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ABSTRACT

Stereotype Threat, Role Models, and Demographic Mismatch in an Elite Professional School Setting*

Ten years of administrative data from a diverse, private, top-100 law school are used to examine the ways in which female and nonwhite students benefit from exposure to demographically similar faculty in first-year required law courses. Arguably causal impacts of exposure to same-sex and same-race instructors on course-specific outcomes such as course grades are identified using a two-way (student and classroom) fixed effects strategy. Impacts of faculty representation on long-run, student-specific outcomes such as graduation are identified using an instrumental variables (IV) strategy that exploits transitory variation in the demographic makeup of the faculty. Having an other-sex instructor reduces the likelihood of receiving a good grade (A or A-) by one percentage point (3%) and having an other-race instructor reduces the likelihood of receiving a good grade by three percentage points (10%). The effects of student-instructor demographic mismatch are particularly salient for nonwhite female students. The IV estimates suggest that the share of first-year courses taught by nonwhite instructors increases the probabilities that nonwhite students persist into the second year and graduate on time. These results provide novel evidence of the pervasiveness of role-model effects in elite settings and of the graduate-school education production function.

JEL Classification: I23, J15, J44

Keywords: demographic mismatch, law school, gender, race

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1 Introduction

An emerging literature in the economics of education documents wide-ranging impacts of student-teacher demographic match on both students and teachers. In K-12 classrooms, assignment to an other-race or other-sex teacher has been shown to harm student achievement (Dee, 2004, 2007).[1] Similarly, racial mismatch lowers teachers' perceptions of student behavior (Dee, 2005) and their expectations for students' educational attainment (Gershenson, Holt and Papageorge, 2016). The impact of faculty representation has also been studied in the post-secondary context, particularly among first-year undergraduates (Bettinger and Long, 2005; Carrell, Page and West, 2010; Hoffmann and Oreopoulos, 2009; Fairlie, Hoffmann and Oreopoulos, 2014). These studies typically find modest effects of having a same-sex or same-race instructor on course grades, the likelihood of dropping a class, and choice of major. Lusher, Campbell and Carrell (2015) show similar effects of having a same-race teaching assistant (recitation section leader) on course grades and office-hour and course attendance.

While the precise mechanisms through which student-instructor demographic mismatch affects students' educational outcomes are not known, it is generally thought that role model effects, stereotype threat, and information provision play prominent roles in this phenomenon. Moreover, it is often, either implicitly or explicitly, assumed that relatively young, inexperienced, socio-economically disadvantaged, and information-poor students are particularly susceptible to the deleterious effects of student-instructor demographic mismatch. In the current study, we show that the harms associated with student-instructor demographic mismatch are just as pronounced in an elite, professional school setting as they are in K-12, community college, and first-year undergraduate classrooms. These findings provide novel evidence that mismatch effects are not limited to inexperienced, disadvantaged, or otherwise vulnerable populations.[2] Rather, student-instructor demographic mismatch continues

[1]Mismatch is not universally harmful, however, as Antecol, Eren and Ozbeklik (2015) find that less-prepared female math teachers reduce female students' achievement, but have no such effect on male students.

[2]There is a litany of qualitative and anecdotal evidence of such demographic biases in legal education (Banks, 1988; Darling-Hammong and Holmquist, 2015; Guinier et al., 1994), but to our knowledge there is no credibly identified, quantitative evidence on the impact of law student-instructor demographic match on

to harm the academic performance of even elite law school students, whom we might falsely deem impervious to such threats, given that they are college graduates who successfully navigated the law school application process.[3] This suggests that student-instructor mismatch might affect student outcomes through channels over and above those commonly considered.

Specifically, we use rich administrative data from a top-100 law school in which first-year students are quasi-randomly assigned to course sections in conjunction with an array of arguably causal fixed-effects identification strategies to show that having a demographically mismatched first-year law instructor significantly reduces the probability of receiving a "good grade" (A/A-) in the course. Other-race effects tend to be larger in magnitude than other-sex effects, particularly among nonwhite female students, though both are statistically and economically significant. There are cumulative effects of exposure to demographically mismatched first-semester instructors on second-semester course grades in two-course sequences, suggesting that such effects persist, though we find no evidence of contemporaneous spillover effects of exposure to demographically matched faculty on performance in unrelated courses.[4] Classroom environments such as class size and class composition moderate the impact of student-instructor demographic mismatch in ways that hint at the mechanisms through which such effects operate. That we find such effects in an elite professional school setting suggests that the phenomena of stereotype threat and role-model effects are not solely attributable to a lack of information, confidence, or experience. Rather, these are broader, societal phenomena that permeate beyond relatively vulnerable populations of schoolchildren and community college students and have implications for all social interactions, not just those in which there is a power dynamic (e.g., doctor-patient). Our findings suggest the need to extend our understanding of stereotype threat, role models, and mismatch effects to include other settings and contexts where such effects have been heretofore presumed to

student outcomes.

[3] One previous paper investigated role model effects in a graduate school setting: Neumark and Gardecki (1998) found evidence that increasing female faculty members in economics departments improved time to completion and completion rates for female graduate students.

[4] See Appendix Table A1.

play relatively small roles.

A second contribution of the current study is to enhance our understanding of the production of graduate degrees. Indeed, remarkably little is known about the nature of the law-school education production function, or that for graduate school more generally.[5] This is troubling, as graduate students comprise a nontrivial segment of the U.S. post-secondary student population: about 15 percent of post-secondary students are graduate students and about 40 percent of outstanding student-loan debt was accumulated to finance graduate degrees (Delisle, 2014). Graduate degrees themselves facilitate entrance into many high-status and high-paying professions central to the modern economy. The legal profession is one prominent example: nearly all states require that lawyers hold a Juris Doctor (JD) from an American Bar Association (ABA) accredited law school, lawyers constitute about 1% of the U.S. labor force, and law firm revenues constitute about 1% of U.S. GDP (Azmat and Ferrer, Forthcoming). The current study provides evidence on some of the educational inputs and environments that affect law school students' achievement, skill development, choice of specialization, and persistence.

Finally, and perhaps most importantly, the current study sheds light on the role that institutions play in perpetuating demographic wage, skill, and partnership gaps in the legal profession. For example, female lawyers earn lower salaries and are less likely to be promoted to partner than their male counterparts, even after conditioning on basic employee and firm characteristics (Azmat and Ferrer, Forthcoming; Dinovitzer, Reichman and Sterling, 2009; Wood, Corcoran and Courant, 1993).[6] Azmat and Ferrer (Forthcoming) show that performance gaps explain much of the previously unexplained sex gap in lawyers' earnings, though the exact sources of gaps in performance and specialization among practicing lawyers remain unclear. Law school environments and mentoring practices might contribute to this

[5]Exceptions include recent natural experiments involving first-year law students at Stanford who were randomly assigned to small classes (Ho and Kelman, 2014) and at Minnesota who were randomly assigned to receive individualized feedback (Schwarcz and Farganis, Forthcoming).

[6]This is consistent with "glass ceilings" and pay gaps in top management positions (Bertrand and Hallock, 2001), as well as in the labor force more generally (Altonji and Blank, 1999).

divergence in post-law school productivity, even when male and female students enter law school with similar skills (Bertrand, 2011; Ho and Kelman, 2014). We test this hypothesis by examining whether the demographic match between law students and instructors affects student outcomes. Doing so will inform law-school policy and practice by identifying the malleable factors that influence the success of underrepresented graduate school students and our understanding of the importance that faculty play in the production of graduate education more generally. Indeed, law schools are representative of a broad class of professional graduate schools and programs from which professional service providers are recruited directly into the labor market (e.g., business, engineering) (Oyer and Schaefer, 2015).

Documenting the impact of having an other-race instructor in the law school context is also important due to the social consequences of demographic gaps in the receipt of law degrees and in the career paths of law school graduates (Holder Jr, 2001). For example, the under-representation of racial and ethnic minorities in the U.S. judiciary likely contributes to documented demographic disparities in sentencing (Mustard, 2001). Indeed, implicit association tests (IATs) show that white judges often hold implicit (unconscious) biases against nonwhite defendants (Rachlinski et al., 2008). In the field, emotional shocks associated with the outcomes of football games have been shown to increase the sentences assigned by judges, particularly for black defendants (Eren and Mocan, 2016). And regarding the demographic pay gaps discussed above, a lack of representation among law school faculty and/or how law school faculty interact with and mentor women and students of color can cause sorting into specializations and other behavioral responses that affect prestige, pay, and upward mobility. Ultimately, biases against females and people of color can produce self-fulfilling prophecies in which members of stereotyped groups ultimately conform to what were initially incorrect beliefs (Papageorge, Gershenson and Kang, 2016; Steele, 1997; Loury, 2009). Institutional factors such as faculty composition can therefore perpetuate the under-representation of certain demographic groups in the legal profession (Wilkins and Gulati, 1996).

The paper proceeds as follows: Section 2 describes the administrative data and institutional details. Section 3 introduces the identification strategy. Section 4 presents the results. Section 5 concludes.

2 Data & Institutional Details

This section describes the administrative data analyzed in the current study. Section 2.1 describes the institutional context and the formation of the analytic sample. Section 2.2 summarizes the analytic sample.

2.1 Administrative Data

All analyses use longitudinal administrative data from a private, top-100 law school (LS) located in a major urban center. The LS enrolls approximately 1,000 students, on average, and employs approximately 200 full- and part-time faculty. It is one of the most demographically and geographically diverse top-ranked law schools, as its student body is majority female, almost 40% nonwhite, and includes students from almost every state in the U.S. as well as from several foreign countries.

The most recent U.S. News rankings rank the LS in the same range as the University of Oregon, University of Pittsburgh, and Villanova law schools.[7] Demographically, LS ranks in the top 50 ABA-approved law schools for racial/ethnic minority JD-student enrollment. Its peer institutions in this category include the University of California-Irvine, the City University of New York, and Rutgers University. Similarly, LS ranks in the top 20 ABA-approved law schools in terms of female JD enrollment. Institutions with similar female enrollments include Boston University, University of California-Davis, and the City University of New York law schools.[8] Thus, while LS is one of the more demographically diverse law schools in the U.S., it is not an outlier and is comparable to other highly-ranked, national law schools

[7] `http://grad-schools.usnews.rankingsandreviews.com/best-graduate-schools/top-law-schools/law-rankings/page+4`.

[8] Rankings calculated as average % enrollment from 2009 to 2013 using data obtained from the American Bar Association: `http://www.americanbar.org/groups/legal_education/resources/statistics.html`

in this regard. It also has a relatively diverse faculty, as described below.

The main analytic sample is restricted to students' first-year required courses for three reasons. First, entering students take the same set of courses during their first two semesters of law school. Most courses are semester-specific, meaning that Class A is usually taken in the fall semester and Course B is taken in the spring semester. Second, the majority of first-year courses are assessed using a blind grading system.[9] This speaks to the mechanisms through which observed mismatch effects operate, as it precludes explicit grading biases of the type documented by Lavy (2008) from being the primary mechanism. Finally, the LS claims that student assignments to specific class-sections, made by LS advisors and administrators, are conditionally random. Similarly, the courses taken in each semester of the first year are randomly assigned by school administrators. About 3 to 6 sections of each course are offered in a semester the course is offered, with the exception of one rhetoric course that has smaller class sizes and thus comprises about 25 sections per semester. We verify, and exploit, this random assignment in the empirical analysis.

The administrative data include detailed information on course-specific outcomes such as grades, dropout behavior, and taking a subsequent course in the same concentration, as well as student-level outcomes such as persistence, graduation, and engagement with the LS's Law Journals, for every student who entered the JD program between fall 2000 and fall 2011. Additionally, we observe student demographic characteristics, such as sex, age, and race/ethnicity, as well as LSAT scores, undergraduate GPA, and home zip code. We use home zip codes to construct measures of distance from LS and to collect the median income and fraction of adults who have a college degree in each zip code from the 2000 and 2010 U.S. censuses, which proxy for students' socioeconomic status. Administrative data on instructors include rank (e.g., tenure line, tenured, adjunct) and years at LS. Demographic information (i.e., race/ethnicity and sex) and rank of faculty members' JD-granting institutions were determined by reviewing public resumes, curriculum vitae, and websites.[10]

[9]Unfortunately, the data do not identify which, if any, courses were subject to non-blind grading.

[10]The rank of instructors' JD programs comes from the usual US News Rankings.

2.2 Sample and Summary Statistics

Our aim is to estimate the impact of student-instructor demographic match in first-year required courses. The primary unit of analysis is therefore the student-course level. There are eight required courses in the first year, which cover subjects such as litigation, constitutional law, criminal law, and property law. The main analytic sample includes 37,042 student-course observations from more than 1,000 unique course sections. Panel A of Table 1 summarizes the student-course data, separately by students' race and sex. On average, white students have higher first-year course grades than nonwhite students. There is no appreciable sex-gap in first-year course grades. Dropping first-year required courses is exceedingly rare, likely because they are required and students are generally forbidden from switching sections. White students and nonwhite students have near-equal likelihoods of having an other-sex instructor, while females are more likely than males to have an other-sex instructor. Nonwhite students are much more likely to have an other-race instructor than are white students, as the majority of instructors are white.

Panel B of Table 1 reports descriptive statistics at the student level. The average age of first-year JD students is about 25 for all demographic groups. While females form a majority of both white and nonwhite students, the representation of females is greater among nonwhite students than among white students. White and male students tend to have higher LSAT scores than nonwhite and female students. Among nonwhite students, 21% are black, 37% are Latino, and 35% are Asian. Graduation rates are similar across demographic groups.

Finally, Panel C of Table 1 reports descriptive statistics at the instructor level, for instructors who taught at least one first-year required course between 2000 and 2012. On average, white instructors have more experience at LS than nonwhite instructors, and male instructors have more experience than female instructors. About 46% percent of white instructors are female, while 60% of nonwhite instructors are female. Almost half of nonwhite faculty are black, 23% are Latino, and 29% are Asian. More than 90% of instructors have a JD, though some have other advanced degrees.[11] The average instructor attended a JD program ranked in the top 40 by US News. White and male instructors attended slightly higher ranked programs, on average, than did nonwhite and female instructors, respectively.

Table 2 reports descriptive statistics at the classroom (i.e., course-section) level. There are 1,132 unique first-year required course offerings in the analytic sample. The average class contained about 43 students, 59% of whom were female. The majority (86%) of courses were taught by white faculty, while 8% were taught by black instructors, 4% by Latino instructors, and 2% by Asian instructors. Table 2 also reports the frequency of the 12 courses that were at one time required in the first year between 2000 and 2012. Some courses appear less often either because they had smaller average class sizes, were merged into a single course, or ceased to be required between 2000 and 2012. Basic subject-specific summary statistics are provided in Appendix Table A2.

3 Identification Strategy

This section describes the main identification strategy used to estimate the causal effects of student-instructor demographic match on course-specific outcomes. Section 3.1 introduces the preferred two-way fixed effects specification. Section 3.2 discusses the key identifying assumptions and presents a test of the "endogenous sorting" threat to identification. Finally, Section 3.3 describes a three-way fixed effects specification used to identify the effect of mismatch in the first course of two-course sequences on performance in the second course.

3.1 Baseline Model

Our primary interest is in how student-instructor demographic match affects outcomes (y) at the student-course level. Specifically, we are interested in δ in the linear regression model:

[11] The Legum Baccalaureus (LLB) is an undergraduate degree in law. The Juris Doctor (JD) is the professional doctorate degree in law. The Legum Magister (LLM) is a master degree in law that typically focuses on a specialized legal area. A Ph.D. is a non-legal doctorate of philosophy. Those pursuing the LLM degree are required to have first obtained either an LLB or JD degree.

$$y_{ijcst} = \beta_0 + \beta_1 X_i + \beta_2 W_j + \beta_3 Z_{cst} + \delta Match_{ij} + \epsilon_{ijcst}, \tag{1}$$

where X, W, and Z are vectors of observed student (i), instructor (j), and course-section (cs) characteristics, respectively; t indexes semesters; $Match$ is a vector of variables that measure the degree of demographic similarity between student and instructor; and ϵ represents the unobserved determinants of y. We operationalize $Match$ in various ways, such as a set of four mutually exclusive race-by-sex indicators (i.e., same race and other sex, same sex and other race, same race and same sex, other race and other sex) and simpler definitions that include binary indicators for other sex and/or other race. However, in all specifications race matches are coded as specific matches such as black-black, Hispanic-Hispanic, etc., as opposed to "minority-minority."

Given that course-section assignments are allegedly conditionally (on X) random, OLS estimates of equation (1) might well be unbiased and have a causal interpretation. However, if the quasi-random assignment rule is imperfectly followed, these estimates might be biased. For example, unobserved student characteristics might jointly predict outcomes and assignment to an other-race teacher. Similarly, equation (1) fails to control for unobserved instructor attributes, such as grading policies or teaching style. Accordingly, we follow Fairlie, Hoffmann and Oreopoulos (2014) and augment equation (1) to condition on both student and classroom fixed effects (FE), which yields our preferred specification:

$$y_{ik} = \theta_i + \omega_k + \delta Match_{ik} + \epsilon_{ik}. \tag{2}$$

Several aspects of equation (2) merit attention. First, the vectors X, W, and Z fall out of the model because they are colinear with the FE. Second, we collapse the subscripts $jcst$ into a single k subscript because identification now comes from within-classroom variation in $Match$ and classrooms are instructor, course, section, and semester specific: the classroom FE (ω) subsumes instructor, course, semester, and year FE. Specifically, the classroom FE uniquely identify each course section taught in a given semester and thus control for the course's location (classroom) quality, meeting day(s) and time, class size, and class composition. Thus the classroom FE also ensure that identification comes from students who experienced the same lectures, assignments, and grading practices. Third, equation (2) is only identified for outcomes that vary within-students across courses, such as course grades, due to the student FE (θ). Finally, there is a possible sample selection issue for the analyses of course grades, since grades are only observed for students who complete the course, and it is possible that student-instructor demographic mismatch affects the likelihood that students complete the course. This turns out to be a practically unimportant concern, as dropping courses is quite rare (occurs in only 0.6% of cases) and we find no evidence that demographic mismatch affects course dropouts.[12] We estimate equation (2) using the estimation routine proposed by Correia (2015) and compute two-way cluster-robust standard errors, which allow for correlated ϵ both within instructors across semesters and within students across courses (Cameron, Gelbach and Miller, 2012).

3.2 Sorting Test

While the two-way FE in equation (2) address many threats to validity, one potential threat remains: differential sorting by student race or gender (Fairlie, Hoffmann and Oreopoulos, 2014). For example, the student FE controls for scenarios in which high-ability students sort into female-taught courses, but does not adequately control for gender-specific sorting processes in which high-ability female students sort into female-taught courses and high-ability male students sort into male-taught courses. To discern the extent to which differential sorting on unobservables occurs, we follow Fairlie, Hoffmann and Oreopoulos (2014) in implementing a formal test for differential sorting on observables. The test relies on the intuition of difference-in-differences estimators and the bounding procedure of Altonji, Elder and Taber (2005). It is best illustrated via an example. Suppose we want to test for differential

[12]This is perhaps unsurprising, as we are investigating required first-year courses.

sorting by gender. We would first compute the mean of observed student characteristic L (e.g., LSAT score) in classroom k for each gender g: $\overline{L}_k^g$. Then estimate the linear regression

$$\overline{L}_k^g = \gamma_0 + \gamma_1 Female_k + \gamma_2 1\{Female = g\} + \gamma_3 Female_k \times 1\{Female = g\}, \qquad (3)$$

where *Female* is a binary indicator equal to one if the section-k teacher is female, and zero otherwise; $1\{\cdot\}$ is the indicator function; and γ_3 is the parameter of interest. Specifically, γ_3 represents "the difference-in-differences estimate" of the average difference in observed characteristics between female and male students in female- and male-taught courses. If γ_3 is significantly different from zero, there are differences by student sex in sorting into courses on observables that systematically vary with the sex of the instructor. Alternatively, if the OLS estimate of γ_3 in equation (3) is statistically indistinguishable from zero, there is no evidence of differential sorting on observables, and thus differential sorting on unobservables in a way that would bias the two-way FE estimates of equation (2) is unlikely.

3.3 Cross-Semester Effects in Two-Course Sequences

Finally, we consider whether exposure to an other-race or other-sex instructor in the first course of a two-course sequence affects performance in the second course. Naturally, this analysis can only be conducted for the subset of first-year courses that are part of a required two-course sequence.[13] While this question can be addressed using the baseline two-way FE model given in equation (2), it is also possible to further increase the estimates' validity by augmenting equation (2) to condition on a second-semester course FE (φ).[14] Specifically, we estimate three-way FE models of the form

[13] There are four such sequences: Civil Procedure I & II, Legal Rhetoric I & II, Criminal Law & Criminal Procedure, and Property Law I & II.

[14] This is similar to the identification strategy used by Figlio, Schapiro and Soter (2015) to identify the impact of adjunct instructors, though in that case the first-semester course FE were not included because adjunct status varies only at the classroom level.

$$y_{is2} = \theta_i + \omega_{s1}^{(i)} + \varphi_{s2}^{(i)} + \delta Match_{is1} + \epsilon_{is}, \quad (4)$$

where 1 and 2 index semesters and s indexes subjects. Estimates of δ in equation (4) are robust to excluding the second-semester course FE, which is reassuring because it suggests that the demographic background of the first-semester instructor does not affect second-semester classroom assignments. Estimates of equation (4) report standard errors clustered along three dimensions: student, semester 1 instructor, and semester 2 instructor.

4 Results

This section presents the empirical results. Section 4.1 presents estimates of the sorting test characterized by equation (3). Section 4.2 presents the baseline two-way FE estimates. Section 4.3 tests for heterogeneous impacts of student-instructor demographic mismatch.

4.1 Sorting Test Estimates

Table 3 presents estimates of the sorting test characterized by equation (3).[15] Panel A reports estimates for differential sorting by race, comparing the average characteristics of whites and nonwhites. Panel B does the same for differential sorting by sex, comparing the average characteristics of males and females.

We perform the sorting test for six outcomes: LSAT score, undergraduate GPA, median income in student's home zip code, percent of population with college degree in student's home zip code, a binary indicator equal to one if the student came from the surrounding tri-state area, and student age.[16] The LSAT and undergraduate GPA variables likely measure a combination of students' cognitive and noncognitive skills (Heckman and Kautz, 2012). The zip-code information proxies for the student's socioeconomic background, which is an

[15] The sorting test estimates remain essentially unchanged when course-name and year FE are added to the regression.

[16] Data on undergraduate GPA is missing for the majority of students.

important predictor of undergraduate college success (Bailey and Dynarski, 2011). The "tri-state" indicator provides a crude measure of students' distances from home, which is known to predict undergraduate enrollments (Alm and Winters, 2009; Cooke and Boyle, 2011).

Only 1 of the 12 estimates of γ_3 in table 3 is statistically significant, which suggests little differential sorting on observables by sex or race. Given the multiple hypotheses tested, it is possible that the significant result in Panel A is spurious: indeed, it loses its statistical significance after adjusting for multiple comparisons (Schochet, 2009). Moreover, this result suggests sorting in the "wrong" direction in the sense that nonwhite students assigned to nonwhite faculty are from *lower* socioeconomic backgrounds, which would bias *against* finding a positive impact of demographic match on student outcomes. In sum, the general lack of sorting on observables observed in Table 3 suggests that differential sorting on unobservables is unlikely to bias two-way FE estimates of equation (2). The lack of endogenous sorting is unsurprising given the law school's claims that students were conditionally randomly assigned to classrooms.

4.2 Main Results

Table 4 reports two-way FE estimates of equation (2) using a simple definition of *Other*: binary indicators for whether or not the student had an other-sex and other-race instructor. The first three columns of Table 4 use different definitions of the course grade as the outcome. Column 1 uses a continuous measure of the course grade, which is measured on a 0-4 scale. Having an other-sex and other-race teacher significantly reduced the student's course grade by 0.02 and 0.04, respectively, though these estimates are not significantly different from one another. These effects represent small ($\approx 1\%$) changes from the average course grade of 3.3. While small in magnitude, recall that these are course-specific effects that might add up to nontrivial differences in cumulative GPA that preclude under-represented students from prestigious internships or alter the class rankings in ways that affect initial job placements and starting salaries.

Additionally, these small effects could be due to the effect of student-instructor demographic mismatch operating on particular margins of the course-grade distribution. Accordingly, in columns 2 and 3 we estimate linear probability models in which the outcomes are binary indicators for "good" and "bad" grades, respectively. Consistent with the results in column 1, column 2 shows a significant, negative effect of demographic mismatch on the probability that students earn an $A-$ or A. The racial mismatch effect is larger than the sex mismatch effect, but the difference is not statistically significant. These effects are arguably economically significant, as the other-race effect of 0.03 constitutes 9% of the sample average "good-grade" rate. Column 3 shows that there is no effect of student-instructor demographic mismatch on the likelihood of receiving a "bad grade" ($< B-$). The remaining columns of Table 4 show that there are neither effects of mismatch on the likelihood that the student takes another course in the subject nor on the likelihood that the student drops the course.[17] The latter null result is important, as it suggests that the sample selection inherent in the course-grade analyses is negligible.

Because an important contribution of the current paper is the identification of causal effects of same-race and same-sex instructors on course outcomes, we now leverage the quasi-random assignment of students to course sections to cross-validate the baseline two-way FE estimates. The intuition of the Hausman Test (Hausman, 1978) suggests that if student assignments to course sections were conditionally random, then OLS, one-way student random effects (RE) or FE, and two-way student and classroom FE estimates should be similar to one another. We show that this is so in table 5. This lends additional support to a causal interpretation of the baseline estimates and to the claim that students were quasi-randomly assigned to first-year courses.[18]

[17]The sample size for subsequent course taking is smaller because there are not subsequent courses in all required first-year courses.

[18]Because Table 5 shows that the pooled OLS estimates can be given a causal interpretation, we can also estimate pooled logit models to verify that the baseline linear model provides reasonable approximations of the partial effects of interest. Accordingly, Appendix Table A3 reports logit average partial effects (APE) that are comparable to the Linear estimates reported in Table 4. The logit APE are quite similar to the linear coefficient estimates, suggesting that the main results are robust to the functional form choice.

It is also possible that there are multiplicative effects of having both an other-race *and* other-sex instructor. Table 6 investigates this possibility by specifying *Other* as a set of four mutually-exclusive categorical indicators, with same-sex *and* same-race as the omitted reference category. The course-grade results reported in columns 1-3 are broadly consistent with those in Table 4: there are negative effects of student-instructor demographic mismatch on the probability of receiving a "good grade," which are larger for racial-mismatch than for sex-mismatch, but not on the probability of receiving a "bad grade." Interestingly, however, while the impact of having both an other-race and other-sex instructor is larger than that of having an other-race but same-sex instructor, the difference is not statistically significant.

Finally, Table 7 reports estimates of equation (4), which show the impact of having an other-sex or other-race instructor in the first course of a required two-course sequence on performance in the second course. Two versions of equation (4), with and without second-semester classroom FE, are estimated for each of three outcomes: course grade, a binary indicator for "good grade" (i.e., A or A-), and a binary indicator for "bad grade" (i.e., $<$B-). For each outcome, the point estimates are robust to excluding the second-semester course FE, which suggests that the demographic background of the first-semester instructor does not affect second-semester classroom assignments. This is to be expected, as first-year course-section assignments are conditionally random, but is reassuring nonetheless.

The results are broadly similar to the baseline two-way FE estimates reported in Table 4: there are negative effects of student-instructor mismatch in the first course on grades and on the probability of receiving a good grade in the second course. Once again, the other-race effect is about twice as large as the other-sex effect, though here only the other-sex effect is statistically significant at traditional confidence levels; this is due to the larger standard errors associated with the smaller sample of courses that comprise two-course sequences. That these estimates are qualitatively similar to the baseline estimates reported in Table 4 lends further credence to a causal interpretation of the relationship between student-instructor demographic mismatch and course grades. Moreover, this similarity sheds some light on the mechanisms at work, as the cross-semester effects documented in Table 7 suggest increased subject-specific learning that persists into the subsequent semester.

4.3 Heterogeneity

In this section we test for heterogeneity in the impacts of student-instructor demographic mismatch on the probability of receiving a "good grade" documented in section 4.2. Column 1 of Table 8 estimates an augmented version of the baseline model that allows the other-race and other-sex effects to vary by minority status, as historically under-represented groups tend to be more susceptible to role-model effects. While none of the individual coefficients are statistically significant, the net effects of having an other-sex and other-race instructor are statistically significant for nonwhite students, which suggests that the main results were driven by the responses of nonwhite students to demographic mismatch in the classroom. Moreover, the net effects of -0.02 and -0.04 are arguably economically significant, as they represent effects of 9% and 17%, respectively, from the nonwhite mean of 0.23. Still, the insignificant interaction terms mean that the effect for nonwhites was not significantly different from that for whites.

The impacts of student-teacher demographic mismatch might also vary by student sex. Unfortunately, the classroom-FE identification strategy does not allow for a female-other sex interaction term analogous to the nonwhite-other race interaction term included in column 1. The reason is that sex is coded as a time-invariant binary indicator, there is only one instructor per classroom, and the student and teacher sex indicators are subsumed by the student and classroom FE, respectively. However, we can create a triple interaction between the other-race indicator and the nonwhite and female indicators; we report these estimates in column 2 of Table 8. Like in column 1, the individual coefficient estimates are imprecisely estimated, meaning that the differences in effects are not statistically significant at traditional confidence levels. However, the net effects of having an other-sex and other-race instructor are both marginally statistically significant for nonwhite females, and relatively large in magnitude: they constitute approximately 12% and 22% effects, respectively. Together, these results suggest that the impact of representation among law school instructors is greatest for nonwhite students, particularly for nonwhite females. This is intuitive, as these demographic groups are historically underrepresented in the legal profession and therefore stand to gain the most from exposure to a demographically congruent role model.

We find no evidence of heterogeneity along other observable student dimensions, such as students' ability (LSAT score), age, home region, and zip-code SES. Nor do we find evidence of heterogeneity by observable instructor characteristics, such as experience, rank of JD program, or faculty rank (i.e., adjunct, teaching-track, tenure-line, tenured). These null results are not reported in tabular form in the interest of brevity.

Finally, we test for heterogeneity in the impact of student-instructor demographic mismatch by classroom characteristics, as classroom environments might moderate the impact of mismatch (Ho and Kelman, 2014; Inzlicht and Ben-Zeev, 2000).[19] Whether larger classrooms magnify or dampen the mismatch effects documented previously is theoretically ambiguous, as smaller classrooms could either shine a spotlight on implicit biases or facilitate relationships that supersede stereotypes. Second, we allow the effect of mismatch to vary with the demographic composition of classrooms, as the impact of an other-race or other-sex instructor might be more pronounced in less diverse settings in which female or nonwhite students feel isolated. Given the exploratory nature of this analysis, we model the heterogeneity using quadratics in class size and percent female (nonwhite). The quadratics are at least marginally jointly significant in both cases.

Appendix Table A4 reports the coefficient estimates for these models, though for ease of interpretation we plot the marginal effects as functions of class size and percent female (nonwhite). Figure 1 plots the marginal effects on the probability of receiving an A/A- of having an other-race or other-sex instructor as a function of class size. Interestingly, there is

[19] A relevant question here is whether class characteristics vary by subject. Appendix Table A2 reports mean course characteristics by subject. The primary outlier is legal rhetoric, which has significantly smaller classes than the other subjects. However, we find no evidence of systematic differences between legal rhetoric and other subjects in tests for subject heterogeneity.

essentially no effect of mismatch in the smallest classes. The other-sex effect monotonically increases in magnitude with class size, though at a relatively slow pace. The other-race effect, meanwhile, exhibits a U-shaped pattern. The deleterious effect of having an other-race instructor is largest in classrooms of about 60 students. One possible interpretation of this pattern is that the personal connections and relative anonymity in very small and very large classes, respectively, mitigate the harm associated with having an other-race instructor.

Similarly, Figure 2 plots the marginal effects on the probability of receiving an A/A- of having an other-race (other-sex) instructor as a function of the fraction of the classroom that is nonwhite (female). The other-race effect is fairly constant at about -0.03 or -0.04, regardless of the proportion of nonwhite students in the class. The effect only approaches zero when the fraction nonwhite approaches one, which is an out-of-sample prediction. However, the other-sex effect is highly nonlinear. Intuitively, it is most pronounced when females comprise less than 40% of the class. The other-sex effect approaches zero when 60 to 70% of the class is female. This is suggestive of stereotype threat (Steele, 1997), whereby females disengage with law school when they perceive themselves as outsiders, and consistent with experimental evidence that shows that the gender ratio of a classroom affects female's test performance, but not male's (Inzlicht and Ben-Zeev, 2000).

5 Conclusion

We use rich student-instructor matched administrative data from a large, private, top-100 law school to provide novel evidence on the causal relationship between student-instructor demographic match and student outcomes in the law school context. Two-way student and course fixed-effects models provide arguably causal estimates of the impact of such mismatch on short-run (course-specific) outcomes such as course grades. Sorting tests provide no evidence of endogenous sorting on observables into classrooms, which is consistent with the conditionally random assignment of students to course sections in the law school.

The baseline estimates suggest that having an other-race or other-sex instructor in a first-year required course significantly reduces the likelihood of earning an A/A- in the course. Specifically, having an other-sex instructor reduces the likelihood of receiving a good grade (A or A-) by one percentage point (3%) and having an other-race instructor reduces the likelihood of receiving a good grade by three percentage points (10%). The most comparable estimate in the extant literature comes from Fairlie, Hoffmann and Oreopoulos (2014), who find that having a same-race community college instructor increases the probability of having a good grade ($\geq B$) in first-year undergraduate courses by about three percentage points (5%).[20] That we document similarly sized effects in first-year courses at a top-100 law school suggests that even high-achieving college graduates are susceptible to role model effects.

This result has the potential to contribute to pay gaps, as Oyer and Schaefer (2016) provide descriptive evidence of a wage-class rank gradient in law schools outside the top 10.[21] However, we find no effects of student-instructor demographic mismatch on dropping courses or taking subsequent courses in the same field, nor do we find effects at other points of the grade distribution. Consistent with previous research in the K-12 context, these effects are stronger for nonwhite students, especially nonwhite females. It is remarkable that the same harmful effects of mismatch observed among relatively vulnerable populations of primary school, community college, and first-year college students are observed in an elite law school setting, given the successes and experiences necessary for admission to a top-100 law school. Indeed, a broad takeaway of the current study is that the race- and sex-interactions associated with stereotype threat likely pervade society in substantive, if unexpected ways.

These results suggest that diversity in the legal profession, and the status of women and people of color in the legal profession, would be improved by increasing the diversity of law school faculty. However, whether and how these results would generalize to other law schools, particularly those with less diverse student and faculty populations, remains an open question

[20] Grade inflation in graduate school accounts for the different definitions of "good grade."

[21] Our own analyses of the publicly available *After the JD* survey data confirm the positive association between law school GPA and earnings both overall, and for specific demographic groups, for lawyers who attended non-top 10 law schools. See Appendix B for details.

worthy of future exploration. There are also questions regarding the general equilibrium responses to the hiring of a more diverse faculty, and potential supply-side limitations of such faculty in the short run. For these reasons, another potential policy response is to provide law school (and university) faculty with theoretically-informed implicit bias training, which has proven to be effective in some early pilots (Carnes et al., 2015). Similarly, Darling-Hammong and Holmquist (2015) provide suggestions to law school faculty on how to better serve historically underrepresented students, many of which echo the theoretically-informed, "WISE" interventions and strategies advocated by social psychologists (Okonofua, Paunesku and Walton, 2016; Walton, 2014).

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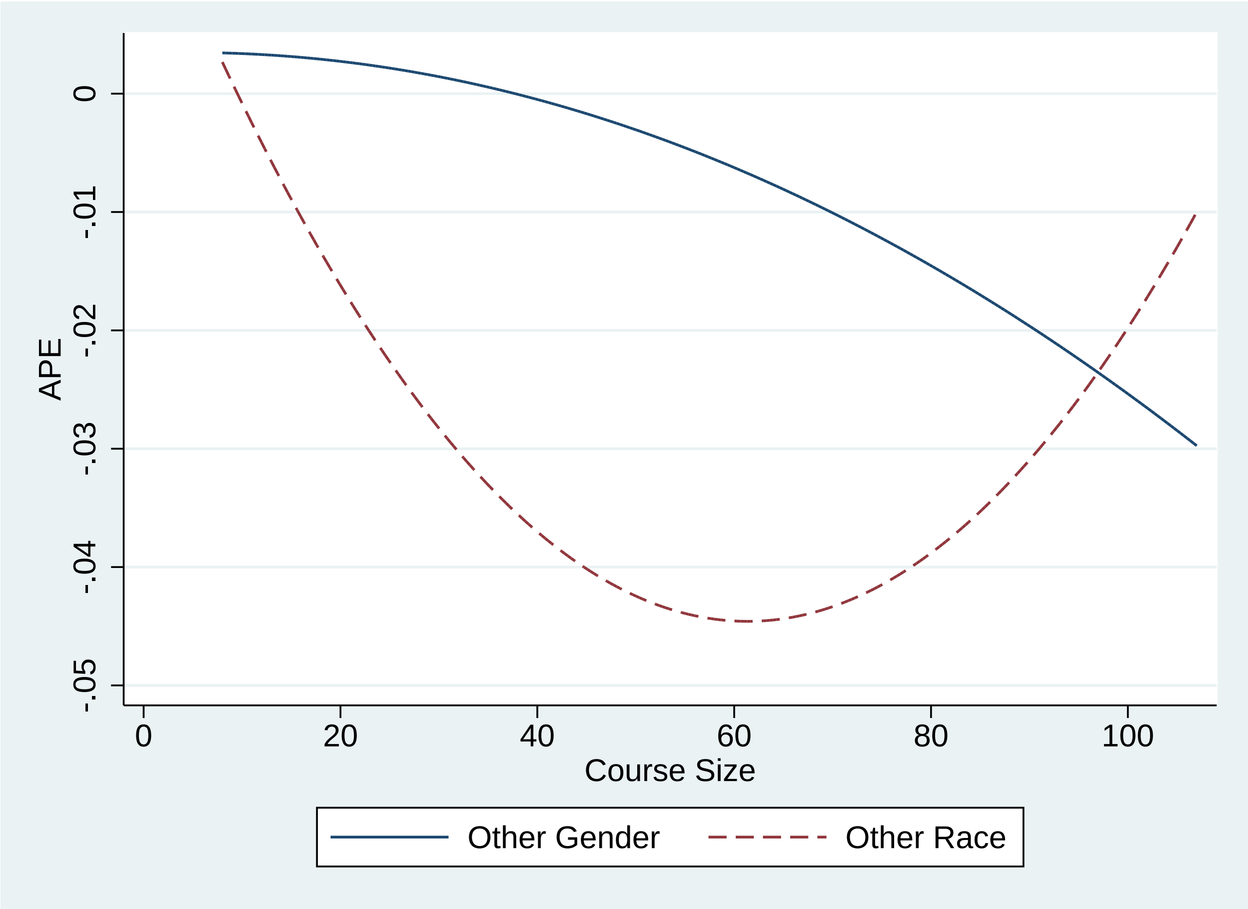

Figure 1: Average Partial Effects (APE) of Student-Instructor Mismatch on the Probability of Receiving a "Good Grade" as a Function of Class Size

"Good Grade" is defined as an A or A-.

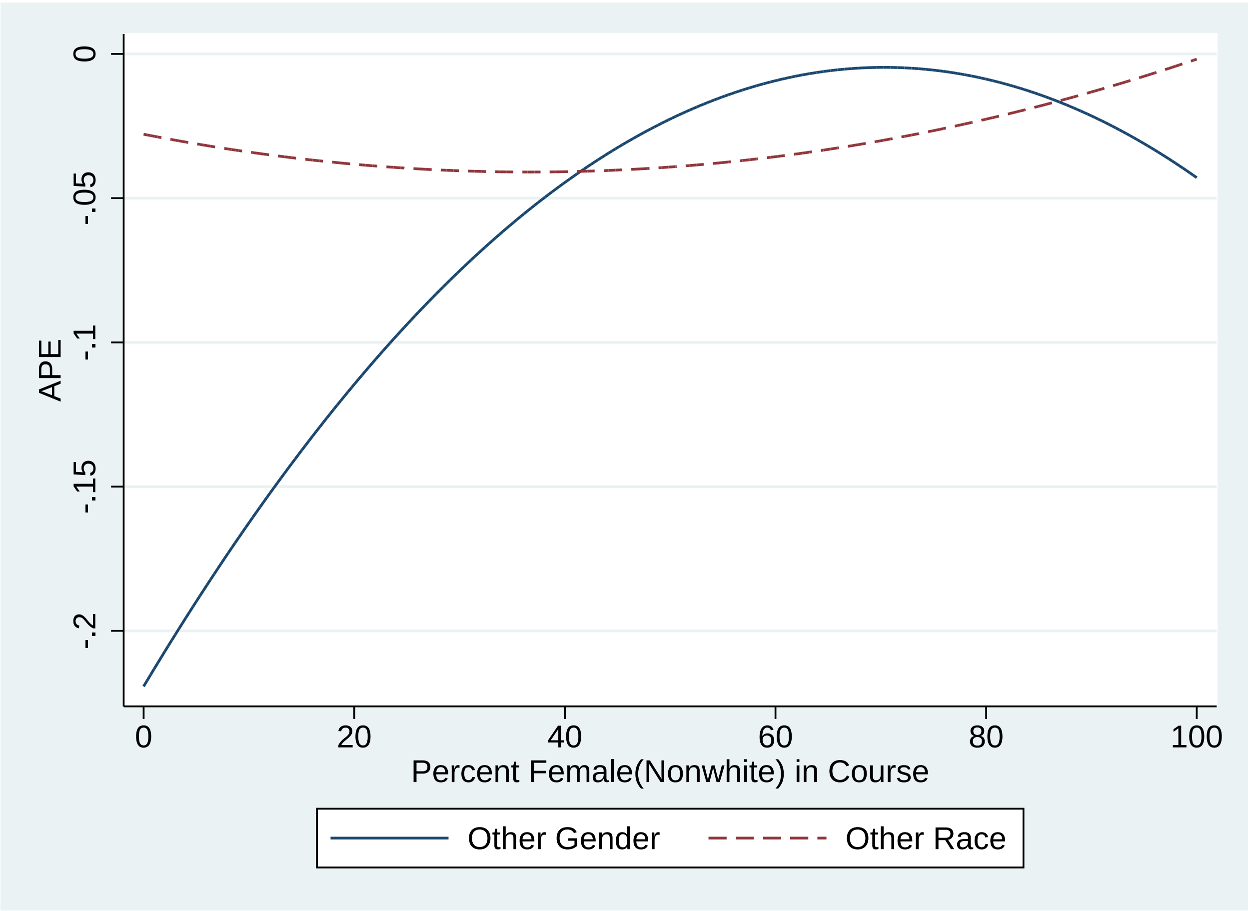

Figure 2: Average Partial Effects (APE) of Student-Instructor Mismatch on the Probability of Receiving a "Good Grade" as a Function of Class Composition

"Good Grade" is defined as an A or A-.

Table 1: Sample Statistics for First-Year Required Courses

	White		Non-white		Male		Female	
Panel A: Student-Course Level	mean	sd	mean	sd	mean	sd	mean	sd
Course Grade (0-4)	3.36	0.46	3.15	0.51	3.27	0.50	3.29	0.49
Take Another Course	0.80		0.81		0.80		0.81	
Dropped Course	0.004		0.004		0.004		0.004	
Grade: A	0.40		0.23		0.33		0.35	
Grade: B	0.56		0.67		0.60		0.60	
Grade: C, D, F	0.04		0.10		0.06		0.06	
Other Gender	0.51		0.52		0.42		0.58	
Other Race	0.18		0.95		0.41		0.50	
Same Instructor	0.91		0.91		0.91		0.91	
Observations	23,532		13,510		15,461		21,581	
Panel B: Student Level								
Age (First Semester)	25.6	2.6	25.4	2.5	25.8	2.7	25.4	2.5
Female Student	0.54		0.65		0.00		1.00	
Black Student	0.00		0.21		0.05		0.10	
Latino Student	0.00		0.37		0.12		0.14	
Asian Student	0.00		0.35		0.10		0.14	
White Student	1.00		0.00		0.70		0.59	
Other Race Student	0.00		0.08		0.03		0.03	
LSAT	161.1	3.4	156.2	4.8	159.9	4.4	158.8	4.8
Persist to Second Year	0.89		0.91		0.88		0.90	
Joined Top Law Review at LS	0.14		0.06		0.11		0.11	
Joined Any Law Journal	0.32		0.27		0.27		0.32	
Graduated in 5 years	0.82		0.82		0.82		0.83	
Observations	3,018		1,736		1,993		2,761	
Panel C: Instructor Level								
Non-white Instructor	0.00		1.00		0.13		0.21	
Black Instructor	0.00		0.49		0.07		0.10	
Latino Instructor	0.00		0.23		0.03		0.05	
Asian Instructor	0.00		0.29		0.04		0.06	
White Instructor	1.00		0.00		0.87		0.79	
Female Instructor	0.46		0.60		0.00		1.00	
Years of Experience at LS	5.87	9.62	2.86	5.62	7.71	11.00	2.98	5.95
Has JD	0.94		0.97		0.93		0.97	
Rank of JD School	37.9	36.0	37.1	42.6	36.4	39.4	39.2	34.6
Has PhD	0.10		0.06		0.09		0.09	
Has LLM	0.09		0.18		0.13		0.07	
Has LLB	0.04		0.00		0.06		0.01	
Observations	171		35		106		100	

Notes: The Dropped Course descriptive statistics are based on slightly larger samples (23,657 for white students, 13,606 for non-white students, 15,559 for male students, and 21,704 for female students) because including dropped courses increases the number of student-course- level observations for students that drop classes. There are no Other Race instructors in the analytic sample. Same instructor in panel A is a binary variable indicating the student had the same instructor in the previous course.

Table 2: Sample Statistics for First-Year Required Courses

Course Level Characteristics	mean	sd	Course Names	Pct
Class Size	42.90	33.30	Civil Procedure	5.39
Female Students	0.59	0.15	Civil Procedure II	2.12
Age (First Semester)	25.90	2.30	Constitutional Law	6.10
Black Students	0.07	0.07	Contracts	5.65
Latino Students	0.13	0.12	Criminal Law	6.10
Asian Students	0.13	0.11	Criminal Procedure I	2.74
White Students	0.64	0.15	Legal Rhetoric I	26.33
Other Students	0.03	0.05	Legal Rhetoric II	28.80
Female Instructor	0.45	0.50	Property	5.57
Black Instructor	0.08	0.27	Property II	1.77
Asian Instructor	0.02	0.15	Torts	5.04
Latino Instructor	0.04	0.18	Legal Ethics	4.42
White Instructor	0.86	0.35	Observations	1,132
More than one instructor race choice term	0.74	0.44		
More than one instructor race choice year	0.76	0.43		
More than one instructor gender choice term	0.94	0.24		
More than one instructor gender choice year	0.95	0.21		
Observations	1,132			

Notes: Classroom level demographics are presented as proportions.

Table 3: Sorting Test Estimates

	Outcome					
	LSAT	UGPA	Median Income (Zip)	% Adult w/ BA (Zip)	In/Nearby State	Student Age
Average:	159.27	3.42	77151.54	37.19	0.52	25.5
Panel A: Sorting by Race						
Nonwhite Instructor	-0.081	-0.035	-2712.934**	4.057***	-0.013	-0.001
	(0.293)	(0.057)	(1345.437)	(1.315)	(0.016)	(0.070)
Nonwhite Student	-4.578***	-0.143***	-2595.760***	-2.134***	-0.019*	-0.112**
	(0.116)	(0.032)	(614.633)	(0.288)	(0.010)	(0.052)
Nonwhite Instructor * Nonwhite Student	**0.397**	**-0.043**	**-2043.493**	**-2.330****	**0.008**	**0.175**
	(0.291)	(0.103)	(1379.186)	(0.949)	(0.027)	(0.115)
Constant	160.392***	3.460***	78717.816***	37.958***	0.530***	25.606***
	(0.102)	(0.023)	(546.117)	(0.445)	(0.006)	(0.034)
Observations	1,960	499	2,159	2,159	2,166	2,166
Panel B: Sorting by Gender						
Female Instructor	0.187	-0.064	-980.866	0.712	0.005	-0.080
	(0.191)	(0.059)	(1128.953)	(0.783)	(0.014)	(0.071)
Female Student	-0.980***	0.124***	-1590.970**	0.485	0.031**	-0.346***
	(0.116)	(0.045)	(734.006)	(0.338)	(0.012)	(0.064)
Female Instructor * Female Student	**-0.019**	**0.027**	**-837.787**	**-0.564**	**-0.009**	**-0.014**
	(0.184)	(0.072)	(1166.259)	(0.546)	(0.018)	(0.092)
Constant	159.140***	3.339***	78744.590***	36.803***	0.502***	25.830***
	(0.130)	(0.037)	(746.885)	(0.541)	(0.009)	(0.052)
Observations	2,037	484	2,269	2,269	2,276	2,276

Note: Each column represents tests for sorting on a different student background characteristic. UGPA is undergraduate grade point average. In/Nearby State is a binary variable indicating the student's home address is within the same state as the institution or a bordering state. Standard errors in parentheses are clustered by course.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Impact of demographic mismatch on first-year required course outcomes

	Continuous Grade (1)	A Grade (2)	A/A- Grade (3)	C, D, F Grade (4)	Take Another (5)	Dropped Course (6)
Other Gender	-0.016**	-0.009**	-0.013**	0.001	0.016	-0.000
	(0.007)	(0.004)	(0.007)	(0.003)	(0.010)	(0.000)
Other Race	-0.037**	-0.015**	-0.028***	0.009	-0.000	0.001
	(0.016)	(0.007)	(0.011)	(0.007)	(0.008)	(0.001)
Differences in coefficients (P)						
1=2	0.214	0.491	0.203	0.259	0.184	0.259
Observations	37042	37042	37042	37042	18748	37263
Course FE	Yes	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column represents a different model specification. The outcomes are measured as follows: Continuous Grade measures a student's received grade on a 0-4 scale (F-A); A Grade is a binary indicator for whether a student received an A grade; A or A- Grade is a binary indicator for whether a student received an A or A- grade; C-F Grade is a binary indicator for whether a student received a C, D, or F grade; Take Another is a binary indicator for whether a student takes a subsequent elective course in the same field after their first year; and Dropped Course is a binary indicator for whether a student drops the course before the end of the semester. Column 5 has fewer observations because not all required courses correspond to elective course subjects. Difference in Coefficients compares OG effect against OR effect. Standard errors in parentheses are clustered by student and instructor.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Impact of demographic mismatch on first-year required course outcomes

	A/A- Grade			
	(1)	(2)	(3)	(4)
Other Gender	-0.012**	-0.013***	-0.013*	-0.013**
	(0.005)	(0.005)	(0.007)	(0.007)
Other Race	-0.024**	-0.031***	-0.033***	-0.028***
	(0.009)	(0.009)	(0.013)	(0.011)
Female Faculty	0.041***	0.042***	0.042**	
	(0.005)	(0.005)	(0.017)	
Non-white Faculty	0.007	0.004	0.003	
	(0.008)	(0.007)	(0.015)	
Non-white Student	-0.152***	-0.146***		
	(0.010)	(0.010)		
Female Student	0.038***	0.035***		
	(0.008)	(0.008)		
Observations	37042	37042	37042	37042
Course FE	No	No	No	Yes
Student RE	No	Yes	No	No
Student FE	No	No	Yes	Yes

Note: Each column represents a different model specification. The outcomes are measured as follows: A/A- Grade is a binary indicator for whether a student received an A or A- grade. Take Another is a binary indicator for whether a student takes a subsequent course in the same field. Standard errors in parentheses are clustered by student and instructor.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Impact of demographic mismatch type on first-year required course outcomes

	Continuous Grade	A Grade	A/A- Grade	C, D, F Grade	Take Another	Dropped Course
	(1)	(2)	(3)	(4)	(5)	(6)
Same Race, Mismatch Gender	-0.014*	-0.011**	-0.012	0.001	0.034**	-0.000
	(0.008)	(0.005)	(0.008)	(0.003)	(0.013)	(0.001)
Mismatch Race, Match Gender	-0.035**	-0.017**	-0.027**	0.010	0.017*	0.000
	(0.016)	(0.008)	(0.011)	(0.008)	(0.009)	(0.001)
Mismatch Race, Mismatch Gender	-0.053***	-0.024***	-0.041***	0.010	0.017	0.001
	(0.018)	(0.008)	(0.013)	(0.008)	(0.014)	(0.001)
Differences in coefficients (P)						
1=2	0.217	0.474	0.206	0.255	0.170	0.270
1=3	0.027	0.112	0.016	0.270	0.116	0.274
2=3	0.046	0.246	0.086	0.926	0.981	0.758
Observations	37042	37042	37042	37042	18748	37263
Course FE	Yes	Yes	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column represents a different model specification. The outcomes are measured as follows: Continuous Grade measures a student's received grade on a 0-4 scale (F-A); A Grade is a binary indicator for whether a student received an A grade; A or A- Grade is a binary indicator for whether a student received an A or A- grade; C-F Grade is a binary indicator for whether a student received a C, D, or F grade; Take Another is a binary indicator for whether a student takes a subsequent elective course in the same field after their first year; and Dropped Course is a binary indicator for whether a student drops the course before the end of the semester. Column 5 has fewer observations because not all required courses correspond to elective course subjects. Difference in Coefficients compares estimated effects corresponding to assigned number. Standard errors in parentheses are clustered by student and instructor.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Cross-Semester Effects of Demographic Mismatch in Two-Course Sequences

	Continuous Grade		A/A- Grade		C, D, F Grade	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Cross-Semester Effects						
Other Gender	-0.032**	-0.032**	-0.034**	-0.034**	0.004	0.004
	(0.012)	(0.012)	(0.016)	(0.016)	(0.008)	(0.008)
Other Race	-0.079	-0.077	-0.073	-0.072	0.017	0.017
	(0.050)	(0.050)	(0.048)	(0.048)	(0.021)	(0.021)
Course 1 FE	Yes	Yes	Yes	Yes	Yes	Yes
Course 2 FE	No	Yes	No	Yes	No	Yes
Student FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Cross-Semester Effects - Same Instructor						
Other Gender	-0.076	-0.077	-0.125**	-0.124**	0.005	0.005
	(0.064)	(0.063)	(0.061)	(0.061)	(0.031)	(0.031)
Other Race	-0.204***	-0.207*	-0.044	-0.043	0.073*	0.073*
	(0.063)	(0.063)	(0.069)	(0.070)	(0.043)	(0.043)
Same Instructor for Course 1 and 2	-0.456***		-0.408***		0.132	
	(0.130)		(0.070)		(0.085)	
OG * Same Instructor	0.049	0.050	0.101*	0.100*	-0.002	-0.001
	(0.066)	(0.065)	(0.057)	(0.057)	(0.030)	(0.030)
OR * Same Instructor	0.144***	0.146***	-0.031	-0.032	-0.064	-0.064
	(0.054)	(0.054)	(0.058)	(0.059)	(0.039)	(0.039)
Course 1 FE	Yes	Yes	Yes	Yes	Yes	Yes
Course 2 FE	No	Yes	No	Yes	No	Yes
Student FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: N = 4346. Each column represents a different model specification. The outcomes are measured as follows: Continuous Grade measures a student's received grade on a 0-4 scale (F-A). A/A- Grade is a binary indicator for whether a student received an A or A- grade. C,D,F Grade is a binary indicator for whether a student received a C,D, or F grade. Same Instructor indicates the student had the same instructor for both Course 1 and 2 in two-course sequences. Estimates are not shown for Same Instructor in even numbered columns because it is perfectly correlated with the Course 1 and 2 FEs. Standard errors in parentheses are clustered three ways: by student, first instructor, and second instructor. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Heterogeneous Effects of Student-Instructor Demographic Mismatch

	A/A- Grade	
	(1)	(2)
Other Gender	-0.010	-0.010
	(0.007)	(0.007)
Other Race	-0.024	-0.023
	(0.016)	(0.016)
OG * Nonwhite Student	-0.010	0.001
	(0.009)	(0.015)
OR * Nonwhite Student	-0.011	0.010
	(0.030)	(0.041)
OG * Female * Nonwhite Student		-0.017
		(0.023)
OR * Female * Nonwhite Student		-0.032
		(0.039)
Net Effects		
OG Nonwhite APE	-0.020**	-0.009
	(0.009)	(0.014)
OG Nonwhite Female APE		-0.026*
		(0.015)
OR Nonwhite APE	-0.035*	-0.013
	(0.021)	(0.034)
OR Nonwhite Female APE		-0.045*
		(0.025)
Observations	37042	37042
Course FE	Yes	Yes
Student FE	Yes	Yes

Note: Each column represents a different model specification. The outcome A/A- Grade is a binary indicator for whether a student received an A or A- grade. Covariates are measured as follows: Other Gender (OG) is a binary indicator for whether the student's gender is different from the course instructor. Other Race (OR) is a binary indicator for whether the student's race is different from the course instructor. Nonwhite is a binary indicator for whether the student's race is different from white. Female is a binary indicator for whether the student is female. APE = average partial effect. Standard errors in parentheses are clustered by student and instructor. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A

Table A1: Baseline Model Allowing for Contemporaneous Spillovers

	Continuous Grade		A/A- Grade	
	(1)	(2)	(3)	(4)
Other Gender	-0.017**	0.017	-0.012*	-0.004
	(0.007)	(0.029)	(0.007)	(0.027)
Another OG	-0.005	0.022	0.008	0.014
	(0.012)	(0.025)	(0.011)	(0.023)
Other Race	-0.037**	-0.051***	-0.028***	-0.026
	(0.016)	(0.019)	(0.011)	(0.019)
Another OR	-0.002	-0.009	-0.001	-0.000
	(0.011)	(0.013)	(0.010)	(0.011)
OG * Another OG		-0.035		-0.009
		(0.029)		(0.028)
OR * Another OR		0.021		-0.003
		(0.021)		(0.022)
Observations	37042	37042	37042	37042
Course FE	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes

Note: Each column represents a different model specification. The outcomes are measured as follows: Continuous Grade measures a student's received grade on a 0-4 scale (F-A). A/A- Grade is a binary indicator for whether a student received an A or A- grade. Standard errors in parentheses are clustered by student and instructor.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Mean course characteristics by subject

Subject	N	Course Size	Female Students	White Students	Female Faculty	White Faculty
Civil Procedure	85	83.1	0.59	0.66	0.21	0.82
Constitutional	69	82.8	0.58	0.64	0.13	0.71
Contracts	64	75.0	0.59	0.62	0.31	0.84
Criminal	100	73.0	0.58	0.65	0.52	0.63
Legal Rhetoric	624	15.5	0.59	0.63	0.50	0.92
Property	83	84.4	0.59	0.63	0.59	0.77
Torts	57	79.2	0.58	0.63	0.42	1.00
Legal Ethics	50	50.0	0.54	0.70	0.54	0.88

Note: The unit of analysis is course sections. Each statistic reported is the average across course sections: average size, percent female students in class, percent white students in class, percent of course sections taught by females, and percent of course sections taught by white faculty.

Table A3: Impact of demographic mismatch on first-year required course outcomes (Logit APE)

	(1) A/A- Grade	(2) C, D, F Grade	(3) Take Another	(4) Dropped Course
Female Instructor	0.040***	-0.003	0.023***	0.001
	(0.005)	(0.002)	(0.006)	(0.001)
Non-white Instructor	0.011	-0.000	-0.022**	0.001
	(0.009)	(0.003)	(0.009)	(0.001)
Non-white Student	-0.154***	0.052***	0.017	-0.000
	(0.011)	(0.005)	(0.011)	(0.001)
Female Student	0.037***	-0.016***	0.002	-0.000
	(0.008)	(0.004)	(0.009)	(0.001)
Other Gender	-0.012**	0.002	0.013**	0.000
	(0.005)	(0.002)	(0.006)	(0.001)
Other Race	-0.026***	0.005	-0.007	0.001
	(0.010)	(0.005)	(0.010)	(0.001)
Observations	37042	37042	18748	37263

Note: Each column represents a different model specification. The outcomes are measured as follows: A/A- Grade is a binary indicator for whether a student received an A or A- grade. C,D,F Grade is a binary indicator for whether a student received a C,D, or F grade. Take Another is a binary indicator for whether a student takes a subsequent course in the same field. Dropped Course is a binary indicator for whether a student drops the course before the end of the semester. Column 3 has fewer observations because not all required courses correspond to elective course subjects. Standard errors in parentheses are clustered by student and instructor.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Heterogeneity by Course Size and Percent Female(Nonwhite) in Course

	Course Size		Percent Female (Nonwhite) in Course	
	(1)	(2)	(3)	(4)
Other Gender	0.003412		-0.219260	
	(0.024841)		(0.167925)	
Other Gender * Course Size	0.000029			
	(0.001040)			
Other Gender * Course Size (Sq)	-0.000003			
	(0.000009)			
Other Race		0.017907		-0.027838***
		(0.024187)		(0.010603)
Other Race * Course Size		-0.002037**		
		(0.000913)		
Other Race * Course Size (Sq)		0.000017**		
		(0.000008)		
Other Gender * Percent Female			0.006104	
			(0.005567)	
Other Gender * Percent Female (Sq)			-0.000043	
			(0.000046)	
Other Race * Percent Nonwhite				-0.000715
				(0.000798)
Other Race * Percent Nonwhite (Sq)				0.000010
				(0.000019)
P-Value for Joint Significance Tests	0.076*	0.007***	0.080*	0.029**
Observations	37042	37042	37042	37042
Course FE	Yes	Yes	Yes	Yes
Student FE	Yes	Yes	Yes	Yes

Note: The covariates are defined as follows: Other Gender is a binary indicator for whether the student's gender is different from the instructor. Other Race is a binary indicator for whether the student's race is different from the instructor. Course Size measures the total number of students in the classroom. Percent Female measures the percentage of female students in the classroom. Percent Nonwhite measures the percentage of nonwhite students in the classroom. Sq indicates quadratic term. Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B

This appendix uses publicly available data from *After the JD* (AJD) to document the descriptive relationship between law school grades and early-career salaries for individuals who earned JDs from non-top 10 law schools.[22] The motivation for this appendix is to show that the impacts of student-instructor mismatch on course grades documented in the current study likely translate into demographic pay gaps among early-career law professionals.

The public-use AJD data report annual earnings in 8 bins: <\$40,000, \$40,000-\$49,999, \$50,000-\$59,999, \$60,000-\$74,999, \$75,000-\$99,999, \$100,000-\$124,999, \$125,000-\$149,999, and >\$150,000. Accordingly, we estimate descriptive ordered-logit models in which this categorical annual-earnings variable is the dependent variable. Appendix Table B1 reports the ordered-logit coefficients for the full sample. The parsimonious specifications in columns 1 and 2 document the unconditional female pay gap and wage-GPA gradient, respectively. The omitted reference category for the GPA variable is <3.0. Column 4 shows that these patterns are robust to controlling for law school quality.

Because the ordered-logit coefficients are not directly interpretable, Appendix Table B2 reports the average partial effects (APE) of these covariates on the probability of being in each earnings band for the fully-specified, full-sample estimates reported in column 4 of Appendix Table B1. Here we see that females are two to four percentage points more likely than males to be in the lowest-earning categories and two to four percentage points less likely than men to be in the highest-earning categories. The APE for the categorical GPA indicators show that each 0.25 increase in GPA is associated with a two to four percentage point increase in the probability of being in one of the high-earnings brackets, and a symmetric decrease in the probability of being in a low-earning bracket. Importantly, this suggests that even a relatively small change in GPA attributable to student-instructor demographic mismatch in first-year law courses might substantively affect early-career earnings.

[22] The AJD is a representative survey of new law-school graduates, conducted by the American Bar Foundation, in 2002, 2007, and 2010. See `http://www.americanbarfoundation.org/publications/afterthejd.html` for further information.

Table B1: Descriptive Ordered-Logit Earnings Regressions: Coefficient Estimates

	(1)	(2)	(3)	(4)
Female	-0.45***		-0.49***	-0.49***
	(0.07)		(0.07)	(0.07)
Black	-0.02		0.11	0.02
	(0.11)		(0.12)	(0.11)
Hispanic	-0.10		0.04	-0.01
	(0.11)		(0.12)	(0.12)
Asian	0.62***		0.63***	0.42***
	(0.13)		(0.14)	(0.13)
Other Race	0.06		0.10	0.06
	(0.19)		(0.19)	(0.20)
> 3.75 GPA		1.82***	1.90***	1.68***
		(0.16)	(0.16)	(0.18)
3.5 - 3.74 GPA		1.59***	1.65***	1.42***
		(0.13)	(0.13)	(0.14)
3.25 - 3.49 GPA		1.04***	1.09***	0.87***
		(0.13)	(0.13)	(0.13)
3.0 - 3.24 GPA		0.56***	0.59***	0.48***
		(0.12)	(0.12)	(0.12)
Missing GPA		1.34***	1.35***	1.16***
		(0.10)	(0.10)	(0.10)
Top 10 Law School				2.21***
				(0.15)
11-20 Law School				1.45***
				(0.13)
21-100 Law School				0.38***
				(0.07)
Observations	3785	3892	3785	3755

Note: Each column represents a different model specification.
Cut points not shown. Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B3 estimates the fully-specified ordered-logit model separately by sex and race. The key results here are that (i) the gender pay gap exists for white, black, and Hispanic lawyers and (ii) that the wage-GPA gradient exists in the male, female, white, and black subsamples. Appendix Table B4 similarly shows that the wage-GPA gradient exists for graduates of all law schools outside the US News Top-10. This is consistent with results reported in Oyer and Schaefer (2016). The US News rank of the law school studied in the

Table B2: Descriptive Ordered-Logit Earnings Regressions: Average Partial Effects

	(1) 0-39K	(2) 40-49K	(3) 50-59K	(4) 60-74K	(5) 75-99K	(6) 100-124K	(7) 125-149K	(8) >150K)
Female	0.04***	0.04***	0.02***	0.00**	-0.02***	-0.02***	-0.02***	-0.04***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Black	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Hispanic	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Asian	-0.03***	-0.04***	-0.02***	-0.00*	0.02***	0.02***	0.02***	0.03***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Other Race	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00
	(0.02)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
> 3.75 GPA	-0.13***	-0.15***	-0.07***	-0.01**	0.06***	0.07***	0.08***	0.13***
	(0.02)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
3.5 - 3.74 GPA	-0.11***	-0.13***	-0.06***	-0.01**	0.05***	0.06***	0.07***	0.11***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
3.25 - 3.49 GPA	-0.07***	-0.08***	-0.03***	-0.00**	0.03***	0.04***	0.04***	0.07***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
3.0 - 3.24 GPA	-0.04***	-0.04***	-0.02***	-0.00*	0.02***	0.02***	0.02***	0.04***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Missing GPA	-0.09***	-0.10***	-0.05***	-0.01**	0.04***	0.05***	0.06***	0.09***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Top 10 Law School	-0.17***	-0.20***	-0.09***	-0.01**	0.08***	0.09***	0.11***	0.18***
	(0.01)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
11-20 Law School	-0.11***	-0.13***	-0.06***	-0.01**	0.06***	0.06***	0.07***	0.12***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
21-100 Law School	-0.03***	-0.03***	-0.02***	-0.00**	0.01***	0.02***	0.02***	0.03***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Observations	3755	3755	3755	3755	3755	3755	3755	3755

Note: Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

current paper falls in the 21-100 range (column 3), for whom grades are quite important.

Table B3: **Descriptive Ordered-Logit Earnings Regressions by Demographic Background: Coefficient Estimates**

	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Female			-0.49***	-0.97***	-0.65**	-0.28
			(0.08)	(0.23)	(0.27)	(0.25)
Black	0.15	-0.09				
	(0.16)	(0.16)				
Hispanic	0.04	-0.09				
	(0.17)	(0.18)				
Asian	0.27	0.53***				
	(0.20)	(0.18)				
Other Race	0.13	-0.03				
	(0.28)	(0.29)				
> 3.75 GPA	1.62***	1.70***	1.69***	17.99***	0.61	1.44**
	(0.29)	(0.22)	(0.19)	(1.07)	(0.84)	(0.59)
3.5 - 3.74 GPA	1.54***	1.31***	1.48***	3.34***	2.86***	0.62
	(0.19)	(0.20)	(0.16)	(0.68)	(0.81)	(0.56)
3.25 - 3.49 GPA	0.92***	0.83***	0.87***	2.41***	0.40	0.48
	(0.18)	(0.19)	(0.15)	(0.64)	(0.53)	(0.35)
3.0 - 3.24 GPA	0.43**	0.53***	0.51***	0.83**	0.42	-0.10
	(0.17)	(0.17)	(0.14)	(0.39)	(0.43)	(0.41)
Missing GPA	1.15***	1.18***	1.27***	1.00***	0.71**	
	(0.14)	(0.15)	(0.12)	(0.29)	(0.33)	
Top 10 Law School	2.26***	2.15***	2.15***	2.49***	3.02***	2.08***
	(0.20)	(0.24)	(0.18)	(0.41)	(0.50)	(0.45)
11-20 Law School	1.47***	1.43***	1.51***	1.53***	0.85	1.03***
	(0.17)	(0.20)	(0.16)	(0.38)	(0.54)	(0.34)
21-100 Law School	0.34***	0.41***	0.42***	0.36	0.33	0.13
	(0.10)	(0.11)	(0.08)	(0.28)	(0.30)	(0.30)
Observations	1995	1760	2703	330	312	341

Note: Each column represents a different model specification. Cut points not shown. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Descriptive Ordered-Logit Earnings Regressions by Law School Rank: Coefficient Estimates

	(1) Top 10	(2) 11-20	(3) 21-100	(4) Outside 100
Female	-0.55**	-0.44**	-0.44***	-0.60***
	(0.24)	(0.20)	(0.10)	(0.12)
Black	0.07	0.11	-0.07	0.06
	(0.33)	(0.28)	(0.17)	(0.23)
Hispanic	0.42	-0.60	-0.00	0.10
	(0.37)	(0.37)	(0.17)	(0.27)
Asian	0.57	0.23	0.33*	0.72***
	(0.37)	(0.30)	(0.20)	(0.27)
Other Race	1.13*	-0.36	-0.28	0.67
	(0.64)	(0.46)	(0.26)	(0.41)
> 3.75 GPA	-0.12	2.72***	1.98***	1.54***
	(1.02)	(0.43)	(0.26)	(0.31)
3.5 - 3.74 GPA	0.80	2.15***	1.62***	1.33***
	(0.85)	(0.38)	(0.21)	(0.26)
3.25 - 3.49 GPA	0.97	1.50***	1.07***	0.50**
	(0.82)	(0.42)	(0.20)	(0.21)
3.0 - 3.24 GPA	0.42	1.99***	0.42**	0.41**
	(0.81)	(0.41)	(0.19)	(0.18)
Missing GPA	0.52	2.40***	1.33***	0.90***
	(0.78)	(0.33)	(0.16)	(0.16)
Observations	370	467	1737	1181

Note: Each column represents a different model specification. Cut points not shown. Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.