	0.023 (0.212)	0.071 (0.183)	0.115 (0.194)
% of first year students undecided							-0.062 (0.244)	-0.281 (0.246)	-0.338 (0.206)	-0.057 (0.220)
Board Score	**0.0035** **(0.0008)**	**0.0035** **(0.0010)**	**0.0034** **(0.0008)**	**0.0034** **(0.0010)**	**0.0034** **(0.0008)**	**0.0034** **(0.0010)**	**0.0035** **(0.0008)**	**0.0035** **(0.0010)**	**0.0036** **(0.0008)**	**0.0035** **(0.0010)**
Rho	**0.111** **(0.014)**	**0.114** **(0.017)**	**0.112** **(0.014)**	**0.115** **(0.017)**	**0.112** **(0.014)**	**0.115** **(0.017)**	**0.110** **(0.014)**	**0.113** **(0.017)**	**0.110** **(0.014)**	**0.113** **(0.017)**
School fixed effects?	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Log likelihood	-149315	-148428	-149126	-148422	-149219	-148424	-149131	-148422	-149133	-148420

Note: regressions also include female and black indicator variables, student's initial preferred specialty, and year indicators
Coefficients in bold are significant at the 95% level