PRELIMINARY AND INCOMPLETE
Do Skill or Credit Constraints Prevent College Enrollment? *

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Abstract

Low levels of college enrollment among low income youths may be due to credit constraints or to lower returns to college education. The primary impediment to distinguishing these explanations is that most data sets lack measures of academic skill that might serve as proxies for the expected return to a college education. This paper overcomes this by being the first to use data, provided by the Massachusetts Department of Education, on the college intentions and test scores of all 2003 and 2004 Massachusetts high school graduates. I show that low income students have lower college attendance rates than their higher income peers but also have dramatically lower academic skills and attend lower-performing school districts. Controlling for skill and school district greatly reduces the college enrollment gap due to low income status, largely because low income students have such low skills. The highest and lowest skilled low income students enroll in college at the same rates as their higher income peers, though low income students in the middle range of ability are significantly less likely to enroll. I argue that the methods used to estimate credit constraints are the best currently available to state governments. For Massachusetts, the results suggest that any increased financial aid should target lower income students in the middle of the skill distribution but that funds might better be spent remedying the wide skill gaps present by high school.

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In the U.S. and other developed countries, rapidly increasing college costs have raised concerns about access to postsecondary education, particularly for low income youths. 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 U.S., advocates of increased financial aid for postsecondary education point to two facts of particular concern. First, youths from low income families enroll in college at significantly lower rates than their higher income peers. Second, low income youths' college enrollment rates seem to react relatively little to changes in the college premium.

There are (at least) two competing explanations for these two facts. The first possibility is that low income youths have similar (or higher) returns to college education than higher income ones but are financially constrained and thus can not afford further education. The second possibility is that low income youths have lower returns to college education, perhaps due to lower academic skill, so that their non-enrollment represents a rational, unconstrained decision. These possibilities are unfortunately easy to conflate given the high correlation between family income and academic skill. The inability to distinguish these explanations creates a public policy quandary because each yields a different policy prescription. If low income youths 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 income youths have low returns due to low skill, increasing financial aid may be ineffective, and instead public funds may be better used attempting to narrow that skill gap earlier on.

Perhaps the primary impediment to distinguishing these explanations is that most data sets lack measures of academic skill that might serve as proxies for the expected return to a college education. This paper overcomes this by being the first to use data, provided by the Massachusetts Department of Education, on the college intentions and test scores of all 2003 and 2004 Massachusetts high school graduates.[1] I show that low income students have lower college attendance rates than their higher income peers but also have dramatically lower academic skills and attend lower-performing school districts. Controlling for skill and school district greatly reduces the college enrollment gap due to low income status, largely because low income students have such low skills. The highest and lowest skilled low income students enroll in college at the same rates as their higher income peers, though low income students in the middle range of ability are significantly less likely to enroll. I argue that the methods used to estimate credit constraints are the best currently available to state governments. For Massachusetts, the results suggest that any increased financial aid should target lower income students in the middle of the skill distribution but that funds might better be spent remedying the wide skill gaps present by high school.

The paper proceeds as follows. Section 1 discusses previous evidence on the role credit constraints play in college enrollment decisions. Section 2 describes the data, including simple analysis of the relation between academic skill, low income status and college enrollment. Section 3 employs a linear probability regression model to explore more rigorously how the relation between low income status and college enrollment changes when controlling for academic skill and school district. Section 4 concludes.

1 Previous Literature

Because most data sets lack a measure of academic skill, papers that have argued for the importance of credit constraints have generally done so indirectly.[2] Kane (1994) argues,

[1] 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' attendance decisions and might thus bias this paper's results.

[2] 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), which argues

for example, that credit constraints may explain why CPS data from the 1970s and 1980s shows that college enrollment of black youths and low income white youths was particularly sensitive to tuition changes. A number of subsequent papers have used various quasi-experiments to show that college enrollment decisions of American youths seem generally quite sensitive to price changes. Such quasi-experiments include discontinuities in a college's financial aid formula, as in van der Klaauw (2001); changes in Pell grant rules, as in Seftor and Turner (2002); the effect of GI bills, as in Bound and Turner (2002); and elimination of Social Security student benefits, as in Dynarski (2003). According to Dynarski (2002), these studies consistently suggest that eligibility for $1,000 in annual aid raises college attendance rates by about 4 percentage points but are split as to whether college subsidies have a greater impact on low- or high-income students. The fact that financial aid has a substantial impact on the college decisions of American high school graduates may indicate the existence of credit constraints.

A variation on this argument is found in Card (1999), which argues that the high returns to education estimated through instrumental variables methods may imply the existence of credit constraints on youths whom the instruments most affect. The only paper to examine the role of wealth is Mazumder (2003), which uses the SIPP to show that college enrollment is most sensitive to current income for youths from families in the 25-50th percentiles of wealth. He suggests that this group of youths may have high enough ability to make college worthwhile but have relatively little access to funds from their parents when current income is low. Without a direct measure of ability, this hypothesis is intriguing but ultimately untestable.

Evidence against credit constraints comes from Cameron and Heckman (2001) and Carneiro and Heckman (2002), both of which exploit the ability variables contained in

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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), which argues that student reactions to debt are suggestive of the existence of credit constraints.

the NLSY to argue that credit constraints are not the primary variable causing a gap in college enrollment between youths from low and high income families. Cameron and Heckman, for example, show that that white-minority gaps in schooling attainment in the NLSY79 disappear or even reverse sign when a measure of academic ability (AFQT score) is controlled for. Carneiro and Heckman group students by ability and income to show similarly small gaps by income once ability is held constant. Their estimates suggest that, at most, 8% of American youths are credit constrained with respect to college enrollment.

Cameron and Taber (2004) note that opportunity costs and direct costs of schooling affect credit constrained and unconstrained youths differently but empirical testing of these predictions yields no evidence of credit constrained youths. Grawe (2004) argues against credit constraints in the Canadian context by finding no earnings persistence between low-earning fathers and their high ability sons, the group he argues should potentially face the strongest credit constraints. Most recently in the American context, Christian (2007) finds no differences in the cyclicality of college enrollment between youths from families who own their home and youths from families who do not.

2 Data Description

The data come from Massachusetts' Student Information Management System (SIMS) and include every 2003 and 2004 public high school graduate, totalling over 100,000 students. The most important variables contained in SIMS for each student are a standardized test score, a low income indicator, a randomized school district identifier, and the student's post-graduation 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 and limited English proficiency status.

The standardized test score comes from the Massachusetts Comprehensive Assessment System (MCAS), a math and English exam that all public school 10th graders must take and eventually pass in order to graduate from high school. I use each student's total MCAS score from their first sitting of the exam and transform this score into both a quintile 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.

The low income indicator is a measure of whether the student is enrolled to receive reduced or free price school lunches, which she qualifies for if her family receives TANF or food stamps, or has income low relative to federal poverty standards. Specifically, students from families whose family income is at or below 130% of the federal poverty line qualify for free lunches, while students whose family income is between 130% and 185% of the federal poverty line qualify for reduced price lunches. I label all students who qualify for either free or reduced price lunch as "low income". In 2004, the federal poverty line for a family of 4 was $18,850, so that here a low income student (from a family of 4) has family income lower than $34,873 (=1.85*$18,850).[3] For reference, according to the 2004 American Community Survey, Massachusetts' median family income was about $55,600, though it was much lower for black families ($33,300) and Hispanic families ($36,300).

Students' post-graduation 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.). The analysis below examines these categories, as well as aggregates of these categories including: any college, four-year college, two-year college, and years of college. To check that students' reported intentions reflect actual college attendance, I used IPEDS' Residence and Migration data, which reports for each U.S. post-

[3]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 the low income threshold as defined here.

secondary 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' states of residence at the time of admission to the institution. According to IPEDS, 46,846 students originally residing in Massachusetts started college somewhere in the U.S. in 2004, a slightly higher number than the 41,912 (78% of 53,715) reported in the SIMS data. This is likely due to IPEDS' inclusion of GED recipients, private school graduates, and students who enroll one year after graduating high school. The proportions of students attending various categories of college are, however, nearly identical in the IPEDS and SIMS data. According to IPEDS (SIMS), the proportions of these students attending four-year public college is 32.0% (32.9%), two-year public college is 22.6% (21.5%), four-year private college is 43.2% (42.3%), and two-year private college is 2.2% (3.2%). This suggests, at least on average, that reported intentions reflect actual enrollment decisions.

Column (1) of Table 1 shows summary statistics for the entire population of students, while columns (2) and (3) separate low income and non-low income students. Column (4) shows the differences between these two groups. The gaps in college attendance rates are striking. The rate of four-year college attendance among low income students is 27 percentage points lower than among non-low income students, a gap split roughly evenly between public and private colleges. Conversely, the rate of two-year college attendance is 10 percentage points higher among low income students, due mostly to two-year public colleges. The net result of these gaps is that low income students' overall college attendance rate is 17 percentage points lower than non-low income students, resulting in an average of 0.88 fewer years of college that low income graduates intend to pursue. This is not necessarily evidence of credit constraints, given that Table 1 also shows that, compared to their non-low income peers, 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 are lower-performing, poorer and larger.

To highlight the extraordinary disparity in academic skills between low income and non-low income students, Figure 1 plots the distribution of low income students' test scores. Panel (A) compares the density of low income students' Z-scores to the normal distribution that would be expected if low income and academic skill were uncorrelated. Low income students are bunched very heavily at the low end of the distribution and are largely absent from the high end. Panel (B) shows a histogram of low income students grouped by skill quintile, where the quintiles are based on the entire student population. If low income and academic skill were uncorrelated, each quintile would contain 20% of low income students, as the dashed line shows. This is not the case. Strikingly, 45% of low income students score in the lowest quintile and another 25% score in the second lowest quintile, whereas only 5% score in the highest quintile. The results would be even more dramatic if the data included high school dropouts, who are disproportionately low income and likely have low academic skills.

To give a simple sense of the extent to which low income students' low skills account for their low college enrollment rates, Figure 2 graphs the proportion of students attending any college as a function of MCAS Z-scores. Unsurprisingly, higher academic skills correspond to higher college enrollment rates for both low income and non-low income students. More interesting is that, at the low and high end of the skill distribution, low income and non-low income students have roughly similar college intentions, though a roughly 10 percentage point gap occurs in the middle of the skill distribution. Figure 3 explores this in more detail, showing in panel (A) that the gap in 2 is due largely to low income students' lower propensity to attend four-year colleges. This gap is offset slightly by low income students' greater propensity to attend two-year colleges, shown in panel (B). Panels (C) and (D) break the four-year college category down further, revealing that most of the enrollment gap stems from low income students in the middle to upper part of the skill distribution being less likely to enroll in four-year public colleges.

These graphs also suggest a hierarchy of college sectors, with four-year private colleges attracting high-skilled students, four-year public colleges attracting medium-skilled students, and two-year colleges (largely public, community colleges) attracting low-skilled students.

3 Regression Results

To quantify the enrollment gaps between low income and non-low income students more precisely, I use a linear probability model of the form

$$Y_{ij} = \beta_1 LowInc_{ij} + \sum_{k=2}^{5} \left[\alpha_k Q_{ij}^k + \beta_k \left(LowInc_{ij} \times Q_{ij}^k\right)\right] + \gamma X_{ij} + D_j + \epsilon_{ij} \quad (1)$$

where Y_{ij} is a college enrollment indicator for student i in district j, $LowInc_{ij}$ indicates low income, Q_{ij}^k is an indicator for the kth skill quintile, X_{ij} is a vector of individual controls (race, gender, etc.), and D_j represent school district fixed effects. Given this specification, the coefficients β_k compare the enrollment decision of low income students to non-low income students in the same (kth) skill quintile and the same school district.

The β's are imperfect measures of credit constraint. They likely underestimate the extent of those constraints because not all of the non-low income students come from high income, presumably unconstrained, families. If the non-low income population contains students who are somewhat constrained, using them as a reference group will understate the extent to which credit constraints explain college enrollment gaps. The β's will also tend to underestimate the size of credit constraints because low income students in this data are positively selected on the basis of being graduates and on the basis of having parents who enroll them in the lunch program. Also, given that enrollment in the program is both voluntary and not subject to rigorous income verification, the low income status variable may be mismeasured, which will bias the results toward zero. Conversely, the β's may overestimate credit constraints because low income graduates may lack skills not captured by MCAS scores. This could reduce the expected return to college and make non-enrollment an optimal decision for some fraction of students, regardless of access to credit. The β's may also be capturing the fact that low income graduates come from families with different tastes and information about college.

Regardless of these complications, coefficients derived from the above specification are the best measure of credit constraint currently available to states for the purposes of financial aid policy. The question of interest to policymakers 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 does it compensate for the differing qualities of the school districts students have attended. The β's therefore represent the state's best 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 as non-low income students have.

Table 2 shows the results of Equation 1, omitting all skill and district controls in order to get a "raw" measure of the enrollment gap between low income and non-low income students. Each column is a separate regression using various measures of college enrollment as outcomes. Thus, controlling only for gender, race and language status, low income students are 15 percentage points less likely to enroll in college, a combination of being 22 percentage points less likely to enroll in four-year colleges but 7 percentage points more likely to enroll in two-year colleges.

Table 3 repeats Table 2's regressions, adding the interactions with skill quintile but continuing to omit the school district fixed effects. The first five coefficients demonstrate clear heterogeneity in the college enrollment gap by skill quintile. Low income students in the lowest quintile show no significant difference in college attendance rates than their higher income peers. In higher quintiles, particularly the third and fourth, a significant gap does appear, with those low income students having college attendance rates 6-11 percentages points lower than their peers. The coefficients on the skill quintiles also imply, unsurprisingly, that students in the lowest quintile are much less likely to attend college than their higher skilled peers. Together, these facts suggest that the vast majority of the college enrollment gap measured in Table 2 stems from the fact that low income students have very low skills, and that low skilled students tend not to attend college, regardless of low income status.

Table 4 includes both the interactions with skill quintile and the school district fixed effects, thus representing the full model in equation 1. The addition of school district fixed effects diminishes the enrollment gaps even further. The first coefficient now suggests that low income students in the lowest skill quintile show no statistically significant difference in college enrollment patterns than their higher income peers in the same school districts. Low income students in the second, third and fourth quintiles are, however, 5-6 percentage points less likely to attend college, a combination of being noticeably less likely to attend four-year colleges and somewhat more likely to attend two-year colleges. Low income students in the highest skill quintile are no less likely to attend college than their peers but only because their 6 percentage point lower rate of four-year college attendance is offset by a similarly increased rate of two-year college attendance.

These estimates imply that the lowest skilled low income students are not credit constrained, while the highest skilled are only mildly constrained. Low income students of medium skill, particularly in the third and fourth quintiles, are the most constrained, an effect due largely to their lower attendance rate at four-year public colleges. Public colleges may offer less financial aid to low income students than do private colleges, which in recent years have made a point of targeting aid toward to low income students of high skill. Column (6) of Table 4 suggests that the cumulative effect of these measured credit constraints is to reduce the years of education low income students initially intend to pursue by 0.2-0.4 years for those in the middle quintiles and by 0.15 years for those in the highest quintile.

The demographic controls in Table 4 are also interesting and may confirm that the data are accurately measuring college enrollment decisions. For example, conditional on academic skill and school district, female students are significantly more likely to enroll in every college category than their male peers, evidence of the increasingly discussed reverse gender gap in higher education. Also intriguing is that black students are nearly seven percentage points more likely to attend college, due entirely to their increased likelihood of enrollment in four-year private colleges, evidence perhaps of affirmative action. Hispanic students, conversely, show fewer clear differences from white students in their college enrollment patterns.

Tables 5 and 6 add one more layer of interactions to the model in equation 1, with gender and race respectively, in order to explore whether credit constraints have heterogeneous effects by demographic subgroup. In table 5, for example, the top five coefficients now represent the main impact of low income status on male students of various skill levels, while the bottom five coefficients represent any differential impact of poverty on female students in those quintiles. The estimates suggest little systematic difference between males and females. The only exception is that the highest skilled low income males are 4 percentage points less likely to attend college than their male peers due to a decreased rate of four-year private college attendance, whereas the highest skilled low income females show no such constraint (i.e. the sum of the male and female coefficients is almost exactly zero).

Table 6 reveals interesting differences between white, black and Hispanic low income students. White low income students, represented by the top five coefficients, are somewhat more credit constrained than the average student represented in table 4, including the lowest skilled students who are now three percentage points less likely to attend college than their higher income peers. The black and Hispanic interactions are consistently opposite in sign to white students' coefficients, suggesting that low income black students are somewhat less constrained and low income Hispanic students are almost entirely unconstrained in their college decisions. This may be a real effect, perhaps due to differential availability of financial aid resources from families, communities or colleges. It may also be a statistical effect from the fact that low income students are being compared to peers within the same school district. Given that low income black and Hispanic students' classmates are poorer than those of low income white students, the credit constrain measure for minorities should be lower because the non-low income students to whom they are being compared nonetheless have relatively low income. The lack of a continuous income measure prevents further exploration of this possibility.

4 Conclusion

The primary result of this paper is that low income high school graduates attend college at much lower rates than their higher income peers largely because they have much worse academic skills. The regression estimates discussed above suggest that, conditional on academic skill and school district, low income status does not constrain the lowest skilled graduates but does constrain those with medium to high skills, particularly with respect to four-year public colleges. Because so many low income graduates are low skilled, these estimates imply that only 2.8% (≈200 a year) of them are constrained overall, or 4.7% (≈350 a year) of them with respect to four-year colleges, costing them on average 0.15 years of intended education.[4]

[4]These estimates come from multiplying the statistically significant coefficients from Table 4 by the number of low income students in the relevant skill quintile, then summing the results. Carneiro and Heckman (2002) use a similar approach.

These numbers do suggest some good news. Conditional on skill, low income seems a small constraint and a surprisingly high 40% of the lowest skilled graduates enroll in some form of college. The bad news lies in the skill distribution, where low income is nearly a guarantee of low skill, the fact that drives this paper's primary result. 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 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 paper could provide a useful tool for each state to identify those sub-populations of students most likely to be financially constrained. This in turn might allow for the design of effective, data-driven financial aid programs.

REFERENCES

1. Bound, J., Turner, S., 2002. Going to war and going to college: did World War II and the G.I. Bill increase educational attainment for returning veterans? Journal of Labor Economics 20, 784-815.

2. Cameron, S., Heckman, J., 2001. The dynamics of educational attainment for black, Hispanic, and white males. Journal of Political Economy 109, 455-499.

3. Cameron, S., Taber, C., 2004. Estimation of educational borrowing constraints using returns to schooling. Journal of Political Economy 112, 132-182.

4. Card, D., 1999. The causal effect of education on earnings. Handbook of Labor Economics, Volume 3A, 1801-63. New York: Elsevier Science, North-Holland.

5. Carneiro, P., Heckman, J., 2002. The evidence on credit constraints in post-secondary schooling. Economic Journal 112, 705-734.

6. Christian, M., 2007. Liquidity constraints and the cyclicality of college enrollment in the United States. Oxford Economic Papers 59, 141-169.

7. Dynarski, S., 2002. The behavioral and distributional implications of aid for college. American Economic Review 92, 279-85.

8. Dynarski, S., 2003. Does aid matter? Measuring the effect of student aid on college attendance and completion. American Economic Review 93, 279-88.

9. Goodman, J., 2008. Who merits financial aid? Massachusetts' Adams Scholarship. Columbia University Economics Discussion Paper No. 0607-13.

10. Grawe, N., 2004. Reconsidering the use of nonlinearities in intergenerational earnings mobility as a test for credit constraints. Journal of Human Resources 39, 813-827.

11. Kane, T., 1994. College entry by blacks since 1970: the role of college costs, family background, and the returns to education. Journal of Political Economy 102, 878-911.

12. Mazumder, B., 2003. Family resources and college enrollment. Federal Reserve Bank of Chicago Economic Perspectives 27, 30-41.

13. Rothstein, J., Rouse, C., 2007. Constrained after college: student loans and early career occupational choices. National Bureau of Economic Research Working Paper 13117.

14. Seftor, N., Turner, S., 2002. Back to school: federal student aid policy and adult college enrollment. Journal of Human Resources 37, 336-52.

15. Stinebrickner, T., Stinebrickner, R., 2007. The effect of credit constraints on the college drop-out decision. National Bureau of Economic Research Working Paper 13340.

16. van der Klaauw, W., 2001. Estimating the effect of financial aid offers on college enrollment: a regression-discontinuity approach. International Economic Review 43, 1249-87.

Figure 1: Ability Distribution of Low Income Students

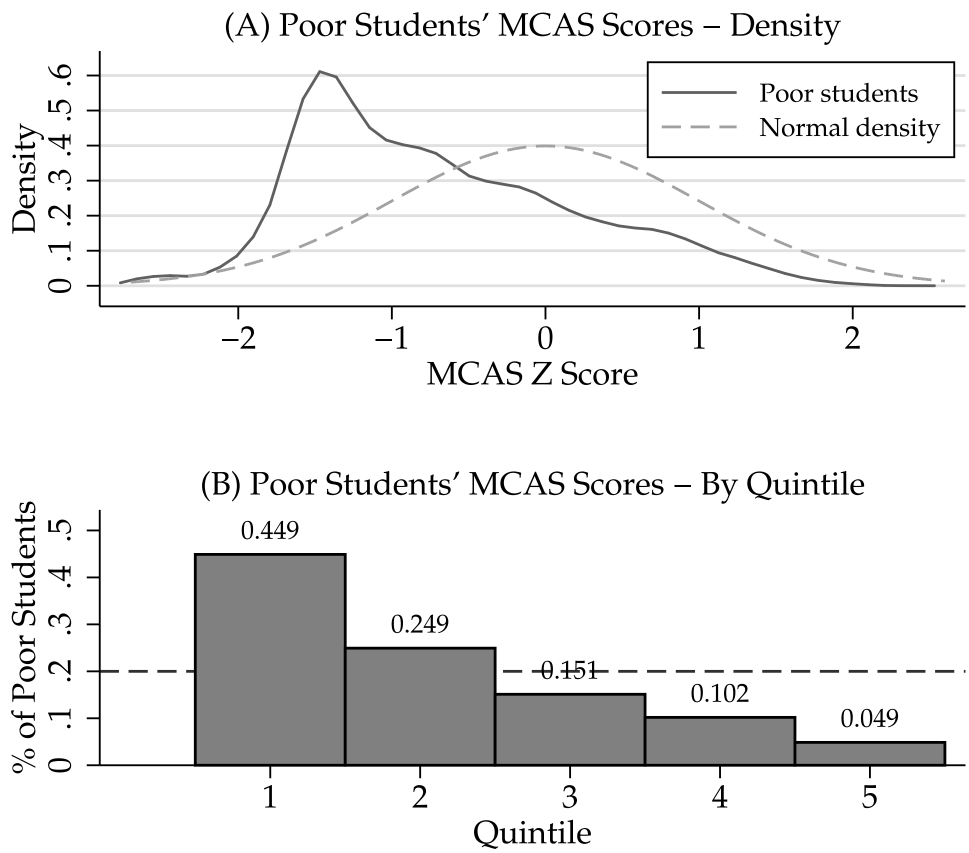

Figure 2: College Enrollment vs. Academic Ability

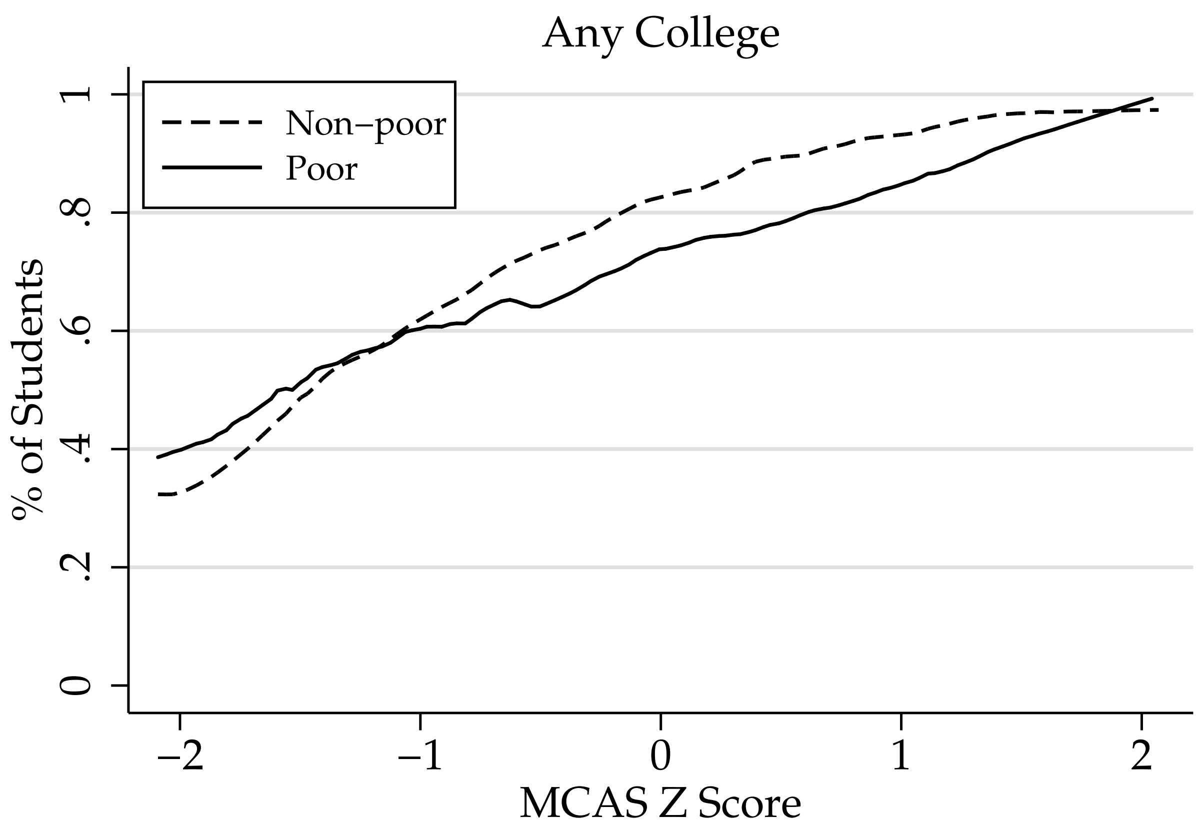

Figure 3: Type of College vs. Academic Ability

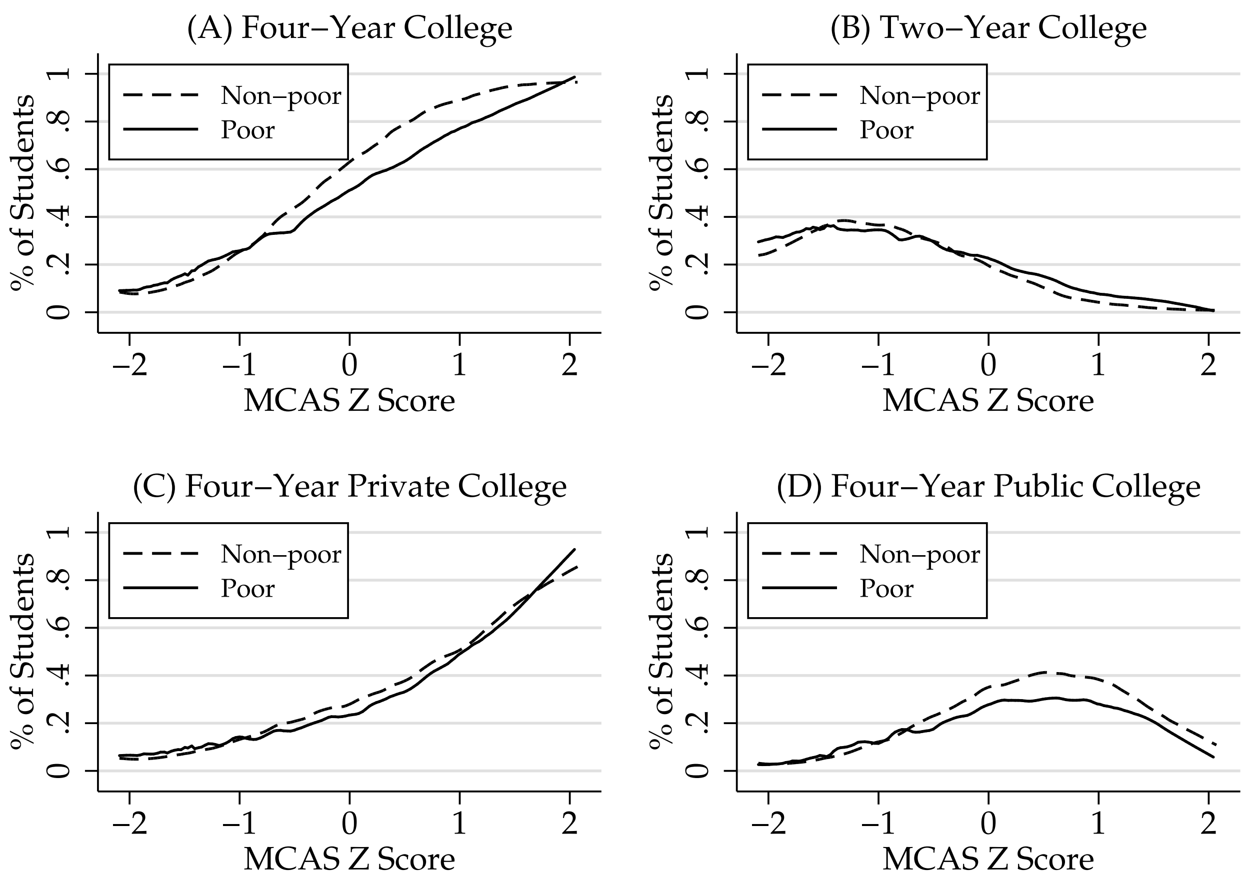

Table 1: Mean Characteristics

	(1)	(2)	(3)	(4)
	All Students	Low Income Students	Non-low Income Students	(2)-(3)
Enrollment				
Any College	0.775	0.627	0.799	-0.172
Four-Year College	0.581	0.349	0.618	-0.269
Two-Year College	0.194	0.278	0.181	0.097
Years of College	2.713	1.951	2.834	0.883
Four-Year Public	0.257	0.161	0.272	-0.111
Four-Year Private	0.324	0.188	0.346	-0.158
Two-Year Public	0.170	0.238	0.159	0.079
Two-Year Private	0.024	0.039	0.022	0.017
Student Variables				
Low income	0.137			
MCAS Z-Score	0.000	-0.689	0.110	-0.799
Female	0.513	0.541	0.509	0.032
Black	0.066	0.229	0.040	0.189
Hispanic	0.060	0.250	0.029	0.221
ESL	0.099	0.364	0.057	0.307
LEP	0.021	0.105	0.008	0.097
District Variables				
Median MCAS	0.010	-0.471	0.087	-0.558
Low income rate	0.137	0.337	0.106	0.231
District size	375.0	747.5	315.7	431.8
N	106,465	14,628	91,837	

Table 2: 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
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)
Female	0.126**	0.113**	0.078**	0.036**	0.012**	0.478**
	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.021)
Black	-0.045	-0.055*	0.007	-0.061**	0.010	-0.200
	(0.044)	(0.026)	(0.013)	(0.021)	(0.024)	(0.137)
Hispanic	-0.114**	-0.204**	-0.116**	-0.088**	0.090**	-0.637**
	(0.025)	(0.019)	(0.015)	(0.012)	(0.024)	(0.074)
Eng. as 2nd lang.	0.037	0.013	0.030	-0.017	0.025	0.100
	(0.022)	(0.026)	(0.021)	(0.010)	(0.016)	(0.089)
Limited Eng. prof.	-0.093**	-0.035	-0.022	-0.013	-0.058	-0.256**
	(0.022)	(0.042)	(0.034)	(0.015)	(0.049)	(0.092)
Constant	0.739**	0.568**	0.308**	0.260**	0.171**	2.614**
	(0.012)	(0.014)	(0.012)	(0.007)	(0.007)	(0.050)
R^2	0.047	0.057	0.023	0.013	0.011	0.063

Robust standard errors are clustered by school district (* p<0.05, ** p<0.01). N=106,465.

Table 3: Enrollment Gap by Skill Quintile

	(1) Any College	(2) Four-Year College	(3) Four-Year Private	(4) Four-Year Public	(5) Two-Year College	(6) Years of College
Low income	-0.018	-0.009	-0.023*	0.014	-0.009	-0.054
	(0.014)	(0.017)	(0.010)	(0.008)	(0.015)	(0.054)
Low income * Quintile 2	-0.069**	-0.076**	-0.037**	-0.039**	0.007	-0.290**
	(0.018)	(0.014)	(0.009)	(0.009)	(0.014)	(0.056)
Low income * Quintile 3	-0.093**	-0.138**	-0.054**	-0.083**	0.045**	-0.463**
	(0.019)	(0.019)	(0.015)	(0.024)	(0.015)	(0.070)
Low income * Quintile 4	-0.114**	-0.171**	-0.051*	-0.120**	0.056**	-0.570**
	(0.022)	(0.023)	(0.020)	(0.033)	(0.013)	(0.086)
Low income * Quintile 5	-0.055*	-0.105**	-0.062**	-0.043	0.051**	-0.319**
	(0.027)	(0.028)	(0.023)	(0.035)	(0.016)	(0.105)
Quintile 2	0.186**	0.236**	0.108**	0.128**	-0.050**	0.844**
	(0.007)	(0.007)	(0.005)	(0.005)	(0.008)	(0.022)
Quintile 3	0.307**	0.483**	0.213**	0.270**	-0.176**	1.581**
	(0.009)	(0.007)	(0.006)	(0.007)	(0.010)	(0.026)
Quintile 4	0.388**	0.676**	0.348**	0.328**	-0.288**	2.128**
	(0.012)	(0.010)	(0.007)	(0.010)	(0.010)	(0.039)
Quintile 5	0.433**	0.776**	0.564**	0.212**	-0.343**	2.419**
	(0.013)	(0.010)	(0.010)	(0.011)	(0.010)	(0.043)
Female	0.110**	0.086**	0.057**	0.028**	0.024**	0.392**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.015)
Black	0.045	0.108**	0.112**	-0.004	-0.063*	0.305**
	(0.039)	(0.017)	(0.010)	(0.019)	(0.026)	(0.110)
Hispanic	-0.028	-0.049**	-0.016	-0.033**	0.021	-0.153**
	(0.023)	(0.011)	(0.013)	(0.011)	(0.024)	(0.054)
Eng. as 2nd lang.	0.049**	0.031*	0.036**	-0.005	0.018	0.160**
	(0.018)	(0.013)	(0.011)	(0.009)	(0.013)	(0.055)
Limited Eng. prof.	-0.055	0.031	0.018	0.012	-0.086*	-0.049
	(0.029)	(0.022)	(0.022)	(0.014)	(0.040)	(0.064)
Constant	0.462**	0.108**	0.047**	0.061**	0.354**	1.140**
	(0.014)	(0.008)	(0.005)	(0.005)	(0.011)	(0.040)
R^2	0.164	0.341	0.178	0.071	0.108	0.304

Robust standard errors are clustered by school district (* $p<0.05$, ** $p<0.01$). N=106,465.

Table 4: Enrollment Gap by Skill Quintile, with District Fixed Effects

	(1) Any College	(2) Four-Year College	(3) Four-Year Private	(4) Four-Year Public	(5) Two-Year College	(6) Years of College
Low income	-0.008	0.007	-0.008	0.015	-0.015	-0.001
	(0.012)	(0.013)	(0.006)	(0.011)	(0.010)	(0.045)
Low income * Quintile 2	-0.051**	-0.058**	-0.026**	-0.032**	0.007	-0.217**
	(0.015)	(0.012)	(0.008)	(0.008)	(0.014)	(0.048)
Low income * Quintile 3	-0.057**	-0.107**	-0.033*	-0.074**	0.050**	-0.329**
	(0.013)	(0.016)	(0.014)	(0.021)	(0.015)	(0.050)
Low income * Quintile 4	-0.064**	-0.130**	-0.022	-0.109**	0.067**	-0.389**
	(0.013)	(0.019)	(0.019)	(0.028)	(0.016)	(0.057)
Low income * Quintile 5	-0.010	-0.064**	-0.025	-0.038	0.053**	-0.148*
	(0.017)	(0.021)	(0.021)	(0.029)	(0.020)	(0.063)
Quintile 2	0.150**	0.201**	0.085**	0.116**	-0.051**	0.703**
	(0.006)	(0.008)	(0.005)	(0.006)	(0.007)	(0.024)
Quintile 3	0.249**	0.426**	0.171**	0.255**	-0.176**	1.350**
	(0.006)	(0.010)	(0.006)	(0.009)	(0.009)	(0.026)
Quintile 4	0.320**	0.598**	0.285**	0.313**	-0.279**	1.836**
	(0.007)	(0.011)	(0.007)	(0.010)	(0.010)	(0.032)
Quintile 5	0.360**	0.679**	0.472**	0.207**	-0.318**	2.078**
	(0.008)	(0.011)	(0.008)	(0.010)	(0.011)	(0.032)
Female	0.102**	0.081**	0.057**	0.024**	0.021**	0.367**
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.012)
Black	0.067**	0.075**	0.066**	0.010	-0.009	0.284**
	(0.010)	(0.011)	(0.010)	(0.008)	(0.008)	(0.040)
Hispanic	-0.023	-0.038**	-0.007	-0.030**	0.014	-0.122**
	(0.013)	(0.009)	(0.006)	(0.007)	(0.012)	(0.038)
Eng. as 2nd lang.	0.052**	0.034**	0.037**	-0.003	0.018**	0.172**
	(0.010)	(0.009)	(0.009)	(0.006)	(0.007)	(0.036)
Limited Eng. prof.	-0.004	-0.000	-0.037**	0.036*	-0.003	-0.008
	(0.013)	(0.021)	(0.011)	(0.014)	(0.018)	(0.060)
Constant	0.317**	-0.059**	-0.034**	-0.025**	0.376**	0.516**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.013)
R^2	0.226	0.386	0.228	0.104	0.150	0.359

Robust standard errors are clustered by school district (* p<0.05, ** p<0.01). N=106,465.
All regressions include school district fixed effects.

Table 5: Heterogeneity by Gender

	(1) Any College	(2) Four-Year College	(3) Four-Year Private	(4) Four-Year Public	(5) Two-Year College	(6) Years of College
Low income * Quintile 1	-0.004	0.004	-0.010	0.014	-0.007	0.000
	(0.012)	(0.009)	(0.009)	(0.010)	(0.012)	(0.036)
Low income * Quintile 2	-0.064**	-0.043*	-0.039**	-0.004	-0.022	-0.215**
	(0.016)	(0.017)	(0.009)	(0.015)	(0.011)	(0.062)
Low income * Quintile 3	-0.066**	-0.102**	-0.050**	-0.052**	0.036**	-0.334**
	(0.016)	(0.017)	(0.014)	(0.014)	(0.014)	(0.059)
Low income * Quintile 4	-0.067**	-0.127**	-0.042*	-0.085**	0.060**	-0.389**
	(0.017)	(0.019)	(0.019)	(0.016)	(0.012)	(0.067)
Low income * Quintile 5	-0.039*	-0.080**	-0.066*	-0.014	0.041*	-0.237**
	(0.017)	(0.025)	(0.028)	(0.031)	(0.019)	(0.078)
Low income * Quintile 1 * Female	-0.017	0.010	0.008	0.002	-0.027	-0.015
	(0.014)	(0.019)	(0.016)	(0.007)	(0.022)	(0.050)
Low income * Quintile 2 * Female	0.009	-0.017	0.010	-0.027	0.026	-0.016
	(0.022)	(0.020)	(0.012)	(0.019)	(0.021)	(0.074)
Low income * Quintile 3 * Female	0.001	-0.001	0.015	-0.016	0.002	0.000
	(0.018)	(0.019)	(0.024)	(0.022)	(0.017)	(0.066)
Low income * Quintile 4 * Female	-0.003	0.007	0.020	-0.013	-0.010	0.008
	(0.022)	(0.031)	(0.026)	(0.036)	(0.019)	(0.101)
Low income * Quintile 5 * Female	0.042*	0.042	0.055	-0.013	-0.001	0.168
	(0.021)	(0.028)	(0.035)	(0.037)	(0.019)	(0.092)
R^2	0.231	0.388	0.228	0.106	0.155	0.361

Robust standard errors are clustered by school district (* $p<0.05$, ** $p<0.01$). N=106,465.
All regressions control for school district fixed effects, ESL, LEP, race, gender, skill quintile and the full set of interactions between skill quintile, low income status and gender.

Table 6: Heterogeneity by Race

	(1) Any College	(2) Four-Year College	(3) Four-Year Private	(4) Four-Year Public	(5) Two-Year College	(6) Years of College
Low income * Quintile 1	-0.032*	-0.006	-0.010	0.005	-0.027	-0.076
	(0.014)	(0.014)	(0.006)	(0.010)	(0.014)	(0.048)
Low income * Quintile 2	-0.070**	-0.075**	-0.043**	-0.032**	0.005	-0.290**
	(0.015)	(0.016)	(0.010)	(0.011)	(0.013)	(0.055)
Low income * Quintile 3	-0.067**	-0.119**	-0.048**	-0.071**	0.052**	-0.372**
	(0.015)	(0.020)	(0.016)	(0.016)	(0.013)	(0.066)
Low income * Quintile 4	-0.069**	-0.117**	-0.032	-0.085**	0.048**	-0.372**
	(0.012)	(0.015)	(0.019)	(0.020)	(0.011)	(0.048)
Low income * Quintile 5	-0.012	-0.051**	-0.035	-0.016	0.039*	-0.126**
	(0.013)	(0.016)	(0.024)	(0.025)	(0.016)	(0.048)
Low income * Quintile 1 * Black	0.049*	0.021	0.013	0.008	0.027	0.140*
	(0.019)	(0.020)	(0.011)	(0.016)	(0.023)	(0.062)
Low income * Quintile 2 * Black	0.022	0.043	0.016	0.027	-0.020	0.130
	(0.025)	(0.037)	(0.030)	(0.015)	(0.025)	(0.116)
Low income * Quintile 3 * Black	0.027	0.065	0.008	0.057	-0.037	0.184
	(0.038)	(0.043)	(0.041)	(0.032)	(0.021)	(0.156)
Low income * Quintile 4 * Black	0.028	0.043	-0.024	0.067*	-0.015	0.143
	(0.040)	(0.050)	(0.054)	(0.032)	(0.024)	(0.174)
Low income * Quintile 5 * Black	0.008	0.025	-0.052	0.077	-0.018	0.066
	0.020)	(0.025)	(0.050)	(0.043)	(0.018)	(0.084)
Low income * Quintile 1 * Hispanic	0.010	0.002	0.013	-0.011	0.008	0.026
	(0.021)	(0.018)	(0.012)	(0.011)	(0.016)	(0.071)
Low income * Quintile 2 * Hispanic	0.040*	0.057**	0.027	0.030	-0.017	0.196**
	(0.020)	(0.021)	(0.018)	(0.020)	(0.021)	(0.069)
Low income * Quintile 3 * Hispanic	0.073*	0.112**	0.026	0.087*	-0.039	0.371**
	(0.036)	(0.036)	(0.031)	(0.036)	(0.026)	(0.134)
Low income * Quintile 4 * Hispanic	0.103**	0.113**	0.051	0.062	-0.010	0.434**
	(0.032)	(0.039)	(0.048)	(0.047)	(0.031)	(0.129)
Low income * Quintile 5 * Hispanic	-0.008	0.013	0.038	-0.024	-0.021	0.011
	(0.058)	(0.055)	(0.077)	(0.056)	(0.044)	(0.209)
R^2	0.227	0.387	0.229	0.105	0.151	0.359

Robust standard errors are clustered by school district (* p<0.05, ** p<0.01). N=106,465.
All regressions control for school district fixed effects, ESL, LEP, gender, race, skill quintile and the full set of interactions between skill quintile, low income status and race.