

The Impact of the Gates Millennium Scholars Program on the Retention, College
Finance- and Work-Related Choices, and Future Educational Aspirations of Low-Income
Minority Students

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Abstract

The Gates Millennium Scholars (GMS) program, funded by the Bill & Melinda Gates Foundation, was established in 1999 to improve access to and success in higher education for low-income and high-achieving minority students by providing them with full tuition scholarships and other types of support. The effects of programs such as the GMS are often difficult to assess, however, because of the non-random nature of selection into the program. This article uses regression discontinuity to ascertain the causal effect of the scholarship on a number of important educational outcomes. While we find some limited evidence that retention is higher for GMS recipients and that GMS recipients, loan debt and work hours during college and parental contributions towards college expenses are lower for GMS recipients than non-recipients and GMS recipients are more likely than non-recipients to report educational aspirations to obtain a Ph.D. degree after completing their bachelor's degree.

Keywords: Regression Discontinuity, Local Polynomial Smoothing, College Retention, Loan Debt Accumulation

I. Introduction

The costs of college in the United States have risen sharply over time. The average yearly increase in tuition rates for all 4 year institutions from 1997 to 2004 was 5.1% (U.S. Department of Education, National Center for Education Statistics), over double the inflation rate for the same time period.¹ This raises the question of the affordability of a college education for high school graduates, especially those from low income households who are disproportionately ethnic minorities.

These high costs of education may dissuade some high school graduates from attending college. Moreover, those who decide to attend college may have to take out student loans and work while in school in order to pay tuition. This, in turn, may delay graduation, reduce performance in college, and saddle students with high debt loads upon graduation. Again, these effects may be particularly salient among low income students.

Given the increasing racial and ethnic diversity of high school graduates and labor force participants, another question is whether this diversity is reflected in the pool of college graduates who fill most of the high paying/prestigious jobs in the economy. Given that racial and ethnic minorities are disproportionately represented among low income households, the answer to this question depends in part on whether low income students have sufficient financial resources available to enable them to attend and graduate from college. Since the parents of ethnic minority high school graduates are less likely to have attended college than the parents of white high school graduates, and parental education is an important determinant of college attendance (see Haveman and

¹ Inflation rates are based on the consumer price index for all urban consumers.

Wolfe, 1995), low income racial and ethnic minorities may have lower college attendance rates than their low income white counterparts.

Because of these disparities in the college attendance rates between whites and racial and ethnic minorities, and the importance of having a greater representation of these minorities in prestigious jobs that typically require a college education, the Bill & Melinda Gates Foundation established the Gates Millennium Scholars (henceforth GMS) program in 1999. The goal of this program is to establish a cadre of future leaders by improving access to and success in higher education for low-income, high-achieving minority students in the United States by providing them with scholarships and other forms of support. Students are eligible for the GMS scholarship (which is administered by the United Negro College Fund) if they meet pre-specified and multiple criteria set by the program.

Approximately 4000 individuals apply for the GMS program each year, of which about 1000 receive scholarships. In order to determine the effectiveness of the program, the Gates Foundation hired the National Opinion Research Center (NORC) to collect data over time from several cohorts of applicants (both those who received scholarships and those who didn't). This unique data collects information on the amount of student debt, student scholarship money received, hours worked while in college, and parental contributions towards college costs and will allow us to study the impact of receiving additional scholarship money (via a GMS award) not only on college enrollment but on the composition of the sources of college funding.

In particular, we are interested in determining how receipt of a GMS award changes the amount of student loan debt an individual accrues while in college. Debt

upon college completion has been found by some (Millett, 2003) to influence whether or not an individual attends graduate school and their early career occupational choices (Rothstein and Rouse, 2007). Working while in college has been found to reduce academic performance (Stinebrickner and Stinebrickner, 2003) and increase college dropout and the time until degree completion among those who persist (Ehrenberg and Sherman, 1987). Because our data on GMS participants only tracks students through the junior year of college, we explore retention rather than college graduation.

Some authors have found that short-term borrowing constraints have little effect on educational attainment (Keane and Wolpin, 2001). Most of the attempts to measure the impact of these constraints are indirect.² An additional purpose of this paper is to determine how an award, that eliminates the need to borrow money to finance a college education, affects college enrollment and persistence providing a more direct assessment of the impact of short-term credit constraints.

Social scientists often evaluate programs into which students are not randomly assigned, and the process by which students become program participants may make valid inferences about program effects difficult. The method by which GMS awards are allocated among applicants enables us to avoid such difficulties. In particular, the awards are made on the basis of applicants receiving at least a particular score on a test where the “cutoff” score is not known in advance. Thus, we employ regression discontinuity methods (See Imbens and Lemieux, 2007, for example) to estimate the impact of a GMS award on various outcomes.

² For a critique of the evidence on short-term credit constraints see Carniero and Heckman (2002).

Briefly, we find evidence that the GMS program improves a number of important student outcomes for low income, high ability, minority students served by the program. While we find some limited evidence that the GMS program increases retention, at least among Asian Americans, we find considerable empirical support for the GMS program lowering loan debt, lowering work hours during college, lowering parental financial contributions to college, and increasing the fraction of students who aspire to a doctoral degree, although the results vary by entering cohort and racial/ethnic group. Thus, our results are consistent with previous studies that indicate little effect on educational attainment of short-term borrowing constraints, although the set of students considered in this study are high achievers and may react somewhat differently from the average low-income college student.

This paper is organized in the following way: In the next section we discuss in more detail the structure of the selection mechanism by which students are chosen for the GMS program. In Section III we discuss the estimation strategies used. Section IV details the results of the analysis conducted and Section V concludes the article.

II. The Gates Millennium Scholars Program

The Gates Millennium Scholars (GMS) program is a \$1 billion, 20-year project designed to promote academic excellence by providing higher education opportunities for low-income, high-achieving minority students. High school students who apply for the program have to meet a number of eligibility criteria before being accepted. Cognitive assessment measures are used to judge the academic potential of applicants (e.g., the academic rigor of their high school course work and their high school grades), but non-

cognitive measures are also used in the selection process. Applicants must provide evidence that their high school grade point average is at least 3.33 (on a 4.00 scale). Regarding the non-cognitive component of selection into the program, students applying for admission are required to answer a series of questions developed to measure an applicant's non-cognitive abilities.³ The answers to each of these questions are scored by trained raters and a total non-cognitive test score is assigned to each applicant.⁴ Thresholds on these non-cognitive tests are established and they vary by racial/ethnic group and by matriculating cohort.⁵ These thresholds or "cut scores" are used as another program selection mechanism. In keeping with the goal of the program to fund needy students, applicants also have to demonstrate financial need by documenting that they are eligible for the federal Pell grant program. Finally, applicants need to be citizens or legal residents of the United States and have to complete all the required application materials to be eligible for the scholarship.

Of the 3,000 to 4,000 students who apply for the program in a given year, 1,000 of them are eventually selected for the program. Table 1 presents the distribution of outcomes for applicants in Cohorts II and III (the fall 2001 matriculants are known as Cohort II and the fall 2002 matriculants are known as Cohort III). The vast majority of

³ The eight areas measured by these non-cognitive variables are positive self-concept, realistic self-appraisal, successfully handling the system, preference for long-term goals, availability of strong support person, leadership experience, community involvement, and knowledge acquired in a field. For additional information on the development and use of the non-cognitive measures see Sedlacek (1998, 2003, 2004).

⁴ For a more detailed explanation of the non-cognitive essay scores, see Appendix A.

⁵ The GMS scholarship program designates that a certain fraction of scholarships go to each ethnic group. The thresholds are set by moving down the distribution of total scores on non-cognitive tests until all scholarships for that racial group are allocated. Thus, the threshold depends on the number of applicants within a racial group for that year. For our purposes this limits whether a applicant can "game" the system since the threshold is not known in advance.

applicants who do not receive a scholarship are disqualified due to a score on the non-cognitive test that is lower than the “cut” score.

Once in the program the students receive a scholarship that is a “last dollar” award meaning that it covers the unmet need remaining after the Pell and any other scholarships or grants are awarded. The GMS scholarship is portable to any institution of higher education of the student’s choice in the United States and can be used to pay tuition and fees, books, and living expenses. The average award to freshman is about \$8,000 and the average award to upper division students (juniors and seniors) is about \$10,000-\$11,000. The average award also differs by institution type, with students attending public institutions of higher education receiving about \$8,000 and private school attendees receiving slightly more than \$11,000 in financial support. As undergraduates, students are eligible for the GMS financial support for up to five years and they can apply for additional support if they decide to attend graduate school in engineering, mathematics, science, education, or library science.⁶

In the spring of their freshman year in college all GMS recipients and a random sample of approximately 1300 non-recipients are surveyed by the NORC at the University of Chicago. The overall response rate was 69% in Cohort II and 81% in cohort III. The response rates were higher for GMS recipients in both cohorts (83% versus 58% in Cohort II and 90% versus 75% in Cohort III). In this “baseline” survey students are asked to respond to questions that provide information about their backgrounds, enrollment status, academic and community engagement, college finances and work, self-concept and attitudes, and future plans. These students are also

⁶ In this paper we examine the GMS effects on undergraduates only.

resurveyed in the late spring of their junior year in college, constituting the first “follow-up” survey.

The sample used in the analyses described below was constructed by matching data from a number of sources including the baseline and follow-up surveys mentioned above, a file containing the non-cognitive scores of applicants, and a data set containing the reasons why students were eligible or not. Cohorts II and III were combined and after removing a few (less than 20) inaccurate cases, the effective sample used in the analysis contains about 3,500 (see Table 2) students, nearly evenly divided between GMS participants and non-participants. For these two cohorts of scholars, the initial notification of being awarded the Gates scholarship was made after most individuals with multiple college acceptances would have had to make a decision about which school to attend (i.e., the notification was made after May 1). Thus, the receipt of the Gates scholarship may only have a limited effect on (at least) the initial college choice.⁷

There are observable differences in the overall sample including more (fewer) Latino/a (Asian American) students receiving (not receiving) scholarships than in the non-recipient group. Given the selection criteria, the parents of GMS scholars tend to have lower incomes and lower levels of education compared to their non-recipient counterparts. The SAT scores and percent of students who have less than four years of mathematics in high school are roughly equivalent between program participants and non-participants. In the Cohort II and III sample used in this study, nearly all the freshman are retained to the fall of their sophomore year. The average retention rate is about 98 percent (compared to about 74 percent nationally), with GMS participants

slightly more likely to be retained in college in their freshman year (about 99 percent) compared to their non-GMS counterparts (about 98 percent; this difference is significant at $p=.004$). Through their junior year of college we observe very little additional attrition, with about 97 percent of all students being retained overall, and similar differences in the GMS/non-GMS retention rates as in the freshman year (98 vs. 97 percent, respectively; $p=.03$).

The dollar amount of loans borrowed in the freshman year is about \$2,140 for the full sample. Not surprisingly, GMS participants borrow much less than their non-GMS colleagues, the former borrowing about \$1,000 in their freshman year compared to about \$3,200 for non-participants. Using National Postsecondary Student Aid Study (NPSAS) 1999-2000 data, we calculated freshman loan levels for high ability, non-white Pell eligible students and the average was slightly lower (at about \$2,800) than the overall average in Cohorts II and III of non-participants. Average cumulative loan levels through the junior year of college for the full sample are about \$6,800, with GMS students borrowing about \$3,400 and their non-recipient counterparts borrowing about \$10,200. NPSAS data indicates cumulative borrowing for similar non-white students (high ability, low income) to be about \$6,100 on average.

The NPSAS data also contains information on hours worked while students are enrolled in college. In 1999-2000, high-ability, low income students worked about 19 hours per week in their freshman and 19.5 hours per week in their junior year of college. The average number of hours worked in the Cohort II and III sample during the freshman year was substantially smaller (at slightly less than 13 hours) than national averages

⁷ In later cohorts notifications were made before May 1 for a substantial fraction of applicants.

during the freshman year. GMS participants worked about 11 hours during an average academic year work-week, whereas the non-recipient group reported working 13.4 hours (difference significant at $p=.0000$). During their junior year, students in the Gates sample reported increasing their work effort to about 16 hours, with the difference between GMS recipients (15 hours) and their non-recipient colleagues (19 hours per week) being about four hours (significant at $p=.0000$). The reduction in hours worked during the freshman year may be beneficial if this extra time is used for additional studying and/or students become more engaged in the academic and social fabric of the institution.

III. The Estimation Strategy

In the early 1960s Thistlewaite and Campbell (1960) used the regression discontinuity (RD) technique to study the effects of the National Merit Scholarship program on career choice. Since then the method has also been used to examine the effects of compensatory education programs, especially Title I programs (Trochim, 1984) and in recent years RD has been used to examine school district and housing prices (Black, 1999), the effect of class size on student achievement (Angrist and Lavy, 1999), the effect of school funding on pupil performance (Guryan, 2000), how student financial aid affects student enrollment behavior (van der Klauuw, 2002; Kane, 2003), how teacher training impacts student achievement (Jacob and Lefgren, 2002), the incentive effects of social assistance programs (Lemieux and Milligan, 2004) and the relationship between failing the high school exit exam and graduation from high school and/or subsequent postsecondary education outcomes (Martorell, 2004).

RD is a non-experimental design (see Cook and Campbell, 1979) where subjects are assigned to the treatment (e.g., GMS participation) and control groups (e.g., GMS non-participants) based on a score on some pre-specified criterion (or criteria). As noted above, to participate in the GMS program students need to have scores on the non-cognitive test or “running variable” above a threshold which varies by race/ethnicity and freshman entering cohort.⁸

Given the selection mechanism operating we expect that students just above and just below the cut point are distributed in an approximately random fashion. If this is the case then the observed and unobserved characteristics of students around the cut score are very similar, akin to a randomized experiment around the cut point. Under these circumstances an evaluation of the effect of the program at this point has strong causal implications. If the program has a positive (or negative) effect on a particular educational outcome, we expect to observe a discontinuity at or near the cut score. This discontinuity helps to identify the causal effect of the GMS program, defined as the vertical distance between the regression intercepts on each side of the cut point.

Figures 1 and 2 provide descriptions of the non-cognitive score densities by race/ethnicity for Cohorts II and III, respectively, for all applicants. The distributions appear more variable for the Cohort II sample than for Cohort III matriculates. The Cohort III sample distributions also appear to be slightly skewed to the left.

We also examine the distributions of demographic and high school performance characteristics of students for the full sample and within one and two-point intervals on

⁸ As mentioned above, students must also meet the criteria for the federal Pell financial aid program and GPA requirements, which are stated on the application (and, so, are known beforehand) in order to receive the scholarship granted to GMS participants.

either side of the cut score. We find no evidence of statistically significant differences for these measures around the cut point (see Table 2). Of course, of greatest concern are the non-random differences around the cut-point that are related to the dependent variables of interest. To examine this we also estimated regression models for each of our four dependent variables which included several predictor variables other than our total non-cognitive score running variable.⁹ Plotting the average predicted values of the dependent variable by total non-cognitive test score, we would expect to see substantial jumps in the average predicted values of these dependent variables at the cut point if these non-random differences are important (See Card, Chetty, and Weber, 2006). Figures 3 through 6 present plots of the average predicted value by total non-cognitive score as well as polynomial regression estimates of the predicted value on the total non-cognitive score. As these figures indicate, there appear to be no discernable jumps at the cut points, with the exception of parental contributions for Asian Americans. These findings further bolster our confidence that, at least approximately, individuals are randomly distributed around the cut point.

i) The Regression Discontinuity Approach

Given the mechanism by which the Gates Millennium scholarships are awarded, we believe it makes sense to analyze a number of important correlates of college completion using regression discontinuity inference. Below we estimate the impact of the

⁹ Models are estimated separately by ethnic group and control for type of high school (public, private, religious), composite SAT score, number of years of science, number of years of math, family size, whether the family owns a home, parents' education, gender and immigrant status. Here we present only outcome variables at the end of the junior year for Cohort III. Outcome variables for the end of the freshman year produce similar results and are available upon request.

GMS scholarship on several outcomes including student retention, debt accumulation, parental contributions towards college education and work behavior. In the next section we briefly outline our empirical approach.

Suppose that the mean value of an outcome variable (y) depends on whether or not a treatment is received which is represented by an indicator variable (D). Thus,

$$(1) \quad y = \beta_0 + D\alpha + \varepsilon$$

where α measures the impact of the treatment (D) on the $E(y)$ and ε is a zero mean random error. In a “sharp” regression discontinuity design there is a variable, x , such that $D = 1$ if $x \geq \tilde{x}$, where the value \tilde{x} is the threshold or cut point, and D equals zero otherwise. Taking expectations of both sides of (1) with respect to x yields

$$(2) \quad E(y | x) = \beta_0 + \alpha + E(\varepsilon | x)$$

when $x \geq \tilde{x}$ and

$$(3) \quad E(y | x) = \beta_0 + E(\varepsilon | x).$$

when $x < \tilde{x}$.

A parametric approach to regression discontinuity models with a sharp design assumes that $E(\varepsilon | x)$ is some parametric function of x (usually a polynomial of some known order, r) and estimates

$$(4) \quad y = \beta_0 + \alpha I(x \geq \tilde{x}) + \beta_1 x + \beta_2 x^2 + \dots + \beta_r x^r + \nu$$

with $E(\varepsilon | \nu) = 0$. The selection of scholars for the GMS program, however, has a “fuzzy” rather than a sharp design since not all students with scores above the cut point receive scholarships because of Pell ineligibility, low GPA, and in rare cases, incomplete information on the application. In a fuzzy design, the discontinuity at the cut point is in

the probability of receiving the treatment. In this situation, $D \neq I(x \geq \tilde{x})$, so (4) no longer yields consistent estimates of the treatment effect. However, since $I(x \geq \tilde{x})$ is positively correlated with D , instrumental variable estimation of

$$(5) \quad y = \beta_0 + \alpha D + \beta_1 x + \beta_2 x^2 + \dots + \beta_r x^r + \nu$$

using $I(x \geq \tilde{x})$ as an instrument yields a consistent estimate of α .

To estimate α without any parametric assumptions about $E(\varepsilon | x)$, we assume that

$E(\varepsilon | x)$ is a smooth function of x so that $\lim_{x \downarrow \tilde{x}} E(\varepsilon | x) = \lim_{x \uparrow \tilde{x}} E(\varepsilon | x)$.¹⁰ In a fuzzy

design similar smoothness assumption are imposed on $E(\theta | x)$ where

$$(6) \quad D = \delta I(x \geq \tilde{x}) + \theta.$$

Under these assumptions one can show that

$$(7) \quad \alpha = \frac{\lim_{x \downarrow \tilde{x}} E(y | x) - \lim_{x \uparrow \tilde{x}} E(y | x)}{\lim_{x \downarrow \tilde{x}} E(D | x) - \lim_{x \uparrow \tilde{x}} E(D | x)}$$

The manner in which the Gates scholars are chosen implies that

$\lim_{x \uparrow \tilde{x}} E(D | x) = 0$ and so (7) becomes

$$(8) \quad \alpha = \frac{\lim_{x \downarrow \tilde{x}} E(y | x) - \lim_{x \uparrow \tilde{x}} E(y | x)}{\lim_{x \downarrow \tilde{x}} E(D | x)}.$$

We estimate the three limit terms in (8) using local linear regression (see Fan and Gijbels, 1996). With non-parametric methods, the choice of the bandwidth becomes an issue. The results reported below are based on choosing separate bandwidths for each side of the cut point for the limits in the numerator of (8) where the bandwidth is chosen by minimizing the mean squared error using data only from the same side of the cut point (see the

¹⁰ For more details on non-parametric estimation of regression discontinuity models see Porter (2003).

appendix for details). Results were similar when a single bandwidth was used for the limits in the numerator of (8).

IV. The Results

Due to the relatively small sample sizes, parametric estimates included only linear, quadratic and cubic polynomial functions for the total non-cognitive score. We present only IV estimates using a quadratic specification since they generally fit the Cohort II and III data better than a linear specification, while models with cubic representations do not significantly improve the model fit in most instances. Estimates with and without additional control variables are presented in Table 3 for outcome variables measured at the end of the freshman year of college and Table 4 for outcome variables measured at the end of the junior year of college. Non-parametric results are also discussed but are based on the Cohort III data only because, due to the low number of individuals with scores below the cut point being sampled for Cohort II, the sample size on the left-hand side near the cut point is too small.¹¹

i) Scholarships

While the GMS award is a last dollar award, the possibility exists that colleges may offset the award to some extent by reducing other forms of scholarships. To investigate this possibility we used a regression discontinuity approach using self-reported total amounts of scholarships as the dependent variable. The results for the

¹¹ Results discussed below are in the form of percentage differences between the treatment mean (Y_t) and the counterfactual mean (Y_c) defined as $100 * [(Y_t - Y_c) / Y_c]$. Thus, when discussing “differences,” “increases,” or “decreases” in outcomes below the relevant comparison groups are students who received funding from the GMS program relative to the counterfactual group, that is, the expected outcomes if GMS participants did not receive the “treatment.”

freshman year survey are presented in column (1) of Table and the results for the junior year survey are presented in column (1) of Table 4. Panel (a) of the tables present results without additional control variables while panel (b) present results with the additional control variables.

As can be seen from the tables the impact of a GMS award on the total amount of scholarships is positive and statistically significant for the combined sample for both the freshmen and junior years. The estimate effect, however, varies by ethnic group with the estimated impact being largest for Asian Americans ranging from approximately \$5,600 to \$13,000 depending on year and model specification. For African Americans estimated effects range from \$2,200 to \$8,500 and are statistically significant in all but one case while the estimated effect for Hispanics ranges from \$2,200 to \$5,800 and is statistically significant only for the largest estimate.

Non-parametric estimates presented in Figure 7 for the junior year yield similar results. Thus, while there may be some offsetting effects via reductions in other scholarship money, the receipt of a Gates scholarship does have a big impact on the total amount of scholarship money received. Figure 8 provides the estimates of the numerator in (8) while Figure 8 provides the estimates of the denominator in (8).¹²

ii) Retention

Given that most attrition from college happens during the freshman year or in the summer prior to the sophomore year (Tinto, 1987) there is interest in knowing the extent

to which programs such as the GMS increase freshman to sophomore year retention. Descriptively, the overall retention rate for African Americans is 98.1 percent, with GMS participants' retention at 99 percent and their non-participants colleagues being retained at 97.2 percent ($p=.04$). Asian American (Latino/a) students' overall retention is 98.6 (99.3) percent, with GMS awardees having retention levels of 99.2 (99.6) percent (respectively) compared to non-participants whose rates are 98.1 (98.9) percent, respectively (these differences are not statistically significant at conventional levels).

Given these extremely high rates of retention to the sophomore year, only the IV procedure with a linear term for the total non-cognitive score variable was estimated for the pooled sample and different racial/ethnic subgroups. As shown in panel (a) of Table 3, there is no evidence that the scholarship improved students' freshman-to-sophomore retention rate either.¹³ Adding other controls to the model does not modify this conclusion (see panel b of Table 3).

We also investigate whether there is evidence that the GMS program produces retention differences through the junior year of college. Descriptive results indicate small differences in the overall and race/ethnic-specific retention levels through the junior year of college. Overall, African Americans and Asian Americans have nearly identical overall retention rates at 97.5 and 97.4 percent, respectively. Latino/a students' average retention is slightly higher at 97.7 percent. Differences in retention for GMS participants compared to their non-participating colleagues are about two percentage

¹² In all the non-parametric estimates of the effect of GMS on different outcome variables the denominator estimate is the same and shown in Figure 8.

¹³ Formally, the improvement is for students near the cut point since we only identify the local treatment effect at the cut point.

points for Asians (98.8 vs. 96.5), less than a point for Latino/a students (97.9 vs. 97.3), and one and one-half percentage points (98.3 vs. 96.8) for African American students.

The pooled (overall sample) IV estimates indicate no significant differences in retention rates for the GMS students compared to their non-GMS counterparts. However we did find some weak evidence (p-value <0.06) that the GMS program increased retention rates of Asian Americans through the junior year (see Table 4, panel a). Adding control variables, however, reduces the estimated effect which is no longer statistically significant at the 10% significance level (See Table 4, panel b).

The non-parametric RD estimates for junior year retention are displayed in Figures 9 when all bandwidths are set equal to 2 which over-smooths relative to the optimal bandwidths at the cut-point. These figures indicate slightly positive effects for African Americans and Asian Americans and slightly negative effects for Latino/a GMS scholars.

Loan Debt

We also investigate whether there is evidence of a causal effect of the GMS program on the loan debt students accumulate in their freshman year. Descriptively, recipients of a GMS award have lower loan debt than non-recipients and this difference varies by race/ethnicity. African Americans debt levels for GMS students is the highest at about \$1,133; Asian students have loan levels about \$1,000 and Latino/a students average loan amount in the freshman year is \$878. Non-GMS students' average loan levels in the freshman year are \$3,070 for African Americans, \$3,166 for Asian American students, and \$3,435 for Latino/a non-recipients. (All these differences are significant at $p < .001$).

The IV estimates provide evidence that overall loan debt in the freshman year is about 62 percent lower for GMS students and the race-specific results are as follows: The estimate is about -46 percent for African American students, indicating that GMS students have loan debt levels about 46 percent lower than the counterfactual group. The point estimates are about -79 percent for Latino/a GMS students and about -54 percent for Asian American students, although the latter is measured imprecisely and not statistically significant.¹⁴ Results are similar when additional control variables are added (see Table 3, panel b).

Next we estimate whether the GMS program is effective in reducing the total loan debt accumulated through the junior year of college. Descriptive statistics indicate that regardless of GMS receipt, African American students have the highest debt load levels through their junior year of college (about \$11,000 for non-recipients vs. about \$4,100 for GMS recipients). At about \$2,800 for each group, the average debt level for Asian American and Latino/a students who are GMS recipients is substantially lower than that of African American GMS recipients. Debt levels for Asian and Latino/a students who are not GMS recipients is closer to the African American non-participant average at about \$10,200 and \$9,300, respectively. (All these differences are significant at $p < .001$).

The quadratic IV estimates indicate that for the full sample, accumulated loan debt is about 67 percent lower for GMS students compared to the counterfactual group. We also find the GMS program reduces accumulated loan debt for Latino/a students by about 75 percent. African American and Asian American students also have lower debt estimates, at 58 and 71 percent lower (respectively) than the counterfactual group. All

¹⁴ Although not reported, the non-parametric estimates indicate a 72 percent lower loan debt amount for

the above results are significant at $p < .05$ even when additional controls are included.¹⁵

The local linear regression estimates using bandwidths equal to 2 shown in Figure 10 display similar results.¹⁶

iii) Weekly Earnings and Hours Worked

When surveyed by NORC, GMS participants and their non-participating counterparts indicate how many hours they worked for pay during an average week for the academic year in question. Reductions in work may improve academic performance among GMS recipients if any reductions are converted to time studying and/or becoming engaged in the social and academic fabric of the institution.

Descriptively, we again observe differences between GMS participants and non-participants and by race/ethnicity. Among GMS recipients, Latino/a students average the most hours worked at about 11.7 hours per week; African American students work about an hour less per week (10.6) and Asian students work the least at 8.7 hours. Non-GMS students work more hours, with African American working about 16 hours per week followed by Latino/a students who average 14.3 and Asian students working about 13.6 hours per week during the academic year.

The conditional IV estimates of hours worked in the freshman year for the full sample indicate GMS recipients work about 25 percent fewer hours than the

African Americans, Asian American loan debt is 92 percent lower, and Latino/a students have freshman year loan debt amounts that average about 59 percent lower than the counterfactual group.

¹⁵ We also investigated whether GMS receipt reduced the probability of having any loan debt. For both the freshman and junior years GMS receipt statistically significantly reduced the probability of having loan debt for all ethnic groups except Asian Americans in the freshman year.

¹⁶ The bias-corrected 95% bootstrap confidence intervals, based on the optimal bandwidths, reported in Table A1 show that for Cohort III the loan reductions are statistically significant for African Americans and for Latinos.

counterfactual. Asian American GMS recipients work considerably fewer hours than non-recipients, with hours worked about 73 percent lower than non-recipients. African American GMS recipients hours of work is about 29 percent lower than African American non-recipients (p-value < 0.06), and the estimated GMS impact on hours worked for Latino/a while negative, is not statistically significant at conventional levels.¹⁷ The results are similar when additional control variables are added (see Table 3, panel b).¹⁸

Column (5) of Table 3 present estimates when reported weekly hours of work are multiplied by the reported hourly wage. For the combined sample, the estimated effect of a GMS award on weekly earnings is to reduce weekly earnings by approximately \$62. By racial/ethnic group, only the estimate for Asian Americans is statistically significant with a point estimate implying that GMS reduces weekly earnings by nearly \$171 dollars. The results for weekly earnings are similar when additional controls are added to the estimations (See Table 3(b) column (4)).

We also estimate the effects that a GMS award had on hours worked in the junior year of college enrollment. Descriptive statistics indicate that African American, Asian American, and Latino/a non-recipients worked more hours per week (19.2, 17.1, and 19.3 hours, respectively) than their GMS recipient counterparts (14.2, 12.1, and 13.2, respectively). RD estimates in Table 4 indicate for the combined sample and for African Americans and Asian Americans that a GMS award lowers hours worked, although in the latter case the statistical significance is weak when additional regressors are included

¹⁷ In all cases the non-parametric estimates are not statistically significant.

¹⁸ We also investigated whether GMS impacted the probability of working. Receiving a GMS statistically significantly reduced the probability of working for both African Americans and Asian Americans in their

(p-value < 0.06). The results produced by the non-parametric estimates are similar (see Figure 11).

The impact of GMS receipt on weekly earnings in the junior year is negative and statistically significant for the combined sample and implies that GMS receipt reduces weekly earnings by \$53. Estimates by ethnic group are statistically significant only for Asian Americans and imply that a GMS award reduces weekly earnings by, on average, \$92 per week. Estimates with additional control variables presented in Table 4 panel (b) yield similar results.¹⁹

iv) Parental Contributions to College

There are large and statistically significant differences in the average parental contribution to college by scholarship status for all race groups for the freshman year. The estimated average difference between scholars and non-scholars is -\$1,668 (p-value < 0.001) or a drop of 72% for African Americans, -\$2,127 (p-value < 0.001) or a drop of 68% for Asian Americans and, -\$1,941 (p-value < 0.001) or a drop of 64% for Latinos.

Regression discontinuity estimates for the effect of a GMS award on parental contributions in the freshman year are presented in column (6) of Table 3a for models without additional regressors and Table 3b for models with additional regressors. The estimated impact of GMS receipt on parental contributions is statistically significant for the combined sample and for Asian Americans in models without additional controls with the point estimate for the combined sample equaling -\$957. When additional

freshman and junior years. While the point estimates were negative for Hispanics in both the freshman and junior year in neither case were the point estimates statistically significant.

¹⁹ The bias-corrected 95% bootstrap confidence intervals, based on the optimal bandwidths, reported in Table A1 show that for Cohort III the reduction in hours worked are statistically significant for Asian Americans and for Latinos.

controls are added to the model, the point estimate for the combined sample increases to -\$653 and the statistical significance is now weak (p -value < 0.09).

Regression discontinuity estimates for the effect of GMS receipt on parental support in the junior year model are presented in column (6) of Table 4a for models without additional regressors and Table 4b for models with additional regressors. The estimated impact of GMS receipt on parental contributions is statistically significant for the combined sample, equaling -\$1,554 when no additional controls are included. Estimates by racial/ethnic group are all negative but only statistically significant for Asian Americans. When additional controls are added to the model, the point estimate of the effect of a scholarship is slightly increased for the combined sample and slightly decreased for Asian Americans with both remaining statistically significant.²⁰ The results are similar for the local linear regression estimates (see Figure 12).²¹

v) *Heterogeneous Treatment Effects*

In order to examine whether the impacts of GMS receipt differs by factors other than race/ethnicity, we estimated models separately by gender, by whether at least one versus no college educated parent, and by whether student attended a public versus

²⁰ We also investigated the impact of GMS on the probability of receiving any parental financial support for college. For Asian Americans receiving a GMS statistically significantly reduced the probability of receiving any parental support in both the freshman and junior years. While the point estimates were negative for both African Americans and Latinos, they were statistically significant only for African Americans in the freshman year and Latinos in the junior year.

²¹ The bias-corrected 95% bootstrap confidence intervals, based on the optimal bandwidths, reported in Table B1 show that for Cohort III the reductions in parental contributions are statistically significant only for Latinos.

private four-year college or university.²² The results for the junior year (with no additional regressors) are presented in Table 5.

In no case does the GMS appear to statistically significantly increase enrollment, although for those attending private schools the effect is positive and but weak (p-value = 0.12). Not surprisingly given the generally higher tuition rates of private versus public schools, the impact of the GMS on the total amount of scholarship received is higher for private four-year institutions compared to public four-year institutions (although the difference is not statistically significant). There is also evidence that the receipt of a GMS increases the amount received more for men than for women (p-value < 0.001). The only other statistically significant difference is that GMS reduces loan debt more for those attending private four-year institutions than those attending public four-year institutions.

vi) ***Other Outcomes: Educational Aspirations, Private School Attendance & Choice of Major***

While we find strong evidence that GMS receipt lowers student debt amounts and the number of hours a student works while in school, there is little or no evidence that GMS receipt increases retention probabilities. The question arises whether GMS receipt has other potential impacts on student outcomes. Recall that Rothstein and Rouse (2007) found some evidence that student loan debt impacts early career choices. While our data (to this point) covers only information available through the junior year of college, the survey did ask a question about educational aspirations so we can explore whether GMS

²² In this last case only students attending a 4-year college or university were included in the estimations.

receipt differentially affects a student's plans for post-baccalaureate education.²³ We first analyzed whether GMS had an impact on whether an individual aspired to some form of graduate education. The results of this analysis for models without additional regressors are presented in panel (a) of Table 6 while results with additional controls are presented in panel (b).²⁴ While all the point estimates are positive, they are imprecisely estimated and not statistically significant.

Next we explored whether GMS receipt had an impact on an individual's aspirations to obtain a PhD. As presented in Table 6, the impact on the probability of reporting to aspire to a PhD education is positive and statistically significant for the combined sample and for the Asian American and Latino sub-samples. The estimate for African Americans, while positive, is small and not statistically significant. Thus, while there is no evidence that GMS receipt raises graduate degree aspirations in general, there is evidence that it raises PhD aspirations for both Asian Americans and Latinos.

By lowering debt and reducing hours worked, it is plausible that receipt of a GMS award may change an individual's college major. Moreover, one aspect of GMS is that recipients can receive support for graduate school if they enter a program in science, technology, engineering or mathematics (STEM). So to investigate this we examined whether GMS receipt affected the probability of being in a STEM major during the student's junior year. The results are reported in column (3) of Table 6. While the point estimate for the combined sample is positive, it is imprecisely estimated and not is

²³ Specifically, individuals were asked: "Now, thinking about the future, what is the highest degree you expect to receive?"

²⁴ Models which include additional regressors yield similar results.

statistically significant. Estimates are also not statistically significant for any of the different ethnic groups.

While the announcement of whether or not a student received a GMS was made for the majority of applicants in Cohorts II and III after the May 1 deadline which, for many schools, is the date by which students must indicate whether or not they plan to enroll in the fall and, if so, put down a deposit, students receiving a GMS may still have had an opportunity to switch colleges between first hearing about the award and the date of the freshman survey. First, some schools don't have such a deadline. Second, individuals receiving a GMS award may choose to withdraw from their original school and forfeit the deposit. Finally, students may have initially matriculated at one college and then transferred to another college between the start of the Fall semester and the time of the freshman survey.

Many aspects of a college matter. In this paper only focus on whether the college was public or private. The results of the regression discontinuity estimates when public/private status is the dependent variable is presented in column (4) of Table 6. As can be seen from the Table, for African Americans receipt of a GMS award statistically significantly increased the probability of attending a private college. For Asian Americans and Latino/as the effect was negative but not statistically significant.

V. Discussion and Conclusions

As noted above, our initial results indicate that the GMS program improves a number of important student outcomes for low income, high ability, and minority students served by the program. There is some limited evidence that retention is higher

for Asian GMS students although the impact is no longer statistically significant in estimations that include additional regressors. We find, however, large differences in loan debt, parental contributions and, in some cases, work hours during college for GMS recipients. To some extent, these results vary by racial/ethnic group and whether we examine the freshman year or results through the junior year of college. Moreover, we find statistical evidence that GMS receipt increases the probability of aspiring to a PhD degree for both Asian American and Latinos increases the probability of attending a private school for African Americans. Our estimates, however, formally apply only to individuals near the cut and this caveat should be kept in mind when interpreting our results.

As was mentioned above, the overall response rates were higher for GMS recipients than for non-recipients. This may impact our results if these differences in response rates persist around the cut point. For Cohort III, we were able to merge data on non-cognitive tests scores and GMS receipt for those invited to participate in the survey with data on whether or not they responded to the survey request. Thus, we used regression discontinuity methods to estimate the effect of GMS receipt on the probability of responding to the survey. While the point estimates were positive, in no case were the estimates statistically significant.

The estimates reported in the Tables 3 through 6 were based on a fuzzy design and included individuals above the cut-point who were disqualified due to being Pell ineligible as well as various other reasons. Almost no individuals who received a GMS actually declined it. So to check the robustness of our results we excluded all those who were disqualified for various (as well as the few who declined the award) and re-

estimated the models using a sharp design. The estimates were similar to obtained using a fuzzy design.²⁵

Although the RD design avoids some of the distributional and other assumptions used in selection models, the RD approach is not “free of problems and difficulties” (Pedhazur and Schmelkin, 1991, p. 298). One of the potential problems is how much data is available on the left hand side of the cut point. Given small amount of data on the left of the threshold in the Cohort II sample, especially for certain race/ethnic groups, we were restricted in some cases to using the Cohort III data only when employing non-parametric methods. This limitation should be less of a problem for subsequent cohorts because NORC is now surveying larger random samples of non-recipients than they did for Cohort II.

The results of this paper on retention are consistent with some findings in educational attainment that suggest that borrowing constraints play little role. The results, however, suggest that GMS students will leave college with substantially reduced debt loads and are more likely to aspire to PhD degrees. With future waves of the data we plan to investigate whether these reduced debt load influences labor market behavior in terms of the type of job worked after college as well as both the propensity of students to attend graduate school and the type of graduate school that they attend.

Our findings that GMS recipients work less non-recipients raises the question of what activities (e.g. studying) GMS student engage in with these additional hours. We are currently undertaking this analysis. Another question raised by our findings is what parents do with this additional income that otherwise would have been spent on the GMS

²⁵ The non-parametric estimates using a sharp design are presented in the lower panel of Appedix **B**.

student's education. Do parents reallocate these savings to the educational expenditures of the GMS's siblings? Unfortunately, our data cannot address this question.

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Appendix A

Non-Cognitive Essay Questions

In Cohorts II and III of the Gates Millennium Scholarship Program applicants (nominees) were asked a series of short essay questions in order to assess the following eight non-cognitive variables (See Sedlacek, 2004).

1. **Positive self-concept:** Demonstrates confidence, strength of character, determination, and independence.
2. **Realistic self-appraisal:** Recognizes and accepts any strengths and deficiencies, especially academic, and works hard at self-development; recognizes need to broaden his or her individuality.
3. **Successfully handling the system (racism):** Exhibits a realistic view of the system on the basis of personal experience of racism; committed to improving the existing system; takes an assertive approach to dealing with existing wrongs, but is not hostile to society.
4. **Preference for long-term goals:** Able to respond to deferred gratification; plans ahead and sets goals.
5. **Availability of strong support person:** Seeks and takes advantage of a strong support network or has someone to turn to in a crisis for encouragement.
6. **Leadership experience:** Demonstrates strong leadership in any are of his or her background.
7. **Community involvement:** Participates and is involved with his or her community.
8. **Knowledge acquired in a particular field:** Acquires knowledge in a sustained or culturally related way in any field.

In addition to scoring applicants on these eight dimensions based on their answers to a series of short essay questions, applicants were also assessed on the rigor of their course work, number of math, science and language courses, and the scholarly quality of their essay(s). Scores were computed by trained raters. Each dimension was given a score between 1 and 8. The total score across all 11 subscales was then used to allocate scholarships. This is referred to as the Total Non-Cognitive Essays Score in the text.

Table A1 shows differences in subscale scores for all 11 subscales between those whose total score was either at or above the cutoff point and for those whose total score was below the cutoff point. In addition Table A1 shows differences in subscale scores between those whose total score was either at or 1 point above the cutoff point and those whose total score was 1 or 2 points below the cutoff point. Most of the statistically significant differences between those “just above” and those “just below” the cutoff are for non-cognitive subscale scores with the exception of the scholarly quality of the essay score.

Table A1

Differences in Non-Cognitive Scores by Subcategory: Cohort III									
Sub-Categories	At or Above				At or 1 or 2 above Below				
	All	Cut	Cut	t-test	All	Cut	Cut	t-test	
1 Positive Self-concept	6.84	7.33	6.22	38.22	6.79	6.88	6.67	3.98	
2 Realistic Self Appraisal	6.67	7.18	6.03	36.56	6.62	6.70	6.50	3.41	
3 Understand and Navigate Social System	6.26	6.90	5.45	35.70	6.24	6.33	6.12	2.78	
4 Prefer Long Range Goals over Short Term Needs	6.68	7.21	6.01	35.87	6.67	6.81	6.49	5.47	
5 Strong Support Person	5.62	5.78	5.41	15.45	5.68	5.67	5.68	-0.18	
6 Leadership	6.53	7.10	5.82	34.62	6.52	6.57	6.46	1.63	
7 Community Service/Involvement	6.30	6.83	5.63	29.66	6.29	6.42	6.13	3.50	
8 Ability to Acquire Knowledge in Non-Traditional Ways	6.43	6.95	5.76	31.70	6.42	6.52	6.30	3.27	
9 Rigor of Course Work	7.08	7.39	6.70	18.29	7.06	7.09	7.03	0.74	
10 Math/Science/Language Courses	6.92	7.26	6.49	18.43	6.93	6.98	6.87	1.31	
11 Scholarly Essay Score	6.21	6.72	5.56	32.02	6.21	6.31	6.09	3.61	
12 Non-Cognitive Score (1)-(8)	51.34	55.27	46.32	53.63	51.23	51.91	50.35	7.77	
13 Cognitive Score (9)-(11)	20.22	21.38	18.75	31.48	20.21	20.39	19.98	2.64	
14 Total Score= Non-Cognitive Score + Cognitive Score	71.57	76.65	65.07	55.03	71.45	72.30	70.34	9.09	

Source: Cohort III African Americans, Asian Americans, Latinos

Notes: All subscores on 8 point scale.

Appendix B

Local Polynomial Regression Estimates and Optimal Bandwidth Determination

$$\alpha = \frac{\lim_{x \downarrow \tilde{x}} E(y | x \geq \tilde{x}) - \lim_{x \uparrow \tilde{x}} E(y | x < \tilde{x})}{\lim_{x \downarrow \tilde{x}} E(D | x \geq \tilde{x}) - \lim_{x \uparrow \tilde{x}} E(D | x < \tilde{x})} = \frac{\lim_{x \downarrow \tilde{x}} E(y | x \geq \tilde{x}) - \lim_{x \uparrow \tilde{x}} E(y | x < \tilde{x})}{\lim_{x \downarrow \tilde{x}} E(D | x \geq \tilde{x})}$$

where the left side of the equality follows in our situation because

$$\lim_{x \uparrow \tilde{x}} E(D | x < \tilde{x}) = 0 \text{ for all } x < \tilde{x}.$$

To derive a consistent estimator of α we need to consistently estimate $E(y | x \geq \tilde{x})$, $E(y | x < \tilde{x})$ and $E(D | x \geq \tilde{x})$ in a neighborhood of \tilde{x} . To obtain consistent estimates of these three terms we apply local polynomial regression.

Consider the regression model

$$y = m(x) + \varepsilon$$

Local polynomial regression estimates of $m(x)$ at a point x_0 by estimating a weighted polynomial regression where points near x_0 receive larger weights. Suppose that a local polynomial regression of order p is estimated. Let \mathbf{X} be the matrix defined by

$$\mathbf{X} = \begin{pmatrix} 1 & (X_1 - x_0) & \cdots & (X_1 - x_0)^p \\ \vdots & \vdots & & \vdots \\ 1 & (X_n - x_0) & \cdots & (X_n - x_0)^p \end{pmatrix}$$

and let \mathbf{y} be the vector

$$\mathbf{y} = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_N \end{pmatrix}$$

Finally, define a diagonal weighting matrix \mathbf{W} by

$$\mathbf{W} = \text{diag}\{K_h(X_i - x_0)\}$$

where K_h is a kernel weighting function with bandwidth h and is defined by

$$K_h(\bullet) = K(\bullet/h)/h$$

for some kernel function. Throughout we use the Epanechnikov kernel function defined by $K(u) = \frac{3}{4}(1-u^2)$ for $-1 < u < 1$. The estimated local polynomial coefficients at x_0 ,

$$\hat{\boldsymbol{\beta}} = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}$$

are then obtained from

$$\min_{\boldsymbol{\beta}} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})' \mathbf{W} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta}).$$

For theoretical reasons (See Fan and Gijbels, 1995 and Porter, 2003) it is preferable to estimate odd ordered polynomial models. In our estimates α we simply estimate a local linear regression ($p = 1$). For our estimate of α we then estimate three local linear regressions for $E(y | x \geq \tilde{x})$ and $E(D | x \geq \tilde{x})$ and use data from the right of the cut point only, and for $E(y | x < \tilde{x})$ we use data to the left of the cut point. Letting x_- be the closet point on our grid of x values to the left of \tilde{x} (which in our case is $\tilde{x} - 0.1$) and x_+ be the point closest on our grid of x values to the right of \tilde{x} ($\tilde{x} + 0.1$), the estimated value of α equals

$$\hat{\alpha} = \frac{\hat{E}(y | x_+) - \hat{E}(y | x_-)}{\hat{E}(D | x_+)}.$$

To implement this technique it is necessary to choose a bandwidth. We choose the bandwidth that minimizes the asymptotic mean squared error.

$$\text{Let, } s_{r,0} = \int_0^\infty K(u)u^r du.$$

Then, it can be shown that for a local linear regression model the optimal bandwidth, to the left of the cut-point equals, (see Fan and Gijbels, 1992, 1995) equals

$$h_{opt}(x_0) = C(K) \left[\frac{\sigma^2(x_0)}{\{m''(x_0)\}^2 f(x_0)} \right]^{1/5} n^{-1/5}$$

where

$$C(K) = \left[\frac{\int_0^\infty [s_{2,0} - ts_{1,0}] K^2(t) dt}{\{s_{2,0}^2 - s_{1,0}s_{3,0}\}^2} \right]^{1/5},$$

$\sigma^2(x_0)$ is the variance of ε at x_0 , $m''(x_0)$ is the second derivative of m at x_0 , and $f(x_0)$ is the density of x at x_0 . For the Gaussian kernel function $C(K) = 0.794$. Several of these

quantities are unknown and so we employ a two step method to obtain the optimal bandwidth.

In the first step we compute what is termed the “Rule of Thumb” (ROT) bandwidth which we denote h_{ROT} . To compute h_{ROT} a fourth order polynomial is estimated globally (i.e., with all data weighted equally). From these estimates we compute

$$\tilde{m}(x) = \hat{\beta}_0 + \dots + \hat{\beta}_4 x^4$$

which results in

$$\tilde{m}''(x) = 2\hat{\beta}_2 + 6\hat{\beta}_3 x + 12\hat{\beta}_4 x^2$$

and $\hat{\sigma}^2$ where

$$\hat{\sigma}^2 = \sum_{i=1}^N (y_i - \tilde{m}(x_i))^2 / (N - 5).$$

Then,

$$h_{ROT} = 0.794 \left[\frac{\hat{\sigma}^2}{\sum_{i=1}^n \{\tilde{m}''(x_i)\}^2} \right]^{1/5}$$

In the second step we estimate a 3rd order local polynomial regression using bandwidth h_{ROT} to compute

$$h_{opt}(x_0) = 0.794 \left[\frac{\hat{\sigma}^2(x_0)}{\sum_{i=1}^n \{\hat{m}''(x_i) K_{h_{ROT}}(x_i - x_0)\}^2} \right]^{1/5}$$

where

$$\hat{\sigma}^2 = \sum_{i=1}^N (y_i - \hat{m}(x_i))^2 / \text{tr} \{ \mathbf{W} - \mathbf{W}\mathbf{X}(\mathbf{X}'\mathbf{W}\mathbf{X})^{-1} \mathbf{X}'\mathbf{W} \}.$$

When computing the optimal bandwidth for $\hat{E}(y | x_+)$ and $\hat{E}(D | x_+)$ we use only data to the right of the cut point \tilde{x} when $x_0 = x_+$. When computing the optimal bandwidth for $\hat{E}(y | x_-)$ we use the data to the left of the cut point and $x_0 = x_-$.

Estimates using this technique are presented in Table A1. We bootstrapped the 95% confidence intervals for $\hat{\alpha}$ using 1000 replications and recomputed the optimal bandwidths for each replication. In the top panel we include those who may have had a score above the cut point but didn't receive a GMS for reasons presented in Table 1. Thus, we use a fuzzy design. In the bottom panel we exclude these individuals and use a sharp design.

Table B1
RD Estimated Impact of GMS on Outcome Variables at End of Junior Year of College

Local Linear Regression: Optimal Bandwidths						
Fuzzy Estimates						
Outcome	African Americans		Asian Americans		Latinos	
	Bias Corrected		Bias Corrected 95%		Point	Bias Corrected 95%
	Point Estimate	95% C.I.	Point Estimate	C.I.	Estimate	C.I.
Enrollment	-0.105	[-0.365, 0.206]	0.054	[-0.645, 0.615]	-0.030	[-0.302, 0.544]
Total Loans	-\$9,605	[-\$20,872, -\$228]	\$2,102	[-\$14,933, -\$31,211]	-\$12,458	[-\$24,776, -\$2,801]
Hours Worked	-3.68	[-18.12, 9.20]	-25.29	[-61.61, -1.51]	-23.39	[-37.55, -8.91]
Parental Contributions	-\$879	[-\$5,128, \$1,881]	-\$2,105	[-\$16,120, \$15,737]	-\$2,989	[-\$7,728, -\$32]
STEM Major	-0.119	[-0.506, 0.237]	0.162	[-0.810, 0.995]	0.077	[-0.361, 0.537]
Attend Private College	0.341	[-0.008, 0.709]	0.084	[-0.945, 0.974]	-0.142	[-0.628, 0.425]
Sharp Estimates						
Outcome	African Americans		Asian Americans		Latinos	
	Bias Corrected		Bias Corrected 95%		Point	Bias Corrected 95%
	Point Estimate	95% C.I.	Point Estimate	C.I.	Estimate	C.I.
Enrollment	-0.033	[-0.180, 0.082]	0.035	[-0.099, 0.250]	0.000	[-0.017, 0.003]
Total Loans	-\$8,944	[-\$18,601, -\$719]	-\$3,662	[-\$13,797, \$7,984]	-\$12,017	[-\$21,059, -\$4,570]
Hours Worked	-5.28	[-16.63, 8.04]	-18.22	[-34.38, -0.27]	-21.41	[-33.33, -8.46]
Parental Contributions	-\$1,002	[-\$4,508, \$1,173]	-\$3,348	[-\$11,694, \$5,960]	-\$2,635	[-\$6,213, -\$75]
STEM Major	-0.139	[-0.416, 0.132]	0.026	[-0.457, 0.477]	0.079	[-0.269, 0.410]
Attend Private College	0.305	[-0.028, 0.609]	0.118	[-0.389, 0.727]	-0.239	[-0.665, 0.224]

Notes: Bias corrected confidence intervals are based on bootstrapped estimates using 1000 replications.

Table 1
Application Outcome by Cohort

Reason	Cohort II	Cohort III
Below Cut Score on Non-Cognitive Test	2,057	1513
Declined GMS Scholarship	3	8
GPA Ineligible	4	15
Incomplete Submissions	564	71
Institution Ineligible	4	0
No Record Of Financial Aid	13	8
Pell Ineligible	424	382
Scholar	1,000	1,000
Total	4069	2997

Notes: Based on data from UNCF data for all applicants.

Table 2
Sample Means and Means Just Above and Below the "Cut Points"
for Demographic and High School Background Variables

Variable Name	Full Sample	GMS Scholars	Non-Scholars	All Applicants with Total Non-Cognitive Scores Equal to the...		p-value
				Cut Score or Cut Score + 1	Cut Score - 1 or Cut Score - 2	
	(1)	(2)	(3)	(4)	(5)	(6)
ACT Composite Score	23.7			23.58	24.12	0.28
SAT Verbal+Math Score	1123.92	1132.07	1116.26	1110.76	1124.86	0.35
Attended Religious High School	0.06	0.06	0.06	0.06	0.04	0.25
Attended Private High School	0.07	0.07	0.07	0.08	0.04	0.12
Years of High School Math	3.87	3.89	3.85	3.88	3.86	0.37
Years of High School Science	3.66	3.65	3.66	3.63	3.69	0.22
Family Size	3.69	3.71	3.67	3.65	3.66	0.96
Born in U.S.	0.61	0.63	0.60	0.61	0.58	0.57
Family Owns Home	0.51	0.48	0.55	0.47	0.50	0.47
Male	0.29	0.30	0.29	0.28	0.29	0.92
<u>Father's education</u>						0.50
Less Than High school	0.20	0.24	0.17	0.19	0.22	
High School	0.27	0.27	0.26	0.27	0.25	
Some College	0.21	0.19	0.23	0.20	0.23	
BA/BS Degree	0.14	0.12	0.16	0.15	0.09	
Post BA/BS Degree	0.10	0.09	0.12	0.10	0.12	
<u>Mother's education</u>						0.97
Less Than High School	0.19	0.23	0.16	0.21	0.18	
High School	0.25	0.26	0.24	0.26	0.27	
Some College	0.28	0.27	0.29	0.26	0.29	
BA/BS Degree	0.18	0.15	0.21	0.18	0.17	
Post BA/BS Degree	0.07	0.06	0.07	0.07	0.06	
Sample Size	3502	1727	1775	202	101	

Notes: Cohorts II and III combined. Cut scores for total non-cognitive score were 71, 72 and 68 for African Americans, Asian Americans and Latinos, respectively in Cohort II and 72, 75 and 69 for African Americans, Asian Americans and Latinos, respectively for Cohort III. All tests of differences were Fisher exact tests for equality based on categorical data except for family size, ACT and SAT scores which were simple t-tests for differences in means.

Table 3
Estimated Impact of GMS on Outcome Variables at End of Freshman Year of College
(a) No Additional Controls

	Total Scholarship Amount	Retention	Total Loans	Hours of Work	Weekly Earnings	Parental Contribution
	(1)	(2)	(3)	(4)	(5)	(6)
Combined	\$2,972.76 (\$744.03)	-0.003 (0.01)	-\$1,916.37 (\$567.43)	-4.07 (1.85)	-\$61.99 (\$25.94)	-\$956.57 (\$332.74)
African Americans	\$2,183.44 (\$1,415.56)	-0.013 (0.022)	-\$1,256.57 (\$425.14)	-3.62 (1.86)	-\$53.22 (\$43.04)	-\$725.80 (\$374.15)
Asian Americans	\$5,614.45 (\$1,986.47)	0.019 (0.028)	-\$1,584.79 (\$1,245.70)	-12.00 (3.71)	-\$149.24 (\$52.93)	-\$2,139.31 (\$1,025.38)
Hispanics	\$2,425.15 (\$1,989.70)	-0.005 (0.012)	-\$2,829.50 (\$1,379.08)	-0.28 (2.89)	-\$24.44 (\$27.56)	-\$574.74 (\$494.53)

**(b) Added Controls for Gender, Parent's Education, Family Size, SAT score, Parents
Income & High School Type**

	Total Scholarship Amount	Retention	Total Loans	Hours of Work	Weekly Earnings	Parental Contribution
	(1)	(2)	(3)	(4)	(5)	(6)
Combined	\$4,088.79 (\$1,029.78)	0.003 (0.012)	-\$1,842.64 (\$648.14)	-5.28 (1.9)	-\$71.44 (\$29.88)	-\$652.60 (\$383.48)
African Americans	\$3,733.94 (\$1,762.71)	-0.005 (0.025)	-\$1,524.91 (\$514.46)	-5.10 (2.30)	-\$82.87 (\$63.08)	-\$796.80 (\$365.42)
Asian Americans	\$7,726.45 (\$2,237.98)	0.025 (0.028)	-\$1,199.12 (\$1,279.47)	-11.44 (3.48)	-\$171.44 (\$62.56)	-\$2,178.91 (\$1,191.08)
Hispanics	\$2,160.23 (\$2,557.41)	0.000 (0.013)	-\$2,766.25 (\$1,726.22)	-1.64 (2.98)	-\$27.47 (\$23.38)	\$377.28 (\$670.37)

Source: Cohorts II and III of Gates Millennium Scholarship Follow-up Surveys. See text for details.

Notes: Standard errors are reported in parentheses. Estimates are based on two-stage least squares with standard errors adjusted for heteroskedasticity and for intra-correlation among individuals with equal total non-cognitive scores. Controls for cohort, total non-cognitive score and its square and their interaction with cohort are included in the race specific estimates; the combined model also includes controls for race and interactions of total non-cognitive score and its square with race.

Table 4
Estimated Impact of GMS on Outcome Variables at End of Junior Year in College
(a) No Additional Controls

	Total Scholarship Amount	Retention	Total Loans	Hours of Work	Earnings	Parental Contribution
	(1)	(2)	(3)	(4)	(5)	(6)
Combined	\$7,287.15 (\$970.25)	0.006 (0.017)	-\$6,915.49 (\$994.76)	-5.36 (1.52)	-\$53.24 (\$19.53)	-\$1,553.86 (\$355.63)
African Americans	\$6,721.49 (\$1,153.79)	0.000 (0.029)	-\$6,231.22 (\$1,466.17)	-6.61 (2.49)	-\$67.07 (\$30.24)	-\$435.14 (\$292.42)
Asian Americans	\$10,759.71 (\$2,366.65)	0.083 (0.043)	-\$7,270.27 (\$2,710.10)	-8.70 (3.56)	-\$91.78 (\$39.64)	-\$5,167.48 (\$1,356.24)
Hispanics	\$5,791.99 (\$2,102.63)	-0.032 (0.017)	-\$7,480.13 (\$1,298.58)	-1.79 (2.76)	-\$12.73 (\$35.21)	-\$721.67 (\$448.22)

**(b) Added Controls for Gender, Parent's Education, Family Size, SAT score, Parents
Income & High School Type**

	Total Scholarship Amount	Retention	Total Loans	Hours of Work	Earnings	Parental Contribution
	(1)	(2)	(3)	(4)	(5)	(6)
Combined	\$7,717.98 (\$989.38)	0.004 (0.018)	-\$6,376.36 (\$1,218.27)	-5.18 (1.82)	-\$46.60 (\$23.26)	-\$1,386.46 (\$410.66)
African Americans	\$8,524.34 (\$1,277.06)	0.015 (0.042)	-\$5,606.03 (\$1,578.60)	-6.48 (2.92)	-\$50.69 (\$30.38)	\$117.77 (\$386.52)
Asian Americans	\$12,979.96 (\$2,642.34)	0.050 (0.037)	-\$7,373.14 (\$2,750.62)	-7.56 (3.92)	-\$87.19 (\$43.23)	-\$5,545.30 (\$1,602.21)
Hispanics	\$3,547.90 (\$2,078.94)	-0.023 (0.018)	-\$6,949.35 (\$1,898.54)	-3.12 (3.16)	-\$30.04 (\$44.80)	-\$550.90 (\$437.87)

Source: Cohorts II and III of Gates Millennium Scholarship Follow-up Surveys. See text for details.

Notes: Standard errors are reported in parentheses. Estimates are based on two-stage least squares with standard errors adjusted for heteroskedasticity and for intra-correlation among individuals with equal total non-cognitive scores. Controls for cohort, total non-cognitive score and its square and their interaction with cohort are included in the race specific estimates; the combined model also includes controls for race and interactions of total non-cognitive score and its square with race.

Table 5

Estimated Impact of GMS on Outcome Variables at End of Junior Year in College by Subgroup						
	Retention	Scholarship Support	Total Loans	Hours of Work	Earnings	Parental Contribution
	(1)	(2)	(3)	(4)	(5)	(6)
Men	-0.014 (0.023)	\$11,955 (691)	-\$8,812 (1866)	-3.88 (2.78)	-\$45.71 (19.53)	-\$1,254 (691)
Women	0.015 (0.021)	\$5,093 (1082)	-\$6,081 (1051)	-5.65 (1.72)	-\$54.12 (23.31)	-\$1,632 (512)
College Degreed Parent	-0.007 (0.022)	\$9,274 (1930)	-\$9,827 (1997)	-4.16 (2.99)	-\$29.47 (39.79)	-\$3,451 (952)
No College Degreed Parent	0.020 (0.021)	\$6,897 (1083)	-\$5,430 (1300)	-6.22 (2.17)	-\$63.48 (18.85)	-\$722 (1959)
Public 4-year	0.004 (0.018)	\$5,818 (832)	-\$4,002 (898)	-4.64 (2.00)	-\$34.13 (23.34)	-\$794 (373)
Private 4-Year	0.043 (0.027)	\$8,633 (1794)	-\$12,609 (2253)	-6.08 (3.04)	-\$68.04 (36.18)	-\$2,749 (1169)

Source: Cohorts II and III of Gates Millennium Scholarship Follow-up Surveys. See text for details.

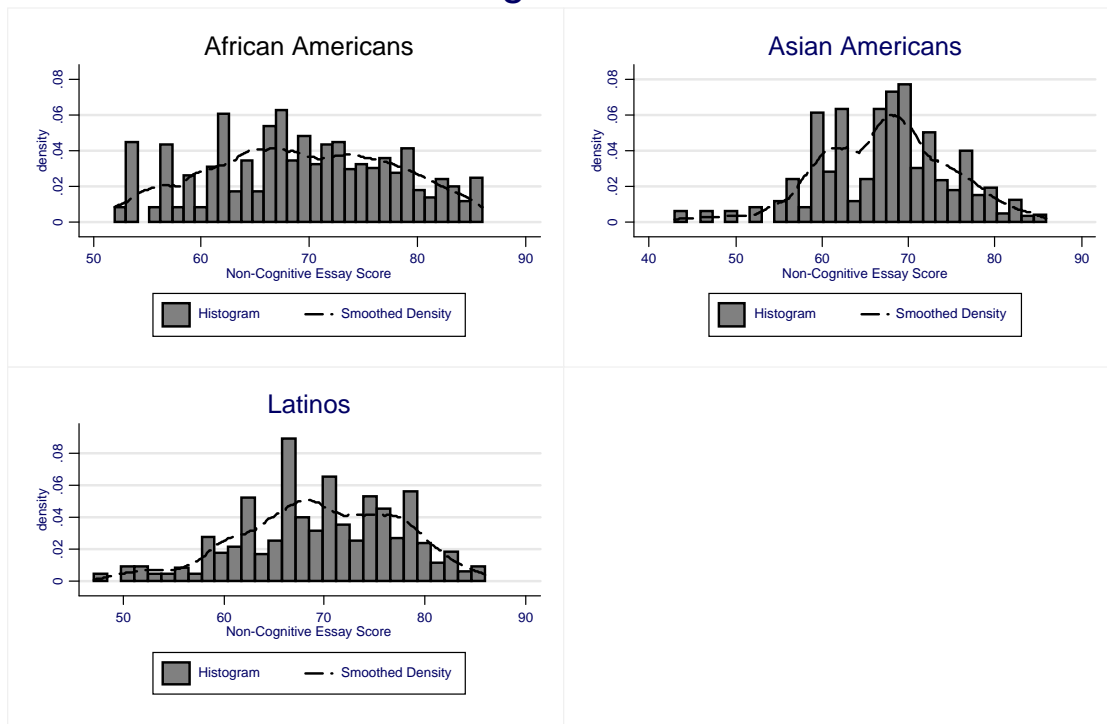
Table 6
Estimated Impact of GMS on Educational Aspirations, STEM Major and Private School Attendance

(a) No Additional Controls				
	Aspirations: Junior Year			Private College: Freshman Year
	Graduate School	Ph.D.	STEM Major: Junior Year	
	(1)	(2)	(3)	
Combined	0.055 (0.046)	0.123 (0.039)	0.016 (0.033)	0.034 (0.034)
African Americans	0.053 (0.068)	0.009 (0.060)	-0.011 (0.042)	0.165 (0.041)
Asian Americans	0.035 (0.110)	0.264 (0.088)	0.028 (0.081)	-0.096 (0.071)
Latinos	0.058 (0.084)	0.175 (0.045)	0.037 (0.046)	-0.029 (0.062)
(b) Added Controls for Gender, Parent's Education, Family Size, SAT Score, Parent's Income & High School Type				
	Aspirations: Junior Year			Private College: Freshman Year
	Graduate School	Ph.D.	STEM Major: Junior Year	
	(1)	(2)	(3)	
Combined	0.055 (0.046)	0.123 (0.039)	0.016 (0.033)	0.034 (0.034)
African Americans	0.053 (0.068)	0.009 (0.060)	-0.011 (0.042)	0.165 (0.041)
Asian Americans	0.035 (0.110)	0.264 (0.088)	0.028 (0.081)	-0.096 (0.071)
Latinos	0.058 (0.084)	0.175 (0.045)	0.037 (0.046)	-0.029 (0.062)

Source: Cohorts II and III of Gates Millennium Scholarship Follow-up Surveys. See text for details.

Notes: Standard errors are reported in parentheses. Estimates are based on two-stage least squares with standard errors adjusted for heteroskedasticity and for intra-correlation among individuals with equal total non-cognitive scores. Controls for cohort, total non-cognitive score and its square and their interaction with cohort are included in the race specific estimates; the combined model also includes controls for race and interactions of total non-cognitive score and its square with race.

Figure 1 Distribution of Non-Cognitive Total Score: Cohort II



Source: Gates Millennium Scholar Surveys: Cohort 2

Figure 2 Distribution of Non-Cognitive Total Score: Cohort III

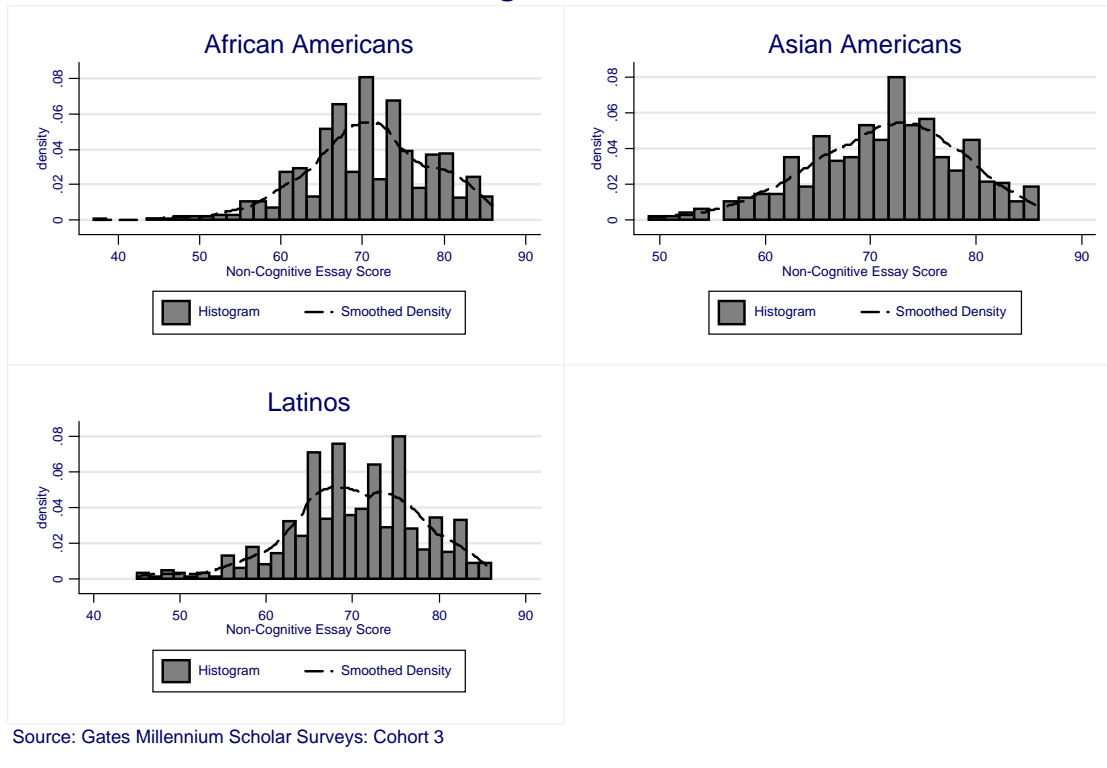
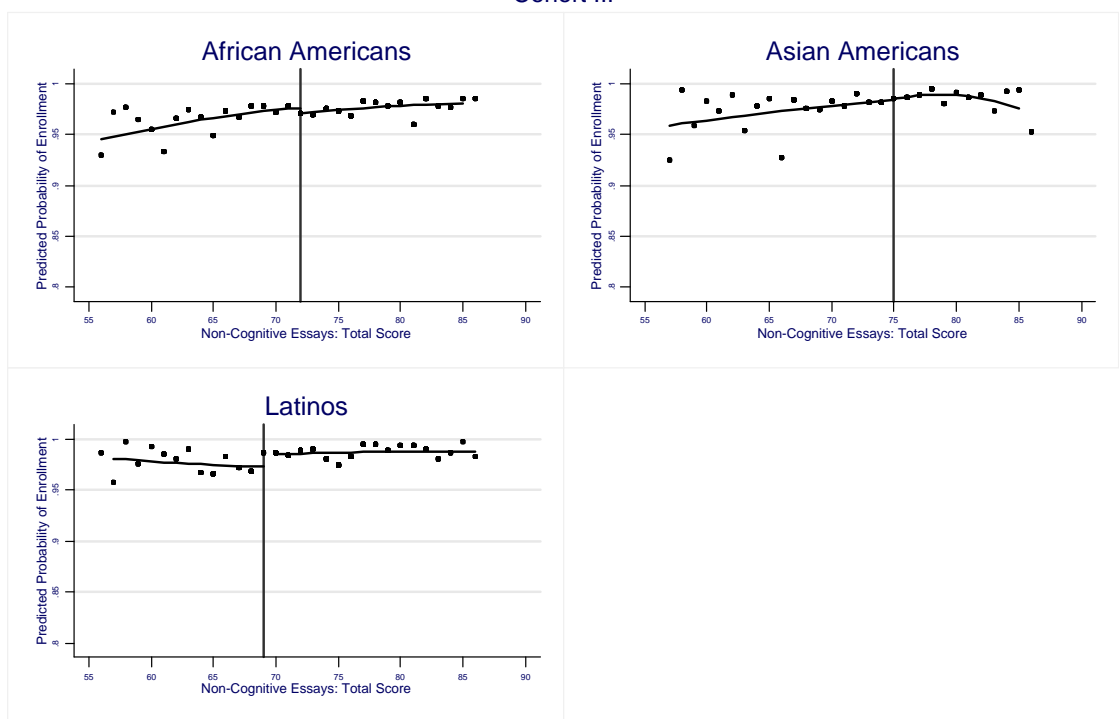
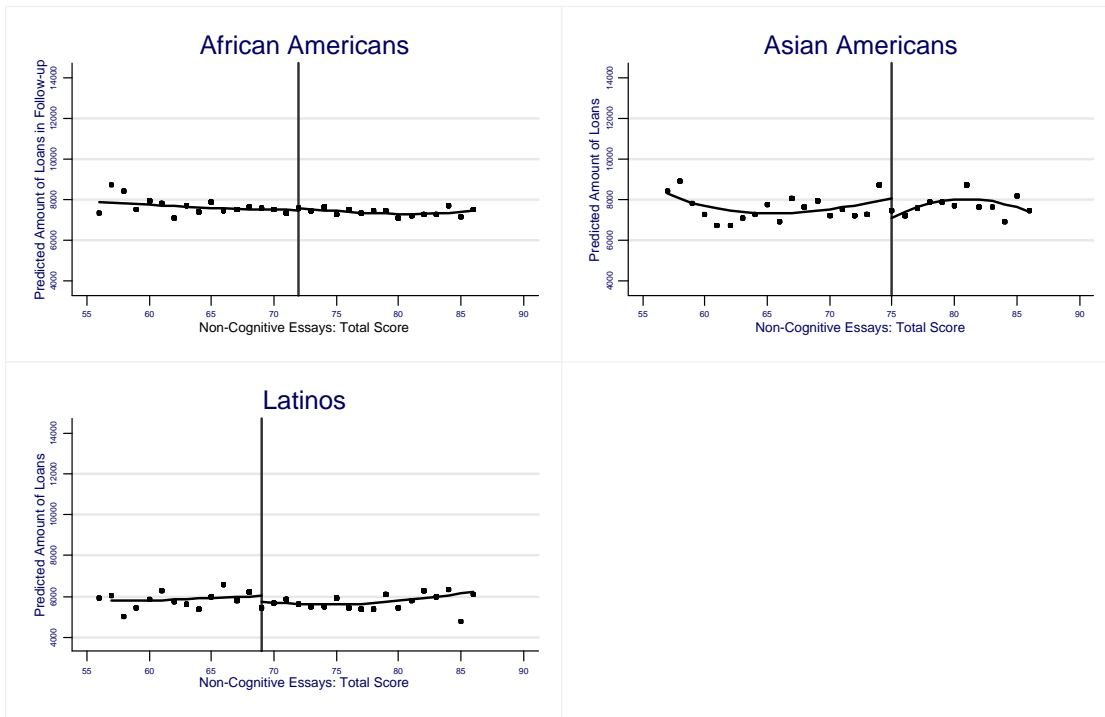


Figure 3
Predicted Probability of Enrollment in Follow-up Survey by Total Non-Cognitive Essays Score
Cohort III



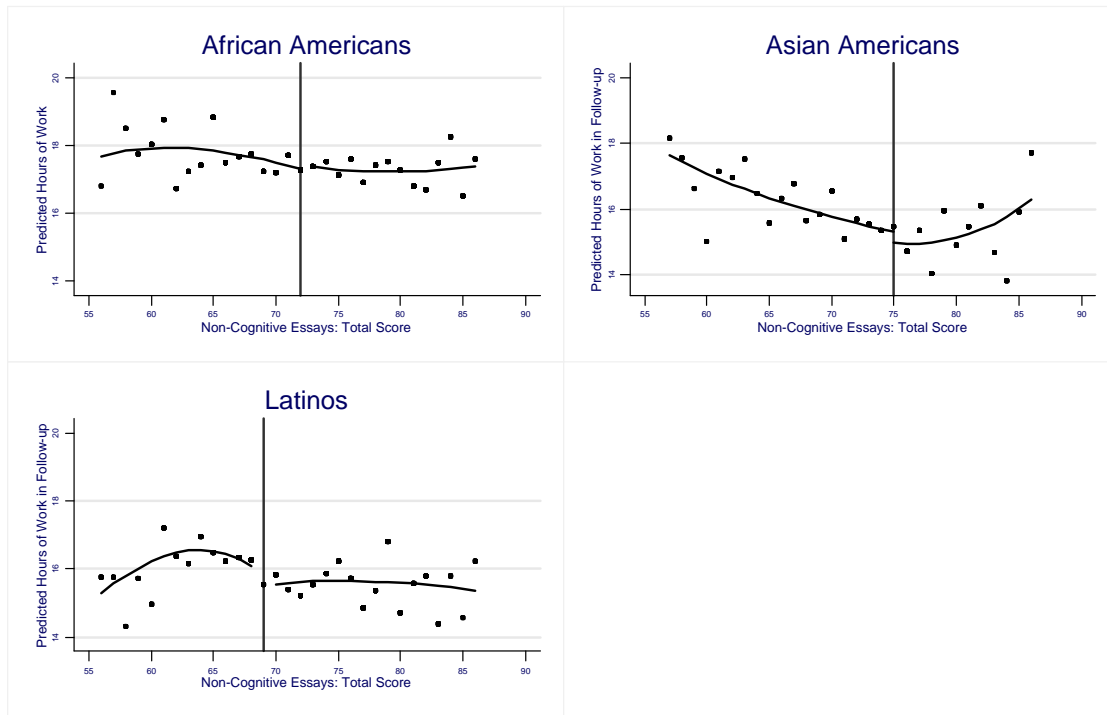
Source: Gates Millennium Scholar Surveys: Cohort III.
Notes: The vertical lines indicate the respective cut points for each ethnic group for the Gates Millennium Scholarship program

Figure 4
 Predicted Total Amount of Loans in Follow-up Survey by Total Non-Cognitive Score
 Cohort III



Source: Gates Millennium Scholar Surveys: Cohort III.
 Notes: The vertical lines indicate the respective cut points for each ethnic group for the Gates Millennium Scholarship program

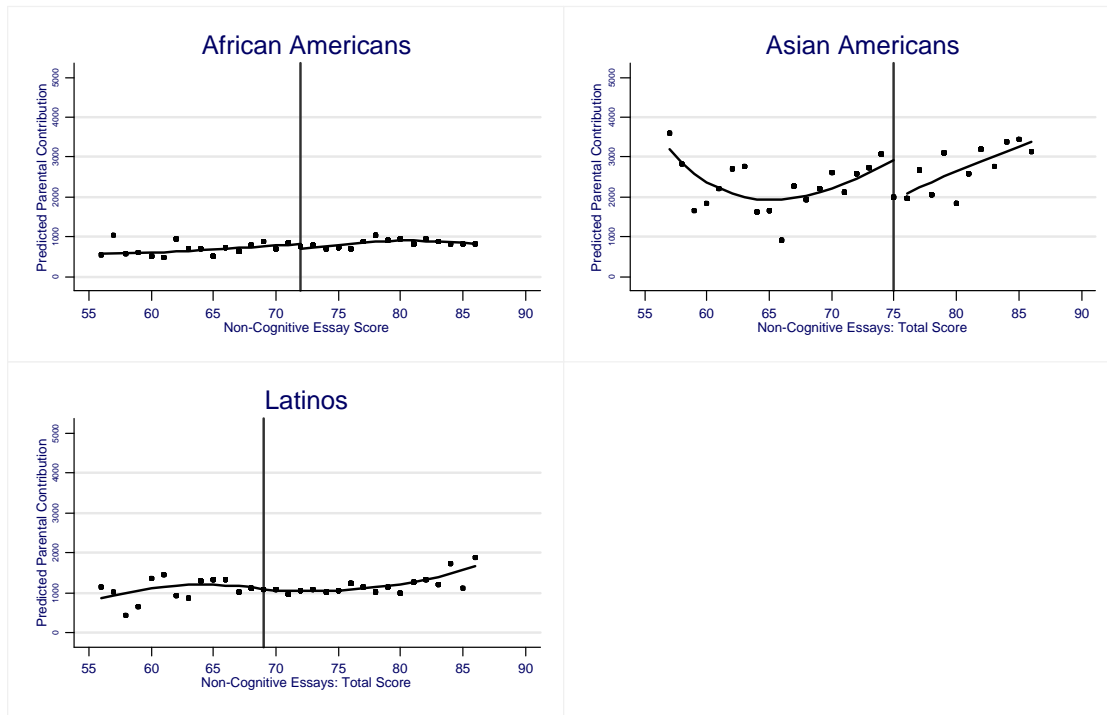
Figure 5
 Predicted Hours of Work in Follow-up Survey by Total Non-Cognitive Essays Score
 Cohort III



Source: Gates Millennium Scholar Surveys Cohort III.

Notes: The vertical lines indicate the respective cut points for each ethnic group for the Gates Millennium Scholarship program

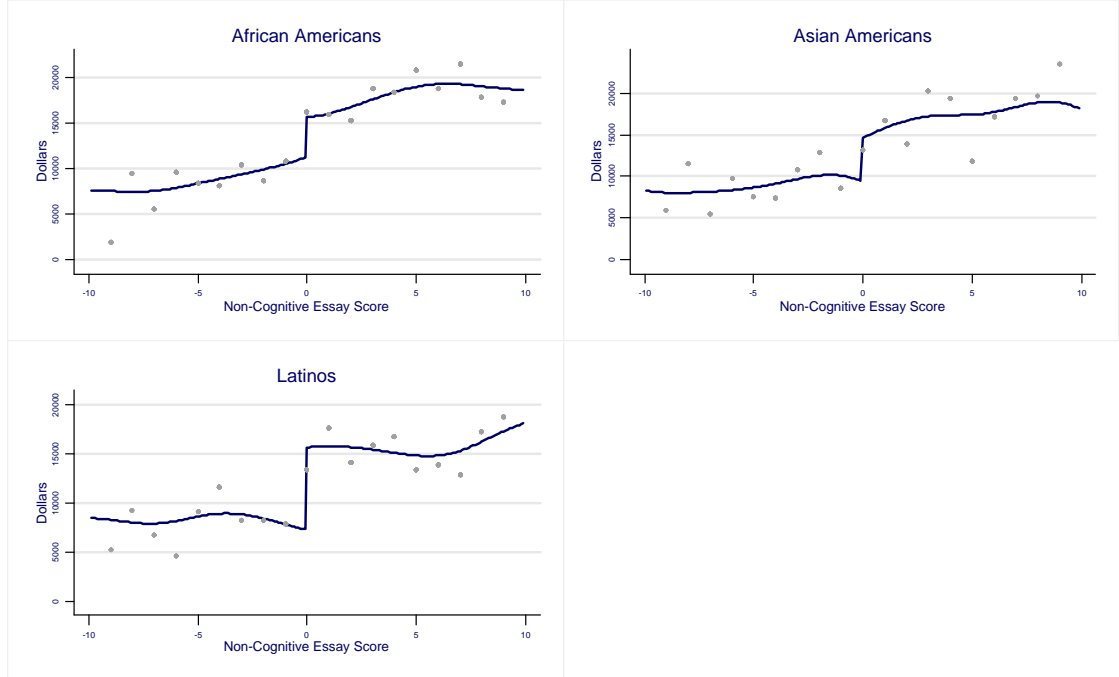
Figure 6
 Predicted Parental Contribution in Follow-up Survey by Total Non-Cognitive Score
 Cohort III



Source: Gates Millennium Scholar Surveys: Cohort III.

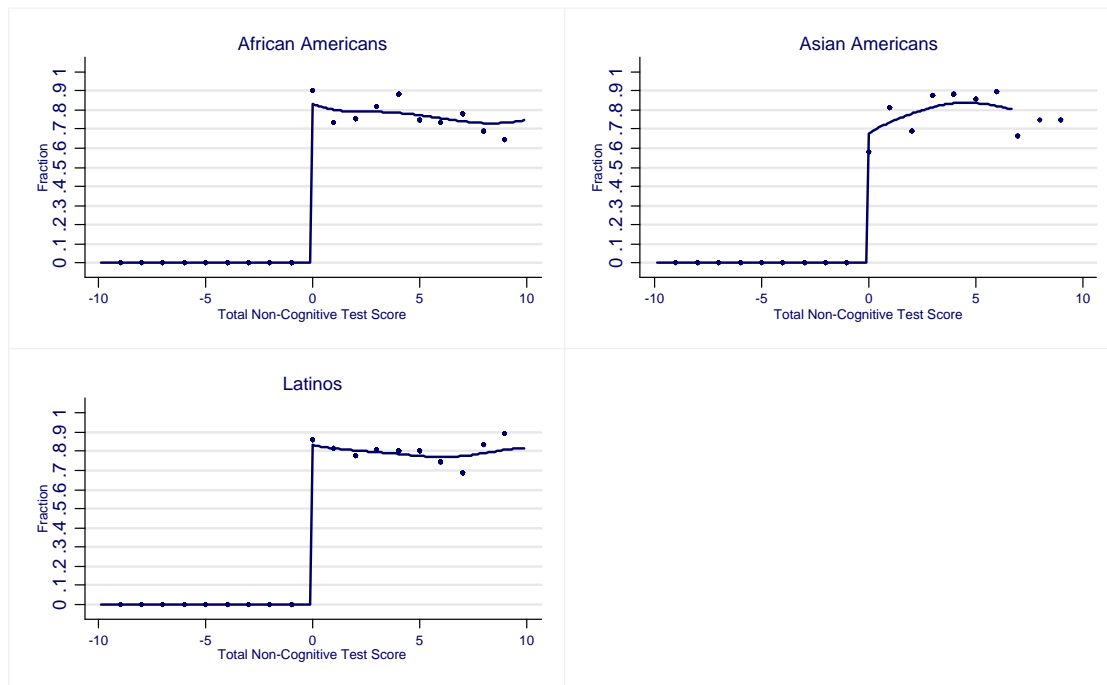
Notes: The vertical lines indicate the respective cut points for each ethnic group for the Gates Millennium Scholarship program

Figure 7
Total Dollar Amount of Scholarships: Junior Year
Cohort III



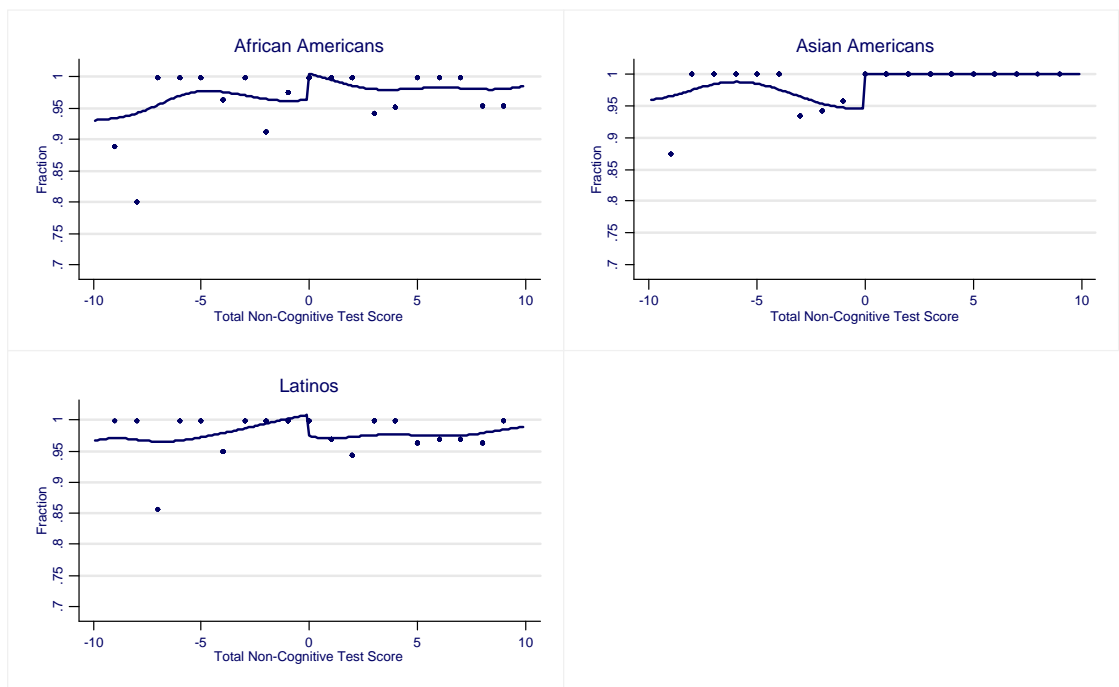
Source: Gates Millennium Scholar Surveys: Cohort III
Notes: 1. Estimates based on local linear regression using using bandwidths equal to 2.
2. Non-cognitive essay score measured as deviation from cut point.

Figure 8
 Fraction of Individuals who are Gates Millennium Scholars
 Cohort III



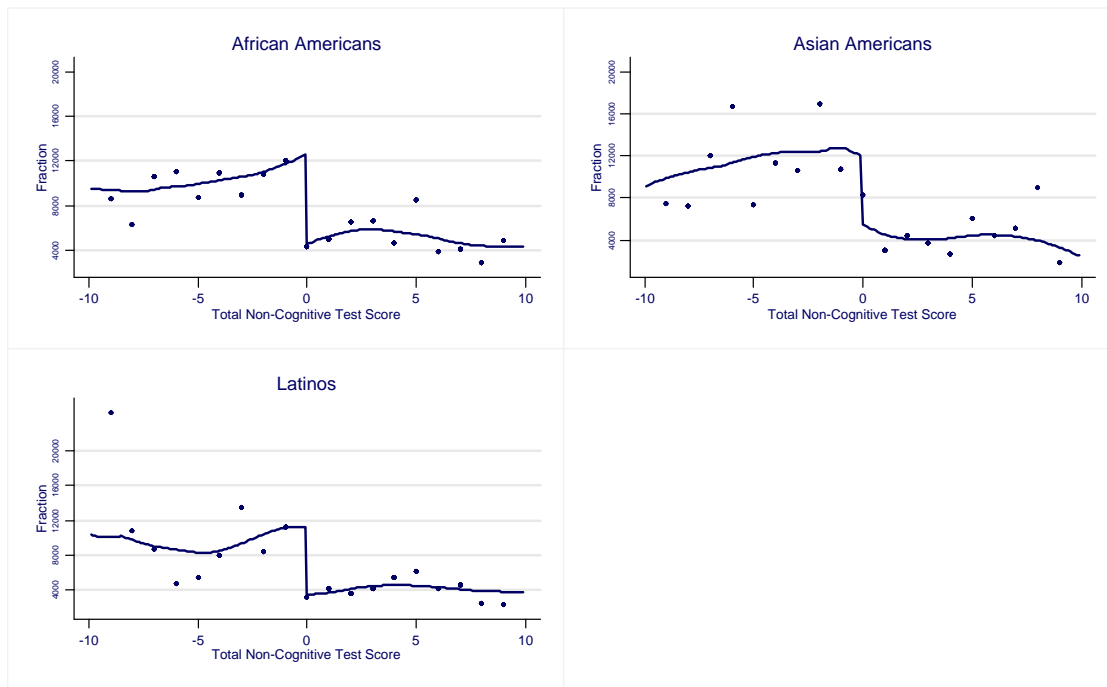
Source: Gates Millennium Scholar Surveys: Cohort III
 Note: 1. Estimates based on local linear regression using bandwidths equal to 2.
 2. Non-cognitive essay score measured as deviation from cut point.

Figure 9
Fraction Enrolled in College: Fall 2004
Cohort III



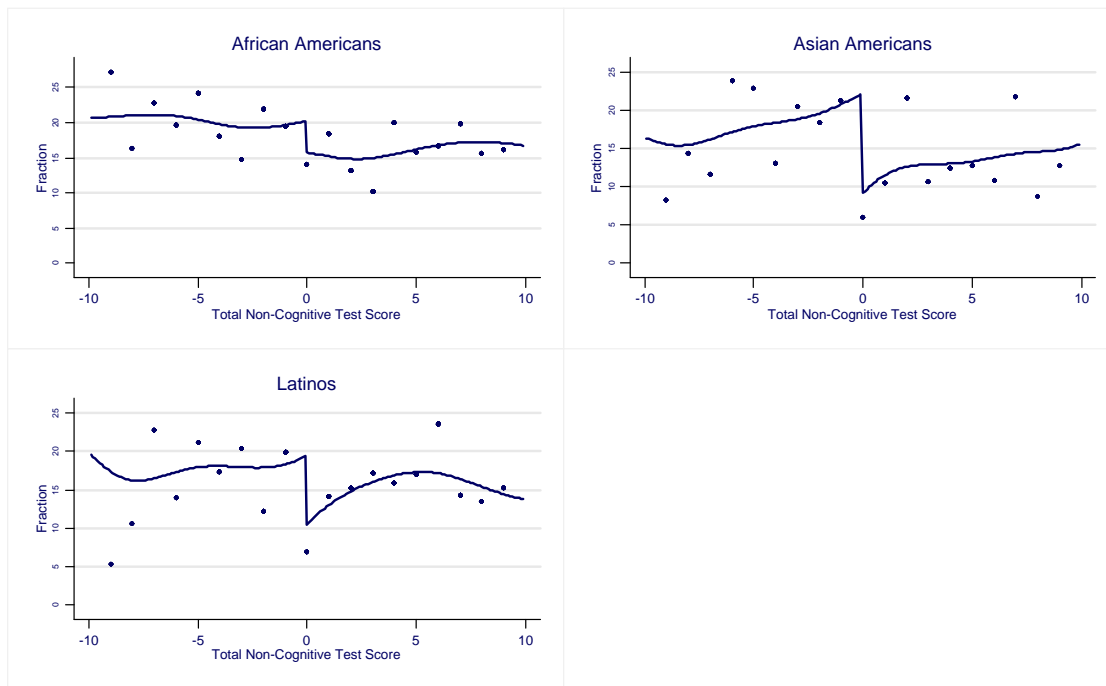
Source: Gates Millennium Scholar Surveys: Cohort III
Notes: 1. Estimates based on local linear regression using bandwidths equal to 2.
2. Non-cognitive essay score measured as deviation from cut point.

Figure 10
 Accumulated Debt from Student Loans: Junior Year
 Cohort III



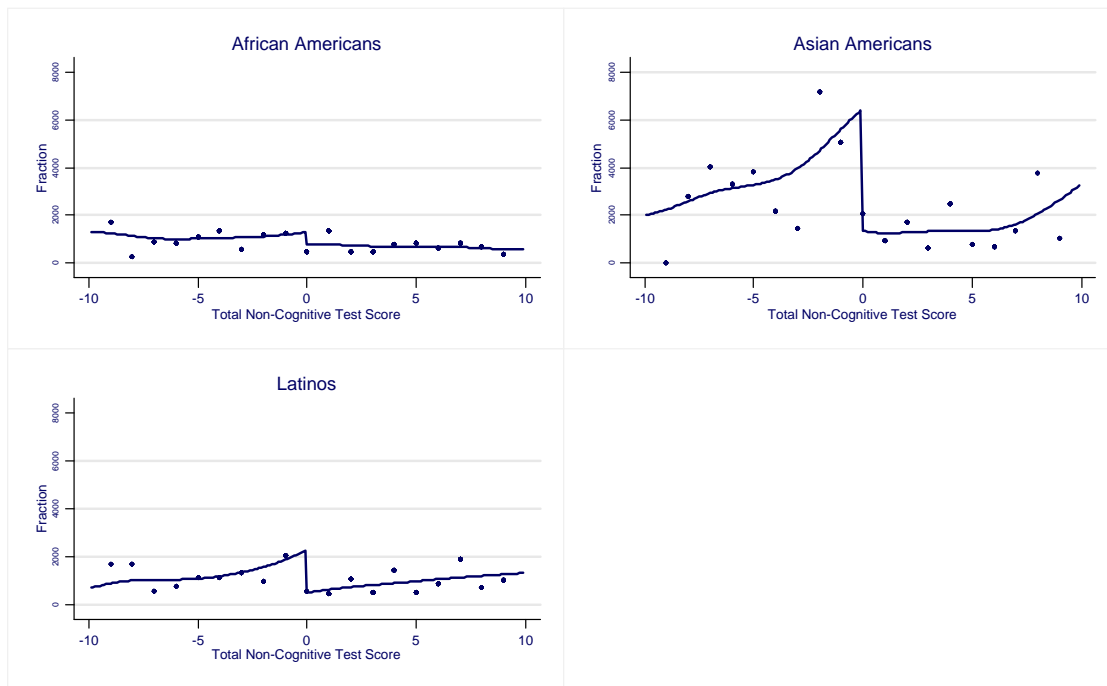
Source: Gates Millennium Scholar Surveys: Cohort III
 Notes: 1. Estimates based on local linear regression using bandwidths equal to 2.
 2. Non-cognitive essay score measured as deviation from cut point.

Figure 11
Hours Worked per Week : Junior Year
Cohort III



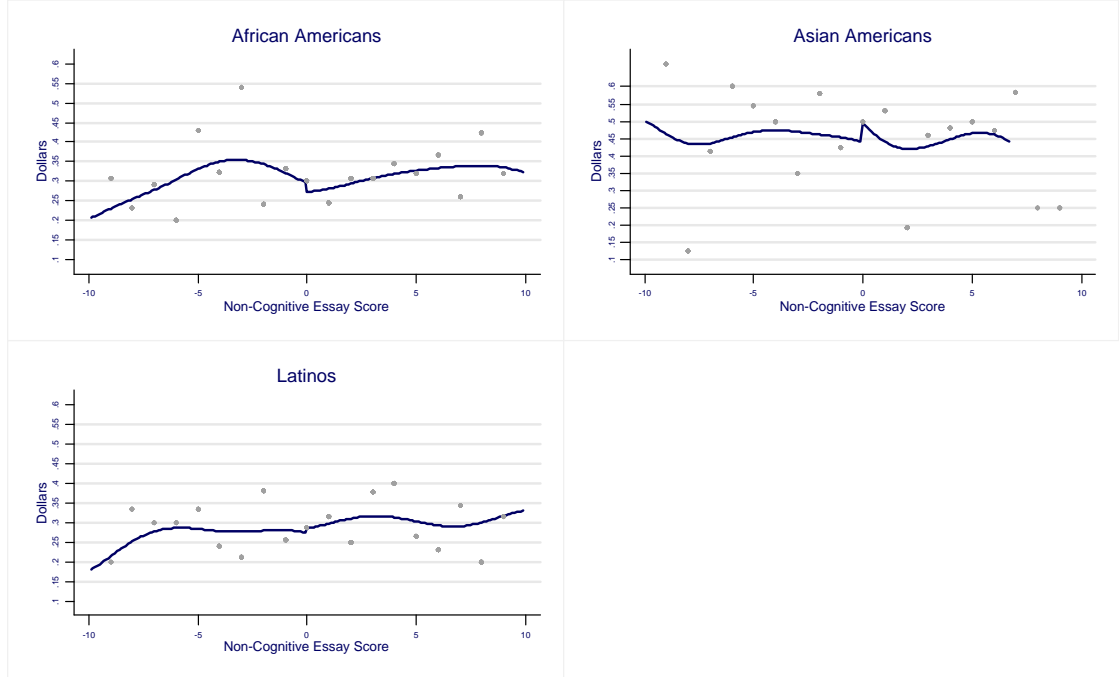
Source: Gates Millennium Scholar Surveys: Cohort III
Notes: 1. Estimates based on local linear regression using bandwidths equal to 2.
2. Non-cognitive essay score measured as deviation from cut point.

Figure 12
 Parental Contribution: Junior Year
 Cohort III



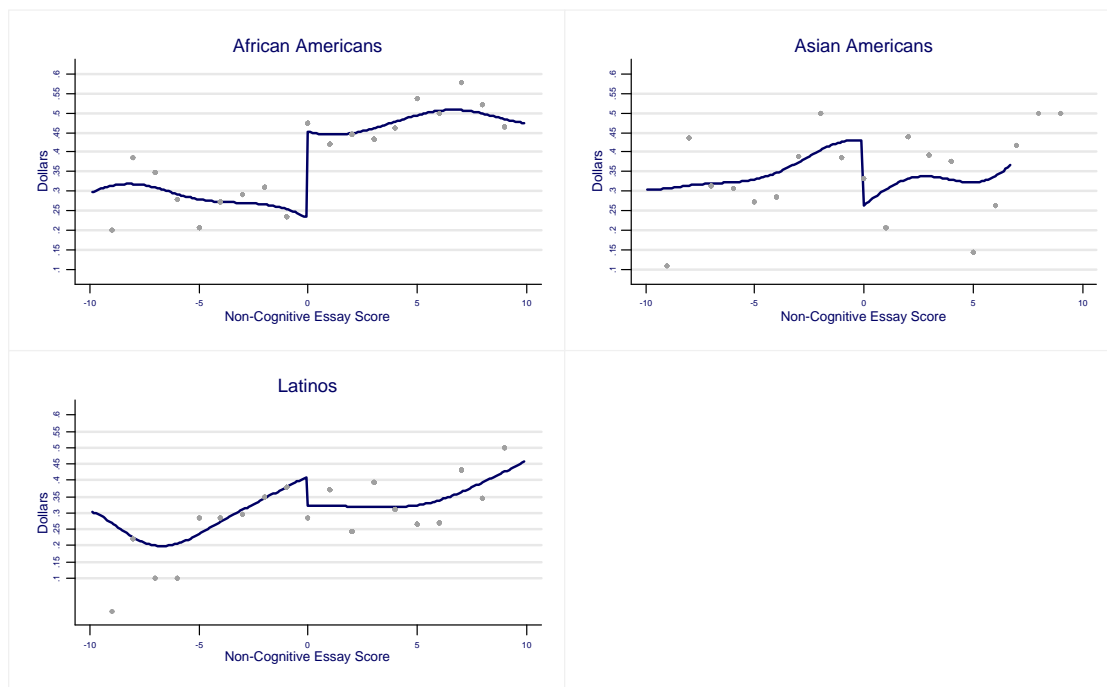
Source: Gates Millennium Scholar Surveys: Cohort III
 Notes: 1. Estimates based on local linear regression using using bandwidths equal to 2.
 2. Non-cognitive essay score measured as deviation from cut point.

Figure 13
Probability of being STEM Major: Junior Year
Cohort III



Source: Gates Millennium Scholar Surveys: Cohort III
Notes: 1. Estimates based on local linear regression using using bandwidths equal to 2.
2. Non-cognitive essay score measured as deviation from cut point.

Figure 14
Probability of Attending Private: Freshman Year
Cohort III



Source: Gates Millennium Scholar Surveys: Cohort III
Notes: 1. Estimates based on local linear regression using using bandwidths equal to 2.
2. Non-cognitive essay score measured as deviation from cut point.