SKILLS, SCHOOLS, AND CREDIT CONSTRAINTS: EVIDENCE FROM MASSACHUSETTS

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Abstract

Low college enrollment rates among low-income students may stem from a combination of credit constraints, low academic skill, and low-quality schools. Recent Massachusetts data allow the first use of school district fixed effects in the analysis of credit constraints, leading to four findings. First, low-income students in Massachusetts have lower intended college enrollment rates than higher income students but also have dramatically lower skills and attend lower-quality school districts. Second, inclusion of skill controls greatly reduces but does not eliminate this intended enrollment gap. Third, inclusion of school district fixed effects has little further impact, with low-income students eight percentage points less likely to intend enrollment than higher income students of the same skill and from the same school district. Fourth, medium- and high-skilled low-income students appear the most constrained. State governments could use the methods employed here to target financial aid more efficiently.

1. INTRODUCTION AND PREVIOUS LITERATURE

In the United States and other developed countries, rapidly increasing college costs have raised concerns about access to postsecondary education, particularly for low-income students. These concerns are heightened by the perceived need to improve the low-skilled segment of the labor force in order to combat downward wage pressures attributed to globalization and skill-biased technological change. In the United States, advocates of increased financial aid for postsecondary education are particularly concerned that students from low-income families enroll in college at significantly lower rates than do higher income students. As of 2004, 49.6 percent of students from families in the lowest income quartile enrolled in college immediately after high school graduation, compared with 79.3 percent of students from families in the highest income quartile, a gap of nearly 30 percentage points.[1]

There are (at least) three potential explanations for this fact. The first is that low-income students have similar or higher returns to college education than do higher income students but are financially constrained and thus can not afford further education. The second is that low-income students have lower academic skill and thus lower returns to college education, so their non-enrollment represents a rational, unconstrained decision.[2] The third, and until now relatively unexplored, explanation is that low-income students generally attend lower-quality high schools than do higher income students, as measured by the academic skills of the student populations, the expectations that students enroll in college, and the resources devoted to factors that help students navigate the college entrance process, such as guidance departments and standardized test preparation.

These three explanations are unfortunately easy to conflate given the high correlation among family income, academic skill, and school quality. The inability to distinguish these explanations creates a public policy quandary because each yields a different policy prescription. If low-income students are financially constrained, public subsidies to reduce college costs may improve the efficiency of human capital markets, an argument for increasing financial aid. If low academic skills or school quality explain enrollment gaps, then increasing financial aid may be ineffective or inefficient and public funds may be better used trying to raise academic skills or improve school quality.

Attempts to distinguish these explanations are often frustrated by data limitations. Most data sets, for example, lack any measure of academic skill,

1. These figures come from the 2004 October Supplement to the Current Population Survey (U.S. Department of Labor 2005).
2. Throughout this article, I use *skill* to denote academic achievement as measured during high school and take no position on the determinants of such achievement. What matters for the results below is that skill defined in this way is a powerful predictor of college enrollment.

so many authors are forced to make indirect arguments about the existence of credit constraints.[3] Supporting the importance of credit constraints are findings that college enrollment rates are highly sensitive to financial aid (Kane 1994; Dynarski 2002) and to current income (Mazumder 2003) and that the existence of constrained students may explain why instrumental variables estimates of returns to schooling exceed ordinary least squares (OLS) estimates (Card 1999). Indirect arguments against the importance of credit constraints come from findings that the cyclicality of college enrollment does not differ by familial access to credit (Christian 2007) and that theoretical predictions about the reactions of credit-constrained students to the opportunity and direct costs of college do not generate empirical support for the existence of such students, at least in significant numbers (Cameron and Taber 2004).

Because the aforementioned articles lack measures of skill, it is hard to know exactly how to interpret their results. More satisfying in this regard are those that exploit the National Longitudinal Surveys of Youth (NLSY), which contain such a measure in the form of the Armed Forces Qualification Test (AFQT) score. Using the 1979 NLSY, Cameron and Heckman (2001) show that white-minority gaps in schooling attainment disappear or even reverse sign when controlling for AFQT score. Similarly, Carneiro and Heckman (2002) group students by skill and income to show small gaps by income once ability is held constant. Their estimates suggest that skill and not income is the greatest constraint to college enrollment.

Using similar methods, research by Ellwood and Kane (2000) and Belley and Lochner (2007) suggests that credit constraints have become more important in recent years. Using the 1992 National Educational Longitudinal Study (NELS), which contains test scores, Ellwood and Kane find that, conditional on ability, students in the lowest income quartile are about 10 percentage points less likely to enroll in college than their higher income peers. They also find that the importance of income as a predictor of enrollment increased between the early 1980s and the early 1990s. Similarly, Belley and Lochner replicate Carneiro and Heckman's work using both the 1979 and the 1997 NLSY cohorts and find that family income plays a much larger role in the determination of college enrollment for the younger cohort than for the older cohort. In a subsequent paper, Lochner and Monge-Naranjo (2008) argue that this fact and the increasing demand by college enrollees for both public and private credit are consistent with increasingly binding credit constraints, particularly on the

3. I focus here on credit constraints and the college enrollment margin. For recent work on whether credit constraints affect the college completion decision, see Stinebrickner and Stinebrickner (2007), who argue that even generous policies to relieve credit constraints would have little impact on dropout rates. For evidence after college graduation, see Rothstein and Rouse (2007), who argue that student reactions to debt are suggestive of the existence of credit constraints.

lowest skilled students. In particular, the authors suggest that these increased constraints stem from rising college costs coupled with the relatively stable level of government financial aid available.

This article uses an approach similar to the articles mentioned in the previous two paragraphs, comparing low-income students to higher income students of similar academic skill, the latter of which are presumed to be an unconstrained control group. Instead of the NLSY or the NELS, this article uses data on the college intentions, test scores, and school districts of all 2003 and 2004 Massachusetts public high school graduates.[4] Though the data set has limitations that will be discussed below, it offers two advantages over the other data sets. First, it contains the universe of very recent public high school graduates from Massachusetts, allowing for a detailed description and precise estimates of one state's college market. Second and more important, it allows for the first use of school district fixed effects in the analysis of credit constraints, making estimates of credit constraints even more convincing by comparing students who have different incomes but attend the same school district.

There are four primary findings. First, low-income students in Massachusetts have lower intended college enrollment rates than higher income students, but they also have dramatically lower academic skills and attend lower-quality school districts. Second, inclusion of skill controls greatly reduces but does not eliminate the intended enrollment gap, with low-income students 7 percentage points less likely to intend enrollment in college than higher income students of the same skill. Third, in districts where higher income students are a plausibly unconstrained control group, inclusion of school district fixed effects does little to reduce intended enrollment gaps, with low-income students 8 percentage points less likely to intend enrollment in college than higher income students of the same skill and from the same school district. Fourth, low-income students in the middle and upper parts of the skill distribution appear the most constrained, particularly with respect to four-year public colleges. State governments could use the methods employed here to identify credit-constrained segments of their student populations in order to target financial aid more efficiently.

The article proceeds as follows. Section 2 describes the data, including simple analysis of the relations among academic skill, low-income status, and intended college enrollment. Section 3 employs a linear probability regression model to explore more rigorously how the relation between low-income status

4. The data also contain the class of 2005, but I omit those students because of the introduction of a merit scholarship program that based college aid directly on the test score employed here as a control. As Goodman (2008) shows, this aid had significant impacts on students' enrollment decisions and might thus bias the results.

and intended college enrollment changes when controlling for academic skill and school district. Section 4 concludes.

2. DATA DESCRIPTION

The data come from the Massachusetts Student Information Management System (SIMS) and include every 2003 and 2004 public high school graduate, totaling over 100,000 students. The most important variables in SIMS for each student are standardized test scores, a low-income indicator, a randomized school district identifier, and the student's postgraduation intentions as reported by her high school's guidance department. The data also contain each student's gender, race, English as a second language status (ESL), and limited English proficiency status (LEP).

The standardized test scores come from the Massachusetts Comprehensive Assessment System (MCAS), a math and English exam that all public school tenth graders must take and eventually pass in order to graduate from high school. I sum students' math and English scores from their first sittings of the exam, transforming this score into both a quartile and a z-score by class in order to account for a slight year-to-year rise in test scores. The randomized district identifier allows identification of students in the same school district as well as construction of measures such as each district's low income rate, median MCAS score, and graduating class size.[5]

The low-income indicator is a measure of whether a student receives free or reduced price school lunches.[6] To receive such subsidies, the student must enroll in the school lunch program, which she qualifies for if her family receives Temporary Assistance for Needy Families (TANF) or food stamps or has income below 185 percent of the federal poverty line. I refer to students receiving the subsidy as "low income" and students not receiving it as "higher income." In 2004, the federal poverty line for a family of four was $18,850, so here a low-income student (from a family of four) has family income lower than $34,873 (1.85*$18,850).[7] For reference, according to the 2004 American Community Survey, median family income in Massachusetts was about $55,600, though it was much lower for black families ($33,300) and Hispanic families ($36,300). In addition, because this variable indicates only those who have chosen to enroll in the lunch program, some of those labeled higher income in the data may be from low-income families that have not enrolled for whatever reason, which will cause underestimation of the size of any credit constraints.

5. Because the district identifier is randomized, I cannot merge this student-level data with external data on the characteristics of the school districts.
6. The data do not distinguish between free and reduced price lunch recipients.
7. Each additional family member adds $3,180 to the federal poverty line, which translates to an additional $5,883 (1.85*$3,180) of family income added to the low-income threshold as defined here.

Students' postgraduation intentions are reported as one of five categories: four-year public college, four-year private college, two-year public college, two-year private college, or other (work, military, etc.). I use these categories to construct the more general outcomes of intended enrollment in any college, any four-year college, and any two-year college.[8] I also construct a measure of years of college in which each student initially intends to enroll, a variable that takes on values 0, 2, and 4.

To check that students' reported intentions reflect actual college enrollment, I use the Integrated Postsecondary Education System's (IPEDS) residence and migration data, which reports for each U.S. postsecondary institution the number of "first-time degree/certificate-seeking undergraduate students who graduated from high school in the past 12 months," broken down by students' state of residence at the time of admission to the institution. The proportions of students attending various categories of college are nearly identical in the IPEDS and the SIMS data. According to IPEDS/SIMS, the proportions of these students attending four-year private college is 43.2 percent/42.3 percent, four-year public college is 32.0 percent/32.9 percent, and two-year college is 24.8 percent/24.7 percent. This suggests, at least on average, that reported intentions reflect actual enrollment decisions, though I cannot confirm for individual students that their intentions and actual enrollment match. If low-income students are less likely than higher income students to follow through with their stated intentions to enroll, the results below will understate the actual enrollment gap by income.

The lack of a continuous income measure in the data means that higher income students are not necessarily *high* income and therefore may not serve as a perfectly unconstrained control group. In particular, in the poorest districts where low-income students are heavily concentrated, their higher income classmates may still be relatively low income and thus credit constrained, so enrollment gaps between them will thus understate the extent of those constraints. I therefore perform the subsequent analysis on three samples: one with all school districts, one with only the 215 "nonpoor" districts in which fewer than 15 percent of the graduates are low income, and one with only the 58 "poor" districts in which more than 15 percent of the graduates are low income. In the nonpoor districts, higher income students are on average from middle- or high-income families and thus represent a better, more unconstrained control group.

Table 1 shows the mean characteristics of these three samples, divided by low-income status. As the bottom row shows, 14,628 (or 13.7 percent) of

8. The two-year category consists almost entirely of public community colleges.

Table 1. Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	All Districts		Nonpoor Districts		Poor Districts	
	Low-income students	Higher income students	Low-income students	Higher income students	Low-income students	Higher income students
Intended enrollment						
Any college	0.627	0.799	0.660	0.834	0.613	0.655
Four-year college	0.349	0.618	0.379	0.665	0.336	0.419
Four-year private	0.188	0.346	0.202	0.379	0.183	0.207
Four-year public	0.161	0.272	0.177	0.286	0.154	0.212
Two-year college	0.278	0.181	0.281	0.168	0.276	0.236
Years of college	1.95	2.83	2.08	3.00	1.90	2.15
Student characteristics						
MCAS z-score	−0.689	0.110	−0.496	0.229	−0.767	−0.391
Female	0.541	0.509	0.527	0.511	0.546	0.498
Black	0.229	0.040	0.113	0.018	0.276	0.132
Hispanic	0.250	0.029	0.122	0.015	0.301	0.091
English as second language	0.364	0.057	0.173	0.036	0.441	0.144
Limited English proficiency	0.105	0.008	0.048	0.003	0.128	0.026
District characteristics						
Median MCAS z-score	−0.464	0.088	0.058	0.262	−0.674	−0.645
Low-income rate	0.334	0.106	0.084	0.052	0.435	0.333
Size of graduating class	743	314	256	244	939	611
N	14,628	91,837	4,203	74,165	10,425	17,672

Notes: Means are shown for students from all districts, from nonpoor districts, and from poor districts. All differences between columns 1 and 2, 3 and 4, and 5 and 6 are significant at 5%.

the students are low income. Only 4,203 of these live in nonpoor districts, while the remaining 10,425 live in poor districts. Columns 1 and 2 show that low-income students are 17 percentage points less likely to intend college enrollment than higher income students. This is due to a striking 27-point gap in intended four-year college enrollment that is partially offset by a 10 percentage point higher rate of intended two-year college enrollment. As a result, low-income students in Massachusetts intend to pursue nearly a year's less college education than do higher income students. Columns 3 and 4 show that very similar gaps appear between low- and higher income students within the nonpoor districts. Columns 5 and 6 show gaps with the same signs but much smaller magnitudes in the poor districts.

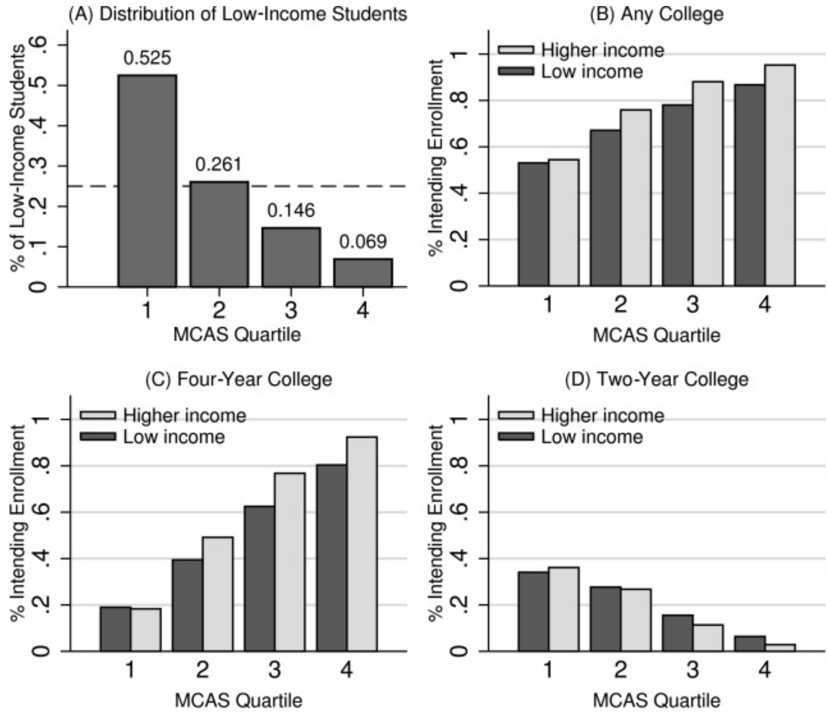

Figure 1. All School Districts. Panel (A) shows the distribution of low-income students by MCAS quartile. Panels (B)–(D) show the fraction of students intending enrollment in college, broken out by MCAS quartile and low-income status.

None of this is necessarily evidence of credit constraints, given that the remainder of table 1 also shows that, compared with higher income students, low-income students score a full 0.8 standard deviations lower on the MCAS and are much more likely to graduate from school districts that have lower median MCAS scores, lower incomes, and larger graduating classes. As with the intended enrollment gaps, these gaps in characteristics of students and their school districts persist within the set of nonpoor districts and are generally smaller in the poor districts.

To highlight the extraordinary disparity in academic skill between low-income and higher income students, panel A of figure 1 shows the distribution of low-income students among the MCAS quartiles. If low income and academic skill were uncorrelated, each quartile would contain 25 percent of low-income students, as the dashed line shows. This is not the case. A remarkable 53 percent of low-income students score in the lowest quartile, and another 26 percent score in the second lowest quartile, whereas only 22 percent score in the top half of the distribution. The results would be even more dramatic if the data included high school dropouts, who are disproportionately low income and have low academic skills.

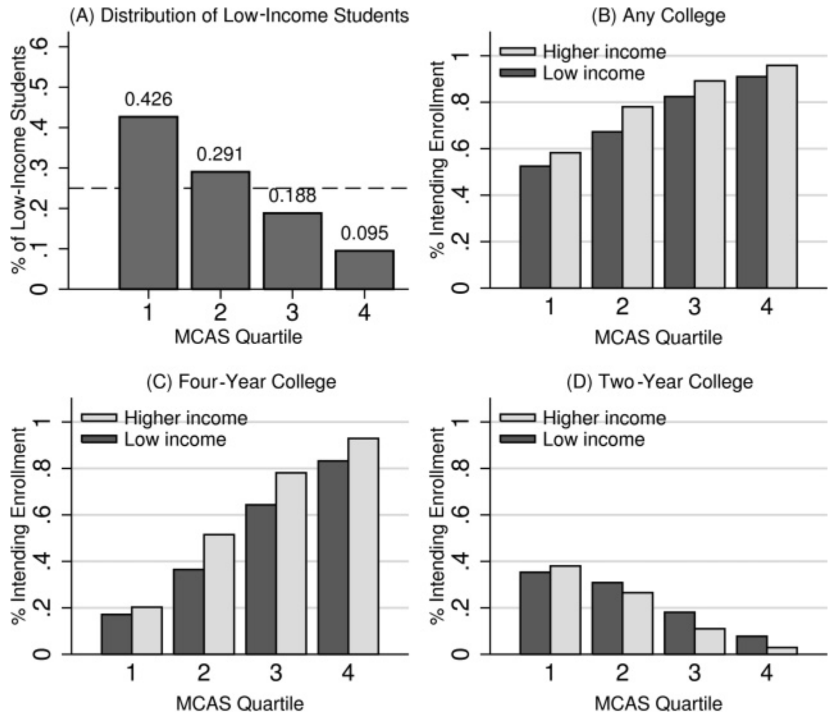

Figure 2. Nonpoor School Districts. Panel (A) shows the distribution of low-income students by MCAS quartile. Panels (B)–(D) show the fraction of students intending enrollment in college, broken out by MCAS quartile and low-income status.

The remaining panels of figure 1 give a simple sense of the extent to which low-income students' low skills account for their low intended enrollment rates by plotting these rates by MCAS quartile and low-income status. Panel B shows that intended enrollment rates and gaps vary by academic skill, with a low rate and nearly no gap for students in the lowest quartile and higher rates and roughly 10 percentage point gaps for the upper three quartiles. Panel C shows a similar pattern for the gap in intended enrollment in four-year colleges, though the gaps are slightly larger for the upper three quartiles than in panel A. This is offset by the fact, as shown in panel D, that low-income students in the upper three quartiles are actually more likely to intend enrollment in two-year colleges than higher income students. In all three panels, the within-quartile gaps are smaller than the overall gaps from table 1. This suggests that a large part of the intended enrollment gap can be explained by the fact that low-skilled students intend enrollment at relatively low rates (regardless of income) and that low-income students tend to have low skills.

Figures 2 and 3 replicate figure 1, with the sample divided into nonpoor and poor districts, respectively. Comparing the two panels A from these figures shows that low-income students from nonpoor districts have a less skewed

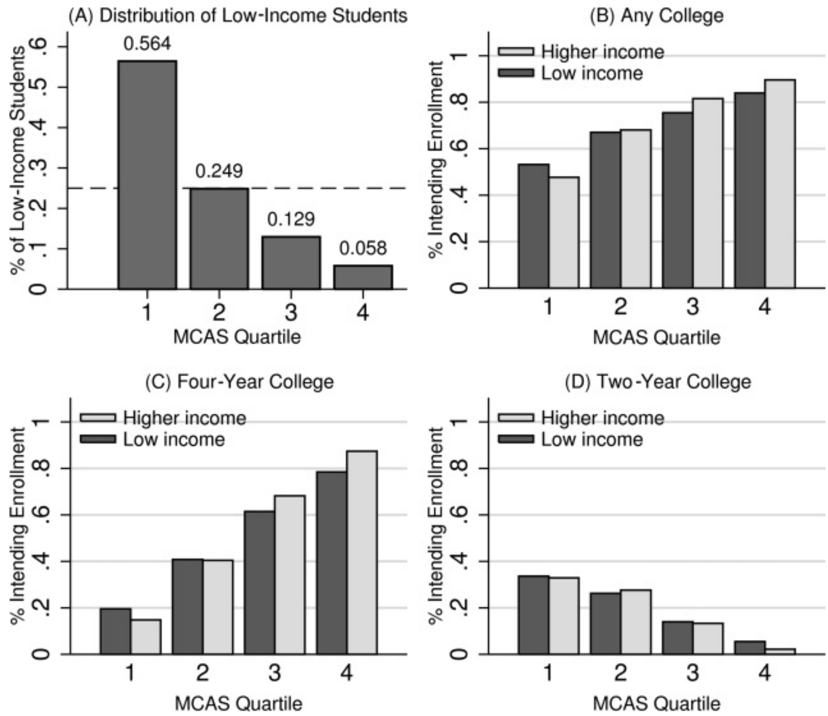

Figure 3. Poor School Districts. Panel (A) shows the distribution of low-income students by MCAS quartile. Panels (B)–(D) show the fraction of students intending enrollment in college, broken out by MCAS quartile and low-income status.

skill distribution than do low-income students from poor districts, though well over two-thirds of the former still fall into the bottom half of the distribution. Interestingly, though the intended enrollment rates by quartile look roughly similar across the two sets of districts, the nonpoor districts show pronounced gaps while the poor districts show much smaller or nonexistent gaps. This may be due to the fact noted above that higher income students in nonpoor districts more closely resemble an unconstrained control group than do higher income students in poor districts.

3. REGRESSION RESULTS

To quantify the intended enrollment gaps between low-income and higher income students more precisely and to compare students within school districts, I use a linear probability model of the form

$$College_{ij} = \sum_{k=1}^{4} \left[\alpha_k Q_{ij}^k + \beta_k \left(LowInc_{ij} \times Q_{ij}^k\right)\right] + \gamma X_{ij} + D_j + \varepsilon_{ij}, \tag{1}$$

where $College_{ij}$ indicates intended enrollment for student i in district j, *LowInc* indicates low income, Q^k is an indicator for the kth MCAS quartile, X is a vector of individual controls (race, gender, ESL, LEP), and D_j represents school district fixed effects. Given this specification, the coefficients β_k compare the enrollment decision of low-income students with higher income students in the same (kth) MCAS quartile and the same school district.[9]

The βs are imperfect measures of credit constraint. As discussed above, they will underestimate the extent of those constraints in districts where higher income students do not come from high-income, presumably unconstrained, families. Conversely, the βs may overestimate credit constraints if, even conditional on school district, they are capturing low-income families' different tastes and information about college. Regardless of these complications, coefficients derived from the above specification are a simple and useful measure of credit constraint currently available to states for the purposes of financial aid policy. The question of interest to policy makers is whether giving a student aid upon graduation from high school increases her probability of attending college. This aid neither remedies skill gaps between students of various income levels nor compensates for the differing qualities of the school districts students have attended. The βs therefore represent the best easily available estimate of the extent to which low-income students' college enrollment patterns would change if they were provided with the same access to credit for postsecondary education that higher income students have.

Table 2 shows the results of equation 1, with each coefficient representing a separate regression using various measures of intended enrollment as outcomes. Panel A includes the full sample, with three specifications run on each outcome. The first specification omits skill and school district controls in order to get a "raw" measure of the intended enrollment gap, the second specification includes skill controls, and the third specification includes both skill controls and school district fixed effects.[10] In panel A, the raw gaps are quite similar to the mean differences seen in table 1, as expected. The inclusion of skill controls more than halves all these gaps, as figure 1 suggested

9. In the regressions that follow, none of the results change significantly if regressions are run separately by MCAS quartile or if probit specifications are used in place of linear probability models. I use linear probability models for consistency given that the school district fixed effects specifications preclude the use of probits.

10. Though not shown, the demographic controls in table 2 are also interesting and may confirm that the data are roughly accurate. For example, conditional on skill and school district, female students are more likely to intend enrollment in every college category than male students, consistent with the increasingly discussed reverse gender gap in higher education. Similarly, black students are 6 percentage points more likely to intend enrollment in four-year private colleges, which suggests either high returns to enrollment or affirmative action. For recent evidence that black students have particularly high returns to college education due to its signaling value, see Arcidiacono, Bayer, and Hizmo (2008). For evidence that affirmative action for blacks is heavily concentrated in private four-year colleges, see Kane (1998).

Table 2. Intended Enrollment Gap

	(1) Any College	(2) Four-Year College	(3) Four-Year Private	(4) Four-Year Public	(5) Two-Year College	(6) Years of College
(A) All districts						
Raw gap						
Low income	−0.145**	−0.218**	−0.143**	−0.075**	0.073**	−0.727**
	(0.014)	(0.024)	(0.021)	(0.008)	(0.018)	(0.070)
R^2	0.047	0.057	0.023	0.013	0.011	0.063
Skill controls						
Low income	−0.072**	−0.083**	−0.054**	−0.028**	0.011	−0.309**
	(0.011)	(0.012)	(0.013)	(0.007)	(0.013)	(0.040)
R^2	0.158	0.332	0.172	0.065	0.106	0.295
District fixed effects						
Low income	−0.040**	−0.046**	−0.026**	−0.021**	0.006	−0.172**
	(0.008)	(0.009)	(0.007)	(0.005)	(0.005)	(0.032)
R^2	0.223	0.380	0.224	0.099	0.148	0.353
(B) Nonpoor districts						
Raw gap						
Low income	−0.168**	−0.273**	−0.177**	−0.096**	0.105**	−0.881**
	(0.013)	(0.017)	(0.016)	(0.008)	(0.011)	(0.057)
R^2	0.032	0.033	0.016	0.005	0.006	0.039
Skill controls						
Low income	−0.085**	−0.112**	−0.071**	−0.041**	0.027**	−0.395**
	(0.011)	(0.013)	(0.013)	(0.007)	(0.009)	(0.044)
R^2	0.143	0.311	0.154	0.052	0.116	0.277
District fixed effects						
Low income	−0.078**	−0.087**	−0.052**	−0.036**	0.009	−0.330**
	(0.010)	(0.011)	(0.011)	(0.007)	(0.008)	(0.038)
R^2	0.190	0.358	0.206	0.085	0.157	0.325
(C) Poor districts						
Raw gap						
Low income	−0.051**	−0.072**	−0.036**	−0.036**	0.021	−0.247**
	(0.013)	(0.016)	(0.012)	(0.008)	(0.013)	(0.051)
R^2	0.039	0.037	0.019	0.016	0.014	0.044
Skill controls						
Low income	−0.023	−0.024	−0.006	−0.018*	0.000	−0.094*
	(0.012)	(0.012)	(0.012)	(0.008)	(0.013)	(0.042)
R^2	0.118	0.267	0.156	0.080	0.068	0.225
District fixed effects						
Low income	−0.016*	−0.020*	−0.008	−0.012	0.004	−0.072*
	(0.008)	(0.009)	(0.006)	(0.006)	(0.006)	(0.030)
R^2	0.200	0.312	0.192	0.119	0.113	0.293

Notes: Robust standard errors are clustered by school district. $N = 106{,}465$ in panel A, 78,368 in panel B, and 28,097 in panel C. “Raw gap” includes only indicators for gender, race, ESL, and LEP. “Skill controls” adds MCAS quartile indicators. “District fixed effects” adds school district fixed effects.
*significant at 5%; **significant at 1%

would be the case. The inclusion of school district fixed effects cuts these gaps roughly in half again. Inclusion of school district fixed effects may be reducing the estimates of credit constraints by controlling for the causal impact of school districts on intended enrollment or by accentuating the comparison of low-income students with their relatively low-income classmates.

To distinguish these possibilities, panels B and C separate the sample into nonpoor and poor districts, respectively. A clear pattern now emerges. For nonpoor districts, like the full sample, inclusion of skill controls reduces intended enrollment gaps by half or more. Inclusion of school district fixed effects, however, has relatively little further impact, so statistically and economically significant gaps remain between low-income students and their higher income classmates. In the poor districts, the raw intended enrollment gap is only 5 percentage points and, as in the upper two panels, is halved by the inclusion of skill controls and then reduced only slightly by further inclusion of school district fixed effects.[11] That inclusion of school district fixed effects has little impact in panels B and C and suggests that their impact in panel A is not causal but instead accentuates the poor districts where most low-income students attend school and where intended enrollment gaps are extremely small.

Three primary conclusions can be drawn from table 2. First, inclusion of skill controls greatly reduces but does not eliminate the intended enrollment gap. Low-income students are 7 percentage points less likely to intend enrollment in any college and intend to enroll in 0.3 fewer years of college than higher income students of the same skill. Second, in nonpoor districts where higher income students are a plausibly unconstrained control group, inclusion of school district fixed effects has little impact on intended enrollment gaps, suggesting that school quality cannot explain the gaps. In these districts, low-income students are 8 percentage points less likely to intend enrollment in any college and intend to enroll in 0.3 fewer years of college than higher income students of the same skill and from the same school district. Third, in poor districts, intended enrollment gaps conditional on skill and school district are extremely small, likely because the higher income control group is itself relatively low income.

One question worth exploring is why, in panel A of table 2, the inclusion of school district fixed effects greatly reduces estimates of the intended enrollment gap. To determine what characteristics of school districts the fixed effects are picking up, table 3 replicates the first column of panel A, where the outcome is intended enrollment in any college. Columns 1 and 2 simply repeat panel A's "skill controls" and "district fixed effects" specifications. Columns 3–7 omit the fixed effects and instead include other district-level characteristics. Columns 3

11. Running these regressions separately by gender yields nearly identical results for males and females.

Table 3. Other District-Level Controls and the Intended Enrollment Gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	**FE**	**Other District-Level Controls**				
Low income	−0.072**	−0.040**	−0.041**	−0.039**	−0.058**	−0.067**	−0.038**
	(0.011)	(0.008)	(0.011)	(0.008)	(0.012)	(0.012)	(0.007)
District median MCAS z-score			0.111**				0.109**
			(0.017)				(0.024)
District low-income rate				−0.270**			−0.093
				(0.077)			(0.211)
District fraction minority					−0.142*		0.120
					(0.072)		(0.136)
Ln(graduating class size)						−0.019	−0.013
						(0.017)	(0.014)
R^2	0.158	0.223	0.175	0.165	0.160	0.159	0.176

Notes: Robust standard errors are clustered by school district. $N = 106{,}465$. Column 1 includes skill controls and indicators for gender, race, ESL, and LEP. Column 2 adds school district fixed effects. The remaining columns omit the school district fixed effects. The outcome variable is intended enrollment in any college.
*significant at 5%; **significant at 1%

and 4 show that inclusion of either the district's median MCAS score or the district's low-income rate has nearly the same impact on the estimated gap as does inclusion of district fixed effects. Conversely, inclusion of the fraction minority or the logarithm of the graduating class size in columns 5 and 6 has little impact on the gap. This suggests that district-level academic skill and income levels, not racial composition and size, are the most critical characteristics of school districts affecting individual students' intended enrollment. To see whether district-level skill or income matters more, column 7 includes all four district-level controls, revealing that only the district's median MCAS score retains any predictive power. Inclusion of the other three controls barely changes the R^2 when column 7 is compared with column 3. As a whole, these results suggest that low-income students' distribution across school districts of lower average achievement levels is the critical fact driving the results in panel A.

Finally, because figures 1, 2, and 3 suggest that intended enrollment gaps differ by skill, table 4 replicates the bottom two panels of table 2, with the low-income indicator fully interacted with indicators for MCAS quartiles. In the nonpoor districts, all four quartiles show intended enrollment gaps. The largest gaps appear in the middle two quartiles, due to a roughly 16 percentage point gap in intended four-year college enrollment. Though low-income students in all quartiles are less likely to intend enrollment in four-year private colleges, only low-income students in the middle two quartiles are less likely to

Table 4. Skill Heterogeneity in Intended Enrollment Gap

	(1) Any College	(2) Four-Year College	(3) Four-Year Private	(4) Four-Year Public	(5) Two-Year College	(6) Years of College
(A) Nonpoor districts						
Skill controls						
Low income * Quartile 1	−0.071**	−0.051**	−0.039**	−0.012	−0.020	−0.245**
	(0.014)	(0.011)	(0.010)	(0.008)	(0.013)	(0.044)
Low income * Quartile 2	−0.118**	−0.166**	−0.085**	−0.081**	0.048**	−0.569**
	(0.018)	(0.021)	(0.018)	(0.013)	(0.015)	(0.071)
Low income * Quartile 3	−0.079**	−0.155**	−0.094**	−0.060**	0.075**	−0.467**
	(0.015)	(0.021)	(0.021)	(0.018)	(0.015)	(0.066)
Low income * Quartile 4	−0.056**	−0.107**	−0.108**	0.001	0.051**	−0.327**
	(0.016)	(0.022)	(0.036)	(0.027)	(0.016)	(0.070)
R^2	0.143	0.312	0.155	0.053	0.117	0.277
District fixed effects						
Low income * Quartile 1	−0.074**	−0.036**	−0.028**	−0.008	−0.038**	−0.219**
	(0.013)	(0.011)	(0.009)	(0.007)	(0.013)	(0.039)
Low income * Quartile 2	−0.107**	−0.140**	−0.070**	−0.070**	0.033*	−0.493**
	(0.017)	(0.019)	(0.017)	(0.013)	(0.014)	(0.067)
Low income * Quartile 3	−0.061**	−0.121**	−0.066**	−0.055**	0.059**	−0.364**
	(0.013)	(0.019)	(0.019)	(0.017)	(0.013)	(0.059)
Low income * Quartile 4	−0.043**	−0.069**	−0.064*	−0.005	0.026	−0.224**
	(0.015)	(0.019)	(0.030)	(0.025)	(0.014)	(0.064)
R^2	0.190	0.358	0.206	0.085	0.157	0.325
(B) Poor districts						
Skill controls						
Low income * Quartile 1	0.021	0.016	−0.007	0.023**	0.005	0.075
	(0.014)	(0.014)	(0.009)	(0.007)	(0.016)	(0.046)
Low income * Quartile 2	−0.044*	−0.027	−0.002	−0.024	−0.018	−0.141*
	(0.019)	(0.019)	(0.012)	(0.017)	(0.017)	(0.067)
Low income * Quartile 3	−0.098**	−0.099**	−0.006	−0.093**	0.001	−0.393**
	(0.017)	(0.025)	(0.029)	(0.019)	(0.018)	(0.078)
Low income * Quartile 4	−0.091**	−0.121**	−0.014	−0.107**	0.030*	−0.423**
	(0.013)	(0.019)	(0.022)	(0.021)	(0.013)	(0.059)
R^2	0.120	0.269	0.156	0.083	0.069	0.228
District fixed effects						
Low income * Quartile 1	0.008	0.009	−0.010*	0.019*	−0.001	0.035
	(0.012)	(0.011)	(0.005)	(0.009)	(0.010)	(0.041)
Low income * Quartile 2	−0.030*	−0.019	−0.005	−0.014	−0.011	−0.099
	(0.012)	(0.017)	(0.007)	(0.014)	(0.010)	(0.054)
Low income * Quartile 3	−0.053**	−0.077**	−0.006	−0.072**	0.024	−0.262**
	(0.016)	(0.019)	(0.021)	(0.015)	(0.015)	(0.063)
Low income * Quartile 4	−0.049**	−0.094**	−0.011	−0.083**	0.045**	− 0.285**
	(0.013)	(0.016)	(0.017)	(0.021)	(0.013)	(0.053)
R^2	0.201	0.313	0.192	0.121	0.114	0.294

Notes: Robust standard errors are clustered by school district. Regressions are identical to those in panels B and C of table 2 except that the low-income indicator is fully interacted with indicators for MCAS quartiles.
* significant at 5%; **significant at 1%

intend enrollment in four-year public colleges. Such students do compensate by intending to enroll in two-year colleges, but the net result is that low-income students in the middle two quartiles intend to pursue 0.5–0.6 fewer years of education than do higher income students of the same skill. Inclusion of school district fixed effects reduces these gaps slightly but leaves the basic conclusions unchanged. In the poor school districts, it is the upper two quartiles that exhibit the largest gaps, even after inclusion of school district fixed effects. Again, gaps in intended four-year public college enrollment primarily drive this result.

4. CONCLUSION

That inclusion of skill controls greatly reduces intended enrollment gaps is already a well-established result. The persistence of such gaps within nonpoor school districts is a new finding that strengthens the argument for the existence of credit constraints, albeit for a relatively small eight percent of the low-income student population. These estimates are remarkably similar to the roughly 10 percentage point gaps found by Ellwood and Kane (2000) and Belley and Lochner (2007) between the lowest income quartile and the average of the upper three quartiles.[12] The lack of a continuous income measure does, however, make it difficult to interpret the small gaps estimated in the poor school districts from which most low-income students graduate.

These numbers do suggest some good news for Massachusetts. Conditional on skill, low income seems a relatively small constraint, and more than 50 percent of the lowest skilled graduates enroll in some form of college. This may be due to the fact that the state has a highly developed postsecondary market, with 30 percent more colleges per 15–19-year-old than the rest of the nation, on average.[13] Perhaps more important, it has college options available at a wide range of price points. As of 2004, there were fifteen community colleges with an average annual tuition of $3,500, as well as seven state colleges with an average annual tuition of $5,400. The state spent an average of about $7,700 per full-time equivalent student enrolled in public postsecondary institutions, the sixth highest of any state. That credit constraints seem small is at least partially due to this extensive state support for higher education. The overall enrollment gap would, for example, be larger if not for the existence of inexpensive two-year community colleges, as seen in table 4.

12. See the third column of table 10.4 in Ellwood and Kane (2000) and the last column of table 3 in Belley and Lochner (2007). Note that the estimates are not strictly comparable because those articles include high school dropouts and measure actual attendance some time after high school graduation.
13. This calculation is based on the number of colleges found in the IPEDS and the number of 15–19-year-olds calculated by the 2004 American Community Survey.

The bad news for Massachusetts lies in its student body's skill distribution, where low income is nearly a guarantee of low skill. The evidence presented here has three implications going forward. First, any further financial aid that Massachusetts plans should target low-income students with medium to high academic skills, possibly through four-year public colleges, if the goal is to most efficiently raise postsecondary education levels. Second, the state should consider devoting more of its budget to remedying the skill gap present by the time low-income students reach high school, a reallocation that might be ultimately more effective at raising college enrollment rates than increased financial aid. Third, given that all states now collect data on students' academic skills, low-income status, and college enrollment, the methods employed in this article could provide a useful tool for each state to identify those subpopulations of students most likely to be financially constrained. This in turn might allow for the design of more effective, data-driven financial aid programs.

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