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Source: *The Quarterly Journal of Economics*, Nov., 1995, Vol. 110, No. 4 (Nov., 1995), pp. 941-974

Published by: Oxford University Press

Stable URL: <https://www.jstor.org/stable/2946645>

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# FINISHING HIGH SCHOOL AND STARTING COLLEGE: DO CATHOLIC SCHOOLS MAKE A DIFFERENCE?\*

WILLIAM N. EVANS AND ROBERT M. SCHWAB

In this paper, we consider two measures of the relative effectiveness of public and Catholic schools: finishing high school and starting college. These measures are potentially more important indicators of school quality than standardized test scores in light of the economic consequences of obtaining more education. Single-equation estimates suggest that for the typical student, attending a Catholic high school raises the probability of finishing high school or entering a four-year college by thirteen percentage points. In bivariate probit models we find almost no evidence that our single-equation estimates are subject to selection bias.

## I. INTRODUCTION

More than ten years ago, James Coleman and his colleagues launched a national debate over the relative quality of public and Catholic schools [Coleman and Hoffer 1987; Coleman, Hoffer, and Kilgore 1982]. Based on their analysis of the *High School and Beyond (HS&B)* data, they concluded that Catholic school students scored significantly higher than public school students on standardized tests, even after controlling for differences in family characteristics. Catholic schools in their study appeared to be particularly effective with minority students.

Almost immediately, the Coleman results generated tremendous interest among both policy analysts and academics. Academic journals devoted special issues to their research on at least six different occasions (*Harvard Education Review* in 1991; *Phi Beta Kappa* in 1981; *Education Researcher* in 1981; and *Sociology of Education* in 1982, 1983, and 1985). Critics raised a number of issues about their work. Several papers showed that the estimated magnitude of the Catholic school effect was very sensitive to the choice of other independent variables (Lee and Bryk 1988; Noell 1982). A number of papers questioned whether the results were driven by a selection bias. Since parents decide whether to send their children to public or Catholic schools, it is inappropriate to estimate the effect of Catholic schools on test scores with a

\*We wish to thank Michael Cheng, Kamala Rajamani, Andrew Kochera, and Sheila Murray for excellent research assistance, and Lawrence Katz and two anonymous referees for helpful comments. We gratefully acknowledge the National Science Foundation which has supported this work under grant SBR9409499.

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*The Quarterly Journal of Economics*, November 1995

single-equation model that treats school choice as an exogenous variable [Goldberger and Cain 1982]. Others argued that the increase in test scores between sophomore and senior years was so small that the Coleman results had little relevance in the debate over school choice [Murnane 1984; Alexander and Pallas 1985; Witte 1992].<sup>1</sup> Based on his review of the Coleman work and subsequent studies, Cookson [1993, p. 181] concluded that "... once the background characteristics of students are taken into account, student achievement is not directly related to private school attendance. The effects that were reported by Coleman and his associates are too small to be of any substantive significance in terms of incrementally improving student learning."

Most of Coleman's work and virtually all of the research that followed focused on the effects of Catholic schools on test scores.<sup>2</sup> In some ways it is surprising that test scores have received so much attention while other important education outcomes have not. Test scores have obvious limitations. It has often been argued that standardized tests in general may be culturally, racially, and sexually biased. Teachers may "teach to the test" and thus inflate scores [Henig 1994]. On the other hand, students often gain little by doing well on an exam and thus may not take the exam seriously. Standardized tests can only measure a student's ability to deal with a particular type of question and cannot measure a student's creativity or deeper problem-solving skills. The particular test included in the original Coleman work was a short and relatively simple exam, and the results may not be indicative of school performance. Perhaps most importantly, there is little evidence that raising test scores has important economic consequences. The impact of test scores on wages, for example, appears to be modest.<sup>3</sup>

This suggests that we consider alternative criteria to evaluate

1. Henig [1994], for example, found that out of 125 questions in *HS&B* dealing with vocabulary, reading, mathematics, science, writing, and civics, public school students improved by 7.16 items (from 67.07 as sophomores to 74.23 as seniors), while Catholic school students improved by 8.98 items. Thus, even before accounting for differences in family characteristics, Coleman's Catholic school effect represents only  $8.98 - 7.17 = 1.81$  additional correct answers.

2. For example, Chubb and Moe [1990], in their 318-page analysis of effective schools, use test scores as virtually their sole measure of school performance. Coleman does discuss differences in dropout rates briefly, but the analysis is limited to simple cross tabulations of the data. Neal [1994] and Sander and Krautmann [1995] are similar in some ways to this paper.

3. For a review of the effects of cognitive development on labor market performance, see Hanushek, Rivkin, and Jamison [1992] and Bishop [1991].

schools that have important economic consequences. Card and Krueger [1994] argue that measures of educational attainment such as completing high school and going on to college are particularly useful measures of schools' success. Unlike test scores, there is a great deal of evidence on the benefits of additional education. Only 65 percent of young male high school dropouts were employed in 1986 as compared with 85 percent of high school graduates [Markety 1988]. Between 1980 and 1985 the unemployment rate for males without a high school diploma was 35 percent higher than the rate for high school graduates and five times as large as the rate for college graduates [Murphy and Topel 1987]. The unemployment rate for young black males without high school degrees was over 40 percent for most of the 1980s. Wages and earnings are substantially lower for those high school dropouts who do find work. In 1987 the median yearly income for 25-to-34 year-old male full-time workers with a high school degree was 21.2 percent larger than the value for those who had not finished high school [Levy and Murnane 1992]. Hashimoto and Raisian [1985] and Weiss [1988] found that an extra year of education that leads to a high school degree has a much larger impact on wages than does an additional year of school that does not lead to a degree. Real wages for young male high school dropouts declined by 23 percent between 1979 and 1988, while young male college graduates experienced a 7 percent real wage increase over the same period [Bound and Johnson 1992]. High school dropouts are far more likely to commit crimes [Thornberry, Moore, and Christenson 1985] and to use illegal drugs [Mensch and Kandel 1988].

Thus, the debate over Catholic schools seems to have missed outcomes with important economic implications. In this paper we have gone back to the *HS&B* data and looked at the impact of a Catholic school education on the probability of, first, finishing high school and, second, starting college. We have paid particular attention to the issue of selection bias. If students with more ability or students from families that place a higher value on education are more likely to attend Catholic schools, then single-equation models would overstate the effects of a Catholic school education. Therefore, the appropriate model must take this endogeneity into account. Because both of our outcome measures and the treatment variable (a Catholic school dummy) are dichotomous, we estimate a set of bivariate probit models.

Our major conclusions are as follows. We find a great deal of

support for the argument that Catholic schools are more effective than public schools. Single-equation estimates suggest that for the typical student, attending a Catholic high school raises the probability of finishing high school or entering a four-year college by thirteen percentage points. Unlike single-equation estimates of the effect of Catholic schools on test scores, these results are qualitatively important and are robust. This Catholic school effect is very large. It is twice as large as the effect of moving from a one- to a two-parent family and two and one-half times as large as the effect of raising parents' education from a high school dropout to a college graduate. In models where we treat the decision to attend a Catholic school as an endogenous variable, we find almost no evidence of selection bias. Bivariate probit estimates of the average treatment effect of Catholic schools on high school graduation and entering college are very similar to single-equation probit estimates.

Our bivariate probit model is properly identified if there is at least one variable that is correlated with whether or not a student attends a Catholic school but is uncorrelated with a student's unobserved propensity to graduate from high school or start college. In most of our work we have used as our instrument a dummy variable that equals 1 if the student is from a Catholic family and 0 otherwise. The credibility of our bivariate probit results obviously hinges on our assumption that high school students who are Catholic are no more likely to graduate from high school or to begin college than students who are not Catholic. As we argue below, once we control for other observed factors, it appears that being Catholic is not an important determinant of most economic outcomes. We also present tests of overidentifying restrictions that indicate that our instruments are valid and additional results where we use the religious composition of the population in the county where a student attends school as an alternative instrument.

In the next section we describe the *HS&B* data set and the basic variables we have used in our analysis. In Section III we present single-equation probit estimates of high school completion and college entrance models. In that section we also present a number of sensitivity tests of our single-equation model. In Section IV we present bivariate probit models that treat the decision to attend a Catholic school as an endogenous variable. We present a brief summary and conclusions in the final section of the paper.

## II. DATA

Most of the data for our study were drawn from the *HS&B* survey, which began in the spring of 1980. The original sample was chosen in two stages. Over 1100 secondary schools were selected in the first stage. In the second up to 36 sophomores and 36 seniors were selected from each of the sample schools. Certain types of schools, including public schools with high percentages of Hispanic students and Catholic schools with high percentages of minority students, were oversampled. The original *HS&B* sample included more than 30,000 sophomores and 28,000 seniors. Follow-up surveys of a stratified random sample of the original sophomore cohort were conducted in 1982, 1984, and 1986. Our sample is drawn from the 13,683 students who were sophomores in 1980 and who were included in both the 1982 and 1984 follow-ups. We eliminated 389 students who attended private non-Catholic schools or whose education level in 1984 is unknown. Thus, our final sample includes 13,294 observations.

*HS&B* contains information on a wide range of topics including individual and family background, high school experiences, and plans for the future. Each student was also given a series of cognitive tests that measured verbal and quantitative ability. The sophomore cohort completed these tests in the initial 1980 survey and again in the first follow-up in 1982 (when most were seniors).<sup>4</sup> School questionnaires, which were completed by an official in each participating school, provided information about dropout rates, staff, educational programs, facilities, and services.

Table I presents definitions and summary statistics for some of the important variables we have used in our study.<sup>5</sup> We classify students as public or Catholic school students based on the school they attended as sophomores. Our study focuses on two measures of educational attainment: high school completion and the decision to begin college. We constructed both variables from the 1984 follow-up data when many of the 1980 *HS&B* sophomores would have been out of high school for two years. *HIGH SCHOOL*

4. The test score we report is the sum of the "formula" score on the mathematics, vocabulary, and reading exams. Students received one point for each correct answer and lost a fraction of a point for each incorrect answer (where the fraction depends on the number of possible answers). The maximum possible score on the *10TH GRADE TEST SCORE* is 68.

5. All individual and school variables were constructed from either the composite variables in the *HS&B* data set or were taken from the base-year survey. The summary statistics in Table I are unweighted and thus do not represent an accurate picture of 1980 high school sophomores. We have not used sample weights in our econometric work.

TABLE I  
SUMMARY STATISTICS: HIGH SCHOOL AND BEYOND DATA SET

Variable name	Definition	Catholic school mean and (std. dev.)	Public school mean and (std. dev.)
<i>HIGH SCHOOL GRADUATE</i>	0-1 dummy variable, = 1 if student graduated from high school by February of 1984	0.97 (0.17)	0.79 (0.41)
<i>COLLEGE ENTRANT</i>	0-1 dummy variable, = 1 if first postsecondary school attended was 4-year college	0.55 <sup>a</sup> (0.50)	0.32 <sup>a</sup> (0.47)
<i>CATHOLIC RELIGION</i>	0-1 dummy variable = 1 if the student is Catholic	0.79 (0.41)	0.29 (0.45)
<i>% CATHOLIC IN COUNTY</i>	Percent of the population in the county where the student attends school that is Catholic	31.65 (13.17)	22.37 (16.82)
<i>FEMALE</i>	0-1 dummy variable, = 1 if student is female	0.56 (0.50)	0.50 (0.50)
<i>BLACK</i>	0-1 dummy variable, = 1 if student is black	0.15 (0.36)	0.13 (0.34)
<i>HISPANIC</i>	0-1 dummy variable, = 1 if student is Hispanic	0.22 (0.41)	0.22 (0.41)
<i>WHITE</i>	0-1 dummy variable, = 1 is student is white, non-Hispanic	0.61 (0.49)	0.58 (0.49)
<i>OTHER RACE</i>	0-1 dummy variable, = 1 if student is other race	0.02 (0.15)	0.06 (0.24)
<i>FAMILY INCOME MISSING</i>	0-1 dummy variable, = 1 if family income is not reported	0.22 (0.41)	0.23 (0.42)
<i>FAMILY INCOME &lt; \$7000</i>	0-1 dummy variable, = 1 if family income < \$7000	0.03 (0.16)	0.07 (0.26)
<i>FAMILY INCOME \$7000–\$12,000</i>	0-1 dummy variable, = 1 if family income ≥ \$7000 and < \$12,000	0.07 (0.26)	0.11 (0.31)
<i>FAMILY INCOME \$12,000–\$16,000</i>	0-1 dummy variable, = 1 if family income ≥ \$12,000 and < \$16,000	0.12 (0.32)	0.15 (0.35)
<i>FAMILY INCOME \$16,000–\$20,000</i>	0-1 dummy variable, = 1 if family income ≥ \$16,000 and < \$20,000	0.14 (0.35)	0.15 (0.35)
<i>FAMILY INCOME \$20,000–\$25,000</i>	0-1 dummy variable, = 1 if family income ≥ \$20,000 and < \$25,000	0.16 (0.36)	0.13 (0.33)
<i>FAMILY INCOME \$25,000–\$38,000</i>	0-1 dummy variable, = 1 if family income ≥ \$25,000 and < \$38,000	0.13 (0.33)	0.09 (0.29)
<i>FAMILY INCOME ≥ \$38,000</i>	0-1 dummy variable, = 1 if family income ≥ \$38,000	0.14 (0.35)	0.07 (0.25)
<i>PARENT EDUCATION MISSING</i>	0-1 dummy variable, = 1 if parents' education not reported	0.09 (0.29)	0.19 (0.40)
<i>PARENT HIGH SCHOOL DROPOUT</i>	0-1 dummy variable, = 1 if parents' highest education < high school graduate	0.23 (0.42)	0.30 (0.46)
<i>PARENT HIGH SCHOOL GRADUATE</i>	0-1 dummy variable, = 1 if parents' highest education is high school graduate	0.19 (0.39)	0.20 (0.40)
<i>PARENT SOME COLLEGE</i>	0-1 dummy variable, = 1 if parent's highest education is some college	0.28 (0.45)	0.19 (0.39)



TABLE I  
(CONTINUED)

Variable name	Definition	Catholic school mean and (std. dev.)	Public school mean and (std. dev.)
<i>PARENT COLLEGE GRADUATE</i>	0-1 dummy variable, = 1 if parents' highest education is college graduate	0.21 (0.41)	0.11 (0.31)
<i>SINGLE MOTHER</i>	0-1 dummy variable, = 1 if student's household is headed by single mother	0.12 (0.32)	0.15 (0.35)
<i>SINGLE FATHER</i>	0-1 dummy variable, = 1 if student's household is headed by single father	0.03 (0.17)	0.05 (0.21)
<i>NATURAL MOTHER/ STEPFATHER</i>	0-1 dummy variable, = 1 if student lives with natural mother and step-father	0.04 (0.19)	0.06 (0.24)
<i>BOTH NATURAL PARENTS</i>	0-1 dummy variable, = 1 if student lives with both natural parents	0.76 (0.43)	0.62 (0.48)
<i>OTHER FAMILY STRUCTURE</i>	0-1 dummy variable, = 1 if student's household has other structure	0.06 (0.24)	0.12 (0.32)
<i>AGE 16</i>	0-1 dummy variable, = 1 if student is <= 16 years of age in February of 1982	0.03 (0.17)	0.03 (0.17)
<i>AGE 17</i>	0-1 dummy variable, = 1 if student is 17 years of age in February of 1982	0.63 (0.48)	0.49 (0.50)
<i>AGE 18</i>	0-1 dummy variable, = 1 if student is 18 years of age in February of 1982	0.32 (0.47)	0.40 (0.49)
<i>AGE 19+</i>	0-1 dummy variable, = 1 if student is 19 years of age or older	0.02 (0.15)	0.08 (0.26)
<i>ATTENDS RELIGIOUS SERVICES REGULARLY</i>	0-1 dummy variable, = 1 if student attends church at least twice a month	0.69 (0.46)	0.44 (0.50)
<i>ATTENDS RELIGIOUS SERVICES OCCASIONALLY</i>	0-1 dummy variable, = 1 if student attends church occasionally	0.17 (0.38)	0.23 (0.42)
<i>NEVER ATTENDS RELIGIOUS SERVICES</i>	0-1 dummy variable, = 1 if student never attends church	0.13 (0.34)	0.33 (0.47)
<i>10th GRADE TEST SCORE</i>	Student's sophomore score on standardized exam	30.06 (14.63)	24.53 (15.87)
<i>TEST SCORE MISSING</i>	0-1 dummy variable, = 1 if sophomore test score is missing	0.08 (0.28)	0.16 (0.37)
<i>No. of obs.</i>		10,767	2527

a. The *COLLEGE ENTRANT* means are conditional on having completed high school.

*GRADUATE* is a dummy variable that equals 1 if the student had completed high school by 1984. *COLLEGE ENTRANT* is a dummy variable that equals 1 if the student had enrolled in a four-year college by February of 1984 (and did not first enroll in a two-year



college or a vocational training program). Since graduating high school is a precondition for starting college, all of our work defines the *COLLEGE ENTRANT* variable for only those students who have a high school degree.<sup>6</sup>

Most of the family characteristics require little explanation. As can be seen in Table I, data on family income and parents' education are missing in a significant number of cases. We suspect that these values are missing in a nonrandom sample of the population. For example, graduation rates among students where the parents' education is missing are ten percentage points lower than the rate for students where the education variable is available.<sup>7</sup> We looked at a number of strategies to deal with this missing data problem including the estimation of a model suggested by Griliches, Hall, and Hausman [1978] in which we treat nonreporting as an endogenous variable. In the end we fell back on a straightforward approach of defining income and parents' education in terms of a set of dummy variables and including "missing data" as a category. We chose the highest income and highest education groups as the reference categories in order to facilitate the interpretation of the results.

Table I shows that, compared with Catholic school students, public school students were more than seven times as likely to drop out of high school and were just over half as likely to start college. That table also indicates that the characteristics of Catholic school students suggest that they were more likely to succeed in school. Public school students scored lower on standardized tests and were far more likely to be eighteen years of age or older, to come from

6. The definition of these two outcome measures is not quite as straightforward as one might think. For example, we do not count students earning GED's as high school graduates. This is a reasonable restriction given recent work by Cameron and Heckman [1993], who find that graduates with GED's do not perform as well in the labor market as students with regular high school diplomas. Similarly, we do not count people who went to college long after graduating from high school and people who attended a two-year college as college students. Restricting our attention to students entering a four-year college is arguable given work by Kane and Rouse [1993] who find that credit hours from two- and four-year colleges are rewarded equally in the workforce. Rouse [1995] also finds that, on net, community colleges increase total years of schooling but do not alter the probability of obtaining an undergraduate degree. As we demonstrate later, these assumptions are not critical.

7. There is reason to believe that most of the missing income values are from families with low income. Students were given a breakdown of family income by thirds and asked in what portion of the income distribution does their family fall. Using sample weights from the second follow-up survey, a total of 29 percent and 27 percent of the students reported being in the top two-thirds of the income distribution, respectively, while only 13 percent said that their family was in the bottom third (the rest did not respond).

low-income families, to have parents who had not finished high school, and to live without their father. The basic question in this paper is whether Catholic schools still have an important impact on high school graduation and college entrance once we control for the effects of these measured differences across students as well as any unmeasured differences. Our sample includes significant numbers of Catholic students who attend public schools and non-Catholic students who attend Catholic schools, thus leaving open the possibility that we can separate the effects of religion from the effects of a religious education.

One simple yet informative test is to compare education outcomes across broad demographic and ability group.<sup>8</sup> These results parallel the discussion in Coleman and Hoffer [1987, Chapter 4]. In Table II graduation and college entrance rates are computed by ability, family income, parents' education, sex, and race. The table shows that the probability that a public school student will graduate varied dramatically across groups. Among Catholic school students, however, these differences were small. For example, the graduation rate for public school students whose parents were high school dropouts was fourteen percentage points lower than the rate for public school students whose parents were college graduates. Among Catholic school students this difference was only four percentage points. As a consequence, the difference in graduation rates between Catholic and public school students is smallest among students with high test scores from high income, well-educated families. However, even for those groups, Catholic school students graduated at higher rates than their public school counterparts.

As one would expect, there is far more heterogeneity across across demographic groups in college entrance rates. Across all groups, however, Catholic school students were more likely to begin college. As with the high school graduation rates, the differences across sectors declines as ability, family income, and parents' education increase, but there are still large differences in college matriculation rates even for the top categories in all groups.<sup>9</sup>

8. The test quartiles were calculated for the entire sample using second follow-up sample weights.

9. Bryk, Lee, and Holland [1993] found similar results for Catholic schools in their analysis of the *HS&B* test score data. Using quantile regression techniques, Evans and Schwab [1993] also found that the benefits of a Catholic education on test scores are concentrated among the least able students, students whose parents have little education and students from low-income families.

TABLE II  
EDUCATIONAL OUTCOMES OF HIGH SCHOOL STUDENTS BY SCHOOL TYPE

Sample	HIGH SCHOOL GRADUATE		COLLEGE ENTRANT <sup>a</sup>	
	Public schools	Catholic schools	Public schools	Catholic schools
Full sample	0.79	0.97	0.32	0.55
<i>SOPHOMORE TEST SCORE MISSING</i>	0.71	0.98	0.22	0.50
<i>SOPHOMORE TEST FIRST QUARTILE</i>	0.63	0.91	0.11	0.25
<i>SOPHOMORE TEST SECOND QUARTILE</i>	0.80	0.96	0.19	0.40
<i>SOPHOMORE TEST THIRD QUARTILE</i>	0.89	0.98	0.37	0.56
<i>SOPHOMORE TEST FOURTH QUARTILE</i>	0.95	0.99	0.62	0.78
<i>PARENT EDUCATION MISSING</i>	0.65	0.92	0.16	0.40
<i>PARENT H.S. DROPOUT</i>	0.77	0.95	0.22	0.41
<i>PARENT H.S. DEGREE</i>	0.82	0.97	0.30	0.54
<i>PARENT SOME COLLEGE</i>	0.87	0.98	0.44	0.62
<i>PARENT COLLEGE GRADUATE</i>	0.91	0.99	0.61	0.67
<i>FAMILY INCOME MISSING</i>	0.74	0.97	0.25	0.48
<i>FAMILY INCOME &lt; \$7000</i>	0.64	0.91	0.19	0.36
<i>FAMILY INCOME \$7000–\$12000</i>	0.76	0.92	0.23	0.44
<i>FAMILY INCOME \$12000–\$16000</i>	0.81	0.98	0.29	0.51
<i>FAMILY INCOME \$16000–\$20000</i>	0.84	0.97	0.33	0.49
<i>FAMILY INCOME \$20000–\$25000</i>	0.84	0.96	0.38	0.57
<i>FAMILY INCOME \$25000–\$38000</i>	0.87	0.99	0.47	0.70
<i>FAMILY INCOME ≥ \$38000</i>	0.86	0.98	0.52	0.66
<i>FEMALE</i>	0.80	0.97	0.33	0.53
<i>MALE</i>	0.78	0.97	0.31	0.58
<i>BLACK</i>	0.76	0.95	0.33	0.62
<i>HISPANIC</i>	0.76	0.93	0.21	0.45
<i>WHITE</i>	0.81	0.99	0.35	0.56
<i>OTHER RACE</i>	0.84	0.98	0.38	0.56

a. The COLLEGE ENTRANT means are conditional on having completed high school.

### III. PROBIT MODELS OF EDUCATIONAL ATTAINMENT

The literature on the effect of Catholic schools on the probability of graduating from high school and going to college has rarely gone beyond the sort of simple cross tabulations in Table II. In this

section we extend this literature by examining the student's decision to complete high school or enter college by estimating a set of probit models.

### A. Single-Equation Probit Models

In the high school graduation version of this model, let the indicator variable  $Y_i = 1$  if student  $i$  completes high school, and let  $Y_i = 0$  otherwise. The choice problem is described by the latent variable model.

$$(1) \quad Y_i^* = X_i\beta + C_i\delta + \epsilon_i,$$

where  $Y_i^*$  is the net benefit a student receives from graduating high school,  $X_i$  is a vector of individual characteristics,  $C_i$  is a Catholic school dummy variable, and  $\epsilon_i$  is a normally distributed random error with zero mean and unit variance. Students will only graduate from high school if the expected net benefits of completion are positive, and thus the probability that a student finishes high school is

$$(2) \quad \text{prob}[Y_i = 1] = \text{prob}[X_i\beta + C_i\delta + \epsilon_i > 0] = \Phi[X_i\beta + C_i\delta],$$

where  $\Phi[\cdot]$  is the evaluation of the standard normal cdf.

In all of our high school graduation and college entrance probit models, we use the set of individual and family characteristics listed in Table I, dummy variables for urban and rural schools, and three indicators for census regions. Maximum likelihood estimates of the high school completion and college entrance models are reported in columns 1 and 3 of Table III. To measure the qualitative importance of all our right-hand-side variables, we report the marginal effect  $\partial \text{prob}(Y_i = 1)/\partial X_i$  for a reference individual in columns 2 and 4.<sup>10</sup> For the *CATHOLIC SCHOOL* dummy variable, we also report at the bottom of Table III the "average treatment effect" which is the average difference between the probability that a student would graduate from high school if he or she attended a Catholic high school and the probability that student would graduate if he or she attended a public school. Thus, if  $n$  is the sample size and  $\beta$  and  $\delta$  are the maximum likelihood estimates of the parameters in equation (2), then the average treatment effect equals  $(1/n)\sum_i [\Phi(X_i\beta + \delta) - \Phi(X_i\beta)]$ . We use the

10. We calculated the marginal effects for the "average" public school student, who we defined as a seventeen-year-old white female, living with both natural parents, in a family where at least one parent has a high school diploma, family income is between \$16,000 and \$20,000, who attends religious services regularly, and who lives in a suburb in the south.

TABLE III  
 PROBIT ESTIMATES OF *HIGH SCHOOL GRADUATE* AND  
*COLLEGE ENTRANT* MODELS

Independent variable <sup>a</sup>	<i>HIGH SCHOOL GRADUATE</i>		<i>COLLEGE ENTRANT</i>	
	Probit coefficient	Marginal effect <sup>b</sup>	Probit coefficient	Marginal effect <sup>b</sup>
<i>CATHOLIC SCHOOL</i>	0.777 (0.056)	0.117 (0.014)	0.384 (0.032)	0.144 (0.012)
<i>FEMALE</i>	0.041 (0.029)	0.006 (0.004)	0.021 (0.026)	0.008 (0.010)
<i>BLACK</i>	0.132 (0.045)	0.020 (0.007)	0.170 (0.042)	0.064 (0.014)
<i>HISPANIC</i>	0.080 (0.037)	0.012 (0.006)	-0.160 (0.036)	-0.060 (0.014)
<i>OTHER RACE</i>	0.346 (0.067)	0.052 (0.011)	0.316 (0.060)	0.118 (0.022)
<i>FAMILY INCOME MISSING</i>	-0.111 (0.068)	-0.017 (0.010)	-0.382 (0.055)	-0.143 (0.021)
<i>FAMILY INCOME &lt; \$7000</i>	-0.300 (0.078)	-0.045 (0.012)	-0.484 (0.080)	-0.181 (0.030)
<i>FAMILY INCOME \$7000-\$12,000</i>	-0.121 (0.073)	-0.018 (0.011)	-0.408 (0.063)	-0.153 (0.024)
<i>FAMILY INCOME \$12,000-\$16,000</i>	-0.035 (0.072)	-0.005 (0.011)	-0.319 (0.056)	-0.119 (0.021)
<i>FAMILY INCOME \$16,000-\$20,000</i>	0.000 (0.070)	0.000 (0.010)	-0.283 (0.055)	-0.106 (0.020)
<i>FAMILY INCOME \$20,000-\$25,000</i>	-0.035 (0.072)	-0.005 (0.011)	-0.196 (0.055)	-0.073 (0.021)
<i>FAMILY INCOME \$25,000-\$38,000</i>	0.037 (0.077)	0.006 (0.012)	-0.025 (0.057)	-0.009 (0.021)
<i>PARENT EDUCATION MISSING</i>	-0.730 (0.061)	-0.110 (0.013)	-0.916 (0.052)	-0.342 (0.020)
<i>PARENT HIGH SCHOOL DROPOUT</i>	-0.522 (0.058)	-0.078 (0.011)	-0.855 (0.043)	-0.320 (0.017)
<i>PARENT HIGH SCHOOL GRADUATE</i>	-0.375 (0.060)	-0.056 (0.011)	-0.602 (0.044)	-0.225 (0.015)
<i>PARENT SOME COLLEGE</i>	-0.204 (0.062)	-0.031 (0.010)	-0.290 (0.042)	-0.108 (0.016)
<i>SINGLE MOTHER</i>	-0.255 (0.041)	-0.038 (0.007)	-0.060 (0.042)	-0.023 (0.016)
<i>SINGLE FATHER</i>	-0.421 (0.063)	-0.063 (0.010)	-0.269 (0.069)	-0.101 (0.026)
<i>NATURAL MOTHER/STEP-FATHER</i>	-0.286 (0.056)	-0.043 (0.009)	-0.263 (0.060)	-0.098 (0.023)

TABLE III  
(CONTINUED)

Independent variable <sup>a</sup>	HIGH SCHOOL GRADUATE		COLLEGE ENTRANT	
	Probit coefficient	Marginal effect <sup>b</sup>	Probit coefficient	Marginal effect <sup>b</sup>
<i>OTHER FAMILY STRUCTURE</i>	-0.155 (0.048)	-0.023 (0.007)	-0.060 (0.053)	-0.023 (0.020)
<i>AGE 16</i>	0.611 (0.089)	0.092 (0.015)	0.655 (0.115)	0.245 (0.043)
<i>AGE 17</i>	1.025 (0.050)	0.154 (0.014)	0.718 (0.087)	0.268 (0.033)
<i>AGE 18</i>	0.699 (0.050)	0.105 (0.012)	0.603 (0.088)	0.225 (0.033)
<i>ATTENDS RELIGIOUS SERVICES REGULARLY</i>	0.321 (0.035)	0.048 (0.006)	0.299 (0.035)	0.112 (0.014)
<i>ATTEND RELIGIOUS SERVICES OCCASIONALLY</i>	0.082 (0.039)	0.012 (0.006)	0.115 (0.041)	0.043 (0.015)
<i>INTERCEPT</i>	0.388 (0.093)		-0.683 (0.107)	
<i>Average treatment effect of CATHOLIC SCHOOL</i>	0.130 (0.007)		0.132 (0.011)	
<i>Log/Likelihood</i>	-5155.26		-3297.87	

Asymptotic standard errors are in parentheses. The number of observations in the *HIGH SCHOOL GRADUATE* and *COLLEGE ENTRANT* models is 13,294 and 10,983, respectively.

a. Other exogenous variables include dummy variables for urban and rural schools, plus three regional dummy variables.

b. Marginal effects are calculated for a seventeen-year old white female, living with both natural parents where at least one parent has a high school degree and family income is between \$16,000 and \$20,000, attends church regularly, and lives in a suburban area in the south.

“delta” method to calculate the variance of the marginal effects and average treatment effects.

The results in Table III show that Catholic school students have a substantially higher probability of completing high school and entering a four-year college than do public school students. Our reference individual’s probability of finishing high school would be twelve percentage points higher if she went to a Catholic school than if she went to a public school. The probability that she would enter college would be fourteen percentage points higher. To place these results in perspective, the impact of Catholic schools on high school completion is more than two and one-half times larger than the effect of moving from the lowest to the highest income group, 50 percent larger than the effect of moving from the lowest to the highest parents’ education category, and three times as large

as the impact of moving from a family headed by a single female to a two-parent family. The estimated marginal effects for *CATHOLIC SCHOOL* reported in Table III are roughly equal to the average treatment effects for the entire sample.<sup>11</sup>

The other results in Table III are consistent with the literature in this field. Females, students from wealthier families, students with better educated parents, and students living with both natural parents are all more likely to graduate from high school and enter college. Students who are at least eighteen are far more likely to drop out of high school, largely because these students are more likely to have repeated a grade, a clear signal that they have struggled in school. The results on student age may also reflect, in part, the fact that compulsory education laws are not binding for older students [Angrist and Krueger 1991]. The effects of family income on high school graduation is large for students from families with incomes below \$12,000 (conditional on parents' education), but increases in income beyond \$12,000 seem to have little additional impact on the chances that a student will graduate. In contrast, the probability of college entrance increases monotonically as income rises. The results also show that although in the raw data blacks and Hispanics drop out at higher rates than do whites, once we control for observed characteristics these groups are actually more likely to finish high school.

### *B. Potential Omitted Variables Bias*

In this section we ask whether our basic results are robust. Our primary concern here is that we have omitted important (measurable) characteristics of the student that are correlated with the Catholic school variable and that, as a consequence, we have overstated the benefits of a Catholic school education. The results of some of these sensitivity tests are shown in Table IV. We reproduce the basic results from Table III in the first line of Table IV.

We begin by asking whether including measures of student ability or achievement would change our basic finding. While we would certainly expect to find that better students are more likely to finish high school and start college, we are hesitant to include

11. All of the college graduation models we present in this paper are estimated on the subsample of students who graduated from high school. Within the entire sample, 26 percent of the public school students and 53 percent of the Catholic school students entered college. The average treatment effect in the college model presented in Table III using the entire sample is 0.217 with a standard error of 0.020.



TABLE IV  
PROBIT ESTIMATES OF HIGH SCHOOL GRADUATE AND COLLEGE ENTRANT MODELS

Model	Additional exogenous variables <sup>a</sup>	HIGH SCHOOL GRADUATE				COLLEGE ENTRANT			
		No. of obs.	Probit coefficient on CATHOLIC SCHOOL	Marginal effect <sup>b</sup>	Average treatment effect	No. of obs.	Probit coefficient on CATHOLIC SCHOOL	Marginal effect <sup>b</sup>	Average treatment effect
(1)		13,294	0.777 (0.056)	0.117 (0.014)	0.130 (0.007)	10,983	0.384 (0.032)	0.144 (0.012)	0.132 (0.011)
(2)	10th GRADE TEST SCORE	11,379	0.632 (0.061)	0.093 (0.013)	0.100 (0.008)	9,567	0.367 (0.036)	0.125 (0.012)	0.111 (0.011)
(3)	10th GRADE TEST SCORE and a dummy variable for missing test score	13,294	0.722 (0.059)	0.112 (0.014)	0.120 (0.007)	10,983	0.392 (0.034)	0.135 (0.012)	0.120 (0.011)
(4)	Measures of peer groups <sup>c</sup>	13,294	0.726 (0.058)	0.129 (0.016)	0.123 (0.007)	10,983	0.308 (0.034)	0.107 (0.012)	0.104 (0.012)
(5)	Dummy variables for whether family owns a calculator, encyclopedia, more than 50 books, or a typewriter	10,797	0.710 (0.062)	0.097 (0.014)	0.111 (0.007)	9,266	0.337 (0.035)	0.130 (0.013)	0.117 (0.012)
(6)	Dummy variables for whether family owns a calculator, encyclopedia, more than 50 books, or a typewriter, and dummy variables for whether these values are missing	13,294	0.764 (0.057)	0.106 (0.013)	0.128 (0.007)	10,983	0.382 (0.032)	0.146 (0.012)	0.130 (0.012)
(7)	State dummy variables	13,294	0.826 (0.058)	0.132 (0.016)	0.136 (0.007)	10,983	0.415 (0.034)	0.134 (0.011)	0.140 (0.012)
(8)	All of the variables in models (3), (4), (6), and (7)	13,294	0.735 (0.061)	0.137 (0.019)	0.120 (0.007)	10,983	0.369 (0.037)	0.111 (0.011)	0.108 (0.012)

Asymptotic standard errors are in parentheses.

a. Other right-hand-side variables include those listed in Table III.

b. Marginal effects are calculated for the individual defined in Table III. The medium public school test scores and average public school values for the peer group measures are used in the appropriate models. For models (5), (6), and (8), individuals are assumed to own all items listed. The reference state used in models (7) and (8) is the state with the most observations in the sample.

c. A set of seven variables that measure the percent of students in a high school whose parents fall into four education categories and whose family falls into three income categories.

measures of ability or achievement in our basic model since they are potentially endogenous variables. Here we set these concerns aside for the moment and include in line (2) the student's sophomore score on the *HS&B* exams in the basic probit models. Not surprisingly, test score is an excellent predictor of both measures of educational attainment. The *t*-statistic on the test score variable is over 13 in both models. Including test score reduces the average treatment effect of Catholic schools from 13.0 percentage points in the dropout model to 10.0 and from 13.2 to 11.1 in the college model. While the effect of Catholic schools is still large in the second line of Table IV, we would argue that these models probably understate the true effect of Catholic schools. The sophomore test score is missing for over 1900 students. It is more likely to be missing for public school students and for students with the highest ex post probability of dropping out.<sup>12</sup> Excluding these observations from the data set would then drag the Catholic school coefficient downward. To illustrate this point more clearly, in line (3) we set the test score equal to zero if the score is missing and include a dummy that equals 1 if the score is missing but equals 0 otherwise. In this specification, including test scores has little impact on our basic conclusions. The average treatment effects in line (3) are very close to the average treatment effects in line (1).<sup>13</sup>

We noted above that Catholic school students are more likely to come from two-parent, high income, well-educated families; i.e., they have "better" observed characteristics. Moreover, they attend schools with peers who, on average, also have better observed characteristics. A number of authors have found that a range of social outcomes is correlated with the quality of the peer group.<sup>14</sup>

12. In our sample, the sophomore test score is missing for 20 percent of the public school students and 11 percent of the Catholic school students. High school completion rates are 84 percent for students with a valid test score, but only 74 percent for students without a score.

13. The marginal effects are calculated for the reference individual defined in Table III. In addition, we assume that this student's test score equals the median public school score in our sample. The marginal effects (standard errors) for the *10TH GRADE TEST SCORE* in the high school completion and college entrance models are 0.004 (0.0002) and 0.013 (0.001), respectively. These results suggest that a one-standard-deviation increase in the test score over the median value (about a fifteen-point increase) would increase high school completion and college entrance probabilities by six and twenty percentage points, respectively.

14. See Jencks and Mayer [1990] for a review of the literature on peer effects, and see Mayer [1991] for an estimate of the effects of peer groups on high school completion rates. Both of these studies are concerned with single-equation estimates of the effects of peers on the economic outcomes of teens. Evans, Oates, and Schwab [1992] argue that because families can choose among schools and neighborhoods, a student's peer group is a potentially endogenous variable. We do not consider the endogeneity of the peer measures in this paper.

Therefore, it is possible that we have overstated the effect of Catholic schools by ignoring peer group effects. We have calculated a set of seven peer group measures for each school in our sample using data from all students in the first wave of *HS&B* (and thus in many cases these peer group measures are based on 72 students). Our peer group measures equal the proportion of students in a school whose parents fall into four education categories and whose family falls into three income categories.<sup>15</sup> In line (4) of Table IV we include these peer group measures in our basic probit. Although a number of the peer variables are statistically significant and indicate that better peer groups do increase the probability of completing high school and entering college, the coefficients on the *CATHOLIC SCHOOL* dummy variable and the average treatment effects change very little.<sup>16</sup>

A number of previous studies have found that measures of the family's inputs to education are important determinants of a student's score on standardized exams [Coleman, Hoffer, and Kilgore 1982; Coleman and Hoffer 1987; Noell 1982]. Coleman, for example, includes indicators for whether the student's family owns a calculator, an encyclopedia, more than 50 books, or a typewriter. As the results in line (5) indicate, including these variables does reduce the impact of a Catholic school education, but the Catholic school effect remains quite large. However, as with the test score data, there are many missing observations for these variables.

15. *HS&B* did collect information at the school level which could be used directly to form peer group measures. As with the test score data, however, these variables are missing for many schools (especially public schools). Although the peer group measures we constructed are based on a sample rather than a census of students from a high school, the large number of observations per school should provide us with a good approximation of the composition of the school. We have tested this argument by using this same procedure to construct a measure of the proportion of the students in a school who are black and comparing this estimate with the figure reported in the school survey. The correlation coefficient for these two series is 0.97.

16. The marginal effects are calculated for a student who has an average public school value of the peer group variables. Because of space limitations, we do not report the parameter estimates for all seven peer group measures in both models. We note that the peer group variables measuring parents' education tended to be more important determinants of high school completion and college entrance than measures of income. In fact, once we included parents' education, the peer measures for income became largely insignificant. The marginal effects (standard errors) for the peer group variables measuring parents' education in the high school completion model are as follows: % *PARENT EDUCATION MISSING* -0.24 (0.06), % *PARENT EDUCATION LESS THAN HIGH SCHOOL* -0.12 (0.05), % *PARENT EDUCATION HIGH SCHOOL GRADUATE* -0.11 (0.04), % *PARENT EDUCATION SOME COLLEGE* -0.20 (0.05). The corresponding values for the college entrance model are -0.63 (0.10), -0.35 (0.07), -0.57 (0.05), -0.50 (0.08). The reference group in both models is the percent of students in the school whose parents are college educated.

Letting the indicator variables equal zero if the value is missing and including four dummy variables that equal one if the variable is missing, we see in line (6) that these four family measures have little impact on the average treatment effect.<sup>17</sup>

Given the variation in state labor market conditions, compulsory schooling laws and state support for higher education, it is possible that there are strong state effects in the models we have estimated. If these state effects are correlated with the probability of attending a Catholic high school, they may have led us to overstate the impact of a Catholic education on educational attainment. *HS&B* does not identify the state in which a student lives. We can, however, identify all of the students who live in the same state (although we do not know which state that is). The Local Labor Market Indicators for *HS&B* (1980–1982) supplemental file reports local labor market statistics at the county, MSA, and state level for the years 1980–1982. There are 51 unique values for the product of all state level unemployment rates for the three years. In line (7) of Table IV we include 50 state dummy variables in the basic probit models. The marginal and average treatment effects in this fixed-effects model are very similar to the estimates in line (1).<sup>18</sup>

Finally, we run one large model that includes the test scores and a dummy for missing test scores, the seven peer group measures, the four measures of home inputs into education and indicators for missing values, and 50 state dummy variables. Including all 67 of these variables decreases the average treatment effect of a Catholic education on high school completion and college entrance by 8 and 17 percent, respectively. For both dependent variables, however, the average treatment effect is still more than ten percentage points. Our results, therefore, appear to be robust to rather different model specification.

### *C. Catholic School Selectivity*

Public schools must accept virtually all students who live within their attendance boundaries, and in general it is very difficult for most public schools to expel a student. Catholic schools, on the other hand, are free to select their students and to expel students because of poor behavior or poor academic performance.

17. To calculate the marginal effects for these two models, we assume that the individual owned all four items.

18. We calculated marginal effects for a student who lived in the state with the most observations in our data set.

Thus, part of the Catholic school effect we have found could be due to the way Catholic schools choose their students. They are in a better position than public schools to avoid students who in the end are likely to drop out.<sup>19</sup>

The bivariate probit models we present in the next section of the paper can address this question. But we can also present some evidence on this point within our single-equation framework. *HS&B* asked school officials whether their schools used entrance exams as part of the admissions process and whether there was a waiting list for the school. If school selection does play an important role in explaining the success of Catholic schools, then we would expect Catholic schools that use entrance exams or that have waiting lists to have lower dropout rates than other Catholic schools. To test this hypothesis, we interacted the Catholic school dummy variable with these school characteristics. The results are presented in Table V. In both instances we do not find a pattern that is consistent with the school selection hypothesis. In all of the models in Table V, we are unable to reject the hypothesis that there is no difference in graduation or college entrance rates across types of Catholic schools.

#### *D. Definition of the Dependent Variables*

As a final sensitivity test in this section, we asked whether our results are robust to alternative definitions of the dependent variables. We have reestimated our models allowing for more inclusive measures of high school graduation and college completion. For example, we have estimated models where we count those with GED's and those who received diplomas after February of 1984 as high school graduates. Counting these students as high school graduates increases the sample average graduation rate to 90.4 percent and decreases the Catholic school average treatment effect to eight percentage points. Given the recent work of Cameron and Heckman [1993], who found that students earning a GED

19. The evidence from the existing literature on the role of student selection in the success of Catholic schools is somewhat mixed. Bryk, Lee, and Holland [1993] argue that, in general, Catholic schools are not highly selective in their admissions. They find that the typical Catholic school accepts 88 percent of the students who apply. They also argue that contrary to widespread belief, very few students are expelled from Catholic schools for either academic or disciplinary grounds. On average, Catholic high schools dismiss fewer than two students per year. Witte [1990] presents evidence that Catholic schools do in fact screen admissions so that they are able to avoid students who are likely to do poorly. For example, he finds that 55.5 percent of Catholic school principals, as compared with only 8.4 percent of public school principals, indicated that prior academic record was an important factor in admission decisions.

TABLE V  
PROBIT ESTIMATES OF HIGH SCHOOL GRADUATE AND COLLEGE ENTRANT MODELS

Independent variables <sup>a</sup>	% of Catholic school students	HIGH SCHOOL GRADUATE			COLLEGE ENTRANT		
		Probit coefficient	Marginal effect <sup>b</sup>	Probit coefficient	Marginal effect <sup>b</sup>	Probit coefficient	Marginal effect <sup>b</sup>
CATHOLIC SCHOOLS WITH ENTRANCE EXAMS	0.842	0.778 (0.064)	0.117 (0.014)	0.388 (0.036)	0.145 (0.013)		
CATHOLIC SCHOOLS WITHOUT ENTRANCE EXAMS	0.158	1.059 (0.178)	0.159 (0.030)	0.333 (0.072)	0.124 (0.027)		
CATHOLIC SCHOOLS WITH WAITING LISTS	0.512			0.850 (0.087)	0.128 (0.018)	0.378 (0.044)	0.141 (0.016)
CATHOLIC SCHOOLS WITHOUT WAITING LISTS	0.488			0.782 (0.081)	0.118 (0.016)	0.379 (0.044)	0.141 (0.016)
-2 loglikelihood test <sup>c</sup>		2.40		0.36		0.52	0.02

Asymptotic standard errors are in parentheses. Answers to the entrance exam and waiting list questions were missing in some cases. The number of observations (mean of dependent variable) in the HIGH SCHOOL GRADUATE and COLLEGE ENTRANT models is 13,033 (0.821) and 10,735 (0.373), respectively.

a. Other right-hand-side variables include those listed in Table III.

b. The marginal effect is calculated for the individual described in Table III.

c. The test statistic is the statistic required to test the equality of the coefficients on the two types of Catholic schools. The test is asymptotically distributed as a  $\chi^2$  with one degree of freedom. The 95 percent critical value is 3.84.

have poorer labor market outcomes than regular high school graduates, it is not clear that equating these two groups is appropriate. We also counted those who entered two-year colleges and those entering any college after February of 1984 as college entrants. This change in definition increases the mean of the dependent variable to 60 percent, but the Catholic school average treatment effect remains roughly twelve percentage points.<sup>20</sup>

#### IV. TESTING FOR SELECTIVITY BIAS

All of the single-equation models we presented in the previous section treat the decision to attend Catholic schools as exogenous. As Goldberger and Cain [1982] and others argue (and Coleman acknowledges), selectivity bias is potentially the most serious problem in the literature on the effectiveness of private schools. The following example illustrates the nature of the error that could arise. Consider a child whose parents care a great deal about his welfare. We would expect this child to do well in school for two reasons. First, his parents will see that he attends a better than expected school and will be more willing to pay the cost of sending him to a private school. Second, he will succeed in part because of factors that cannot be observed but are under his parents' control. They will spend more time reading to him, they will stress the importance of good grades, and they will see that he does his homework. A single-equation model would mistakenly attribute all of this child's success to his private school. More formally, our results would be biased because the school choice variable in the high school completion and college entrance equations would be correlated with the error term. Similar problems will arise if Catholic schools are able to screen potential students on factors such as a personal interview or they expel students on the basis of poor behavior and academic performance.

##### A. A Bivariate Probit Model

In this section we outline a simple bivariate probit model that allows for these possibilities. Following the latent variable model in equation (1), suppose that the net benefits of attending Catholic school  $C_i^*$  can be written as

$$(3) \quad C_i^* = Z_i\gamma + \mu_i,$$

20. These results are available upon request.



where  $Z_i$  is a vector of observables and  $\mu_i$  is a random error. A family will enroll a child in a Catholic school if the net benefits are positive; i.e., if  $C_i^* > 0$ . To allow for the possibility that the unobserved determinants of a student's performance and the unobserved determinants of a family's decision to enroll their teenager in a Catholic school are correlated, we assume that  $\epsilon_i$  and  $\mu_i$  are distributed bivariate normal, with  $E[\epsilon_i] = E[\mu_i] = 0$ ,  $\text{var}[\epsilon_i] = \text{var}[\mu_i] = 1$  and  $\text{cov}[\epsilon_i, \mu_i] = \rho$ . Because both decisions we model are dichotomous, there are four possible states of the world ( $Y_i = 0$  or 1 and  $C_i = 0$  or 1). The likelihood function corresponding to this set of events is therefore a bivariate probit.

This system is identified if at least one variable in  $Z_i$  is not contained in  $X_i$ . Initially, we use as our instrument a dummy variable *CATHOLIC RELIGION* that equals 1 if the student reports that she is Catholic and 0 otherwise. Subsequently, we consider alternative instruments such as whether a student attends school in a predominantly Catholic area and a set of instruments that we form by interacting *CATHOLIC RELIGION* with religious attendance variables. We look at the validity of these variables as instruments below.

The bivariate probit results are summarized in Table VI. We repeat the basic single-equation results from Table III in lines (1) and (6) of Table VI. In lines (2) and (7) we present the maximum likelihood (MLE) bivariate probit estimates using *CATHOLIC RELIGION* as an instrument and the same right-hand variables we use in the basic single-equation models. In both the high school graduate and college entrance models, the MLE estimates of the marginal effect of Catholic schools and the average treatment effect are quite close to the single-equation estimates. The MLE estimate of the correlation coefficient  $\rho$  is negative in the high school completion model and positive in the college model, but in both cases the estimate is small, imprecise, and thus statistically insignificant.

In the remainder of Table VI we look at the impact of adding state effects and tenth grade test scores (variables that appeared to be important when we looked at them in Table IV) to the bivariate probit model. These additional variables have little impact on our basic conclusions in the dropout model. The estimated average treatment effect in lines (3)–(5) is similar to the average treatment effect in (2). Our estimates of  $\rho$  are always statistically insignificant. Adding tenth grade test scores to the college models (regardless of whether we include state effects as well) reduces the average treatment effect and leads to an estimate of  $\rho$  which is positive and

TABLE VI  
MAXIMUM LIKELIHOOD ESTIMATES OF *HIGH SCHOOL GRADUATE* AND  
*COLLEGE ENTRANT* BIVARIATE PROBIT MODEL USING *CATHOLIC RELIGION*  
AS AN INSTRUMENT

		MLE estimates of bivariate probit model				
Model	Other variables in $X_i^b$	Coefficient on <i>CATHOLIC SCHOOL</i>	Marginal effect <sup>c</sup>	Average treatment effect	$\rho$	2SLS estimate of coefficient on <i>CATHOLIC SCHOOL</i>
<i>HIGH SCHOOL GRADUATE</i> <sup>a</sup>						
(1)		0.777 (0.056)	0.117 (0.014)	0.130 (0.007)		0.096 <sup>d</sup> (0.008)
(2)		0.859 (0.115)	0.133 (0.022)	0.141 (0.014)	-0.053 (0.067)	0.127 (0.024)
(3)	<i>10TH GRADE TEST SCORE AND TEST MISSING</i>	0.678 (0.126)	0.078 (0.018)	0.114 (0.017)	0.028 (0.072)	0.103 (0.024)
(4)	<i>STATE EFFECTS</i>	0.911 (0.121)	0.142 (0.027)	0.144 (0.015)	-0.050 (0.072)	0.114 (0.024)
(5)	<i>10TH GRADE TEST SCORE, TEST MISSING, AND STATE EFFECTS</i>	0.746 (0.132)	0.124 (0.028)	0.121 (0.016)	0.025 (0.077)	0.134 (0.030)
<i>COLLEGE ENTRANT</i> <sup>a</sup>						
(6)		0.384 (0.032)	0.144 (0.012)	0.132 (0.011)		0.137 <sup>d</sup> (0.011)
(7)		0.288 (0.079)	0.109 (0.033)	0.098 (0.028)	0.067 (0.049)	0.148 (0.030)
(8)	<i>10TH GRADE TEST SCORE AND TEST MISSING</i>	0.211 (0.083)	0.078 (0.034)	0.064 (0.026)	0.124 (0.052)	0.098 (0.024)
(9)	<i>STATE EFFECTS</i>	0.341 (0.084)	0.110 (0.032)	0.115 (0.029)	0.056 (0.053)	0.092 (0.024)
(10)	<i>10TH GRADE TEST SCORE, TEST MISSING, AND STATE EFFECTS</i>	0.277 (0.090)	0.071 (0.026)	0.082 (0.027)	0.113 (0.046)	0.098 (0.028)

Asymptotic standard errors are in parentheses.

a. Models (1) and (6) are single-equation estimates from Table III. To estimate models (4), (5), (9), and (10), we deleted all states with no Catholic school students. The high school completion and college entrance models contain 10,120 and 8470 observations, respectively. Both models contain data from twenty states. Models (1), (2), and (3) contain 13,294 observations, and models (6), (7), and (8) contain 10,983 observations.

b. Other exogenous variables include those listed in Table III.

c. Marginal effects are calculated for the individual defined in Table III.

d. Estimated *CATHOLIC SCHOOL* coefficient from a linear probability model.

significantly different from zero. Even in these models, however, attending a Catholic high school increases the probability of entering college by more than seven percentage points.

The last column of Table VI presents estimates of a somewhat different econometric model. Although the bivariate probit model is straightforward to estimate, the model is substantially more complicated than a standard two-stage least squares (2SLS) model one could estimate if all potentially endogenous variables were continuous. Fortunately, Angrist [1991] has shown that instrumental variable estimation is a viable alternative to the bivariate probit model. In the notation of equation (1) Angrist showed in a Monte Carlo study that if we ignore the fact that the dependent variable is dichotomous and estimate

$$(4) \quad Y_i = X_i\beta + C_i\delta + \epsilon_i$$

with instrumental variables (IV), the IV estimate of  $\delta$  is very close to the estimated average treatment effects calculated in a bivariate probit model.

A comparison of the third and fifth columns of Tables VI illustrate the Angrist result. The 2SLS estimates of the Catholic school effect and the average treatment effect are very similar in all of the models we have presented in that table. We will take advantage of this result below where we focus on the validity of our instruments.

### *B. The Validity of the Instruments*

If *CATHOLIC RELIGION* is a valid instrument, then (i) it must be a determinant of the decision to attend a Catholic School, but (ii) it must not be a determinant of the decision to drop out of high school or to start college; i.e., it must not be correlated with the error term  $\epsilon$ . Not surprisingly, it is easy to show that it meets the first test. In a probit model that explains the probability a student will attend a Catholic school, the  $t$ -statistic on the *CATHOLIC RELIGION* variable is 36.3. In a simple OLS model where *CATHOLIC SCHOOL* is regressed on *CATHOLIC RELIGION*, the  $R^2$  is 0.16.

Thus, the credibility of our bivariate probit results turns on our assumption that high school students who are Catholic are no more likely to graduate from high school or to begin college than otherwise identical students who are not Catholic. There is little evidence from other studies that would suggest that there are important differences in the education levels of Catholics and non-Catholics. Taubman [1975, Table 3, p. 179], for example, found that the level of education of Jews and Protestants was not significantly different from the level of education of Catholics.

Using the data appendix in Tomes [1984], we find that Catholics and non-Catholics have virtually the same average years of education (12.88 versus 12.64, respectively). However, in the raw *HS&B* data (that is, without accounting for variables that are correlated with the Catholic religion variable), Catholic students are more likely to finish high school and to go to college. In the full sample, 88.4 percent of Catholics graduated from high school as compared with 79.0 percent of non-Catholics. Among students who finished high school, 42.8 percent of Catholics entered college as compared with 33.5 percent of non-Catholics. These differences could lead us to estimate of the effect of a Catholic school education that is large but possibly misleading.

The following simple calculation makes this point clear. With our discrete instrument and assuming a bivariate linear model where the only right-hand-side variable is *CATHOLIC SCHOOL*, we can generate an instrumental variable estimate for the *CATHOLIC SCHOOL* effect through a comparison of means. Using the results in Wald [1940], the instrumental variable estimate is simply the difference in graduation rates for Catholics and non-Catholics, divided by the difference in the probability that Catholics and non-Catholics attend Catholic high schools. In the full sample, 39.1 percent of Catholics and 6.4 percent of non-Catholics go to Catholic schools. Thus, the Wald instrumental variable estimate for the impact of Catholic schools in the dropout model is  $(.884 - .790)/(.392 - .064) = .287$ . For the sample that has completed high school, 43.1 percent of Catholics and 7.8 percent of non-Catholics are in Catholic high schools, implying a Wald estimate for the college entrance model of  $(.428 - .335)/(.431 - .078) = .263$ .

These raw numbers suggest that, on average, Catholics are better educated than non-Catholics. This will pose a problem for our estimation if, *after controlling for other observed characteristics*, the Catholic religion instrument is correlated with a student's unobserved propensity to graduate from high school or enter college. The most straightforward way to address this issue is to include *CATHOLIC RELIGION* in the single-equation probits we discussed in Table III. We recognize that this is not a formal test since if the correct specification is a bivariate probit then single-equation models are misspecified, but it does offer a clear sense of the patterns in the data. If we include *CATHOLIC RELIGION* in a single-equation dropout model, its estimated coefficient is positive but statistically insignificant. The estimated marginal effect of the

*CATHOLIC RELIGION* variable in that model is very small compared with the effect of going to a Catholic school. Although this is not a direct test of whether our instrument is valid, it does indicate that, as a group, Catholics are no different from non-Catholics.

We performed three further tests in order to explore this issue. First, we have constructed additional sets of instruments that recognize that there is heterogeneity in the demand for Catholic schools among Catholics. These models, for example, allow for the possibility that Catholics who attend church regularly are more likely to send their children to Catholic schools than are Catholics who rarely go to church. Second, following Neal [1994] and Hoxby [1994], we have used a very different instrument: the proportion of the population in the county where a student attends school that is Catholic.<sup>21</sup> They argue that it is probable that there will be more Catholic schools in predominantly Catholic areas and thus students (given their observable characteristics) who live in such areas are more likely to attend a Catholic school.<sup>22</sup> There is no reason, however, to suspect that the probability that a student will finish high school or start college depends on her neighbors' religion. Third, we have formed a final set of instruments by combining the Catholic religion and Catholic population variables. The models, like the models that incorporate church attendance, allow for heterogeneity among Catholics (e.g., Catholics who live in heavily Catholic neighborhoods are more likely to send their children to Catholic schools).

This research strategy is particularly attractive since it leads to several models that are overidentified. In those models, we can use Newey's [1985] method of moments specification tests to look

21. The Association of Statistics of American Religious Bodies (ASARB) provided us with data on the Catholic population by county. Their data are drawn from a survey of over 200,000 congregations and churches with total membership of nearly 115 million. See Quinn et al. [1982] for a discussion of these data. With the ASARB data and data from the 1980 Census, we then constructed an estimate of the percent Catholic at the county level. County identifiers are not available in the public use *HS&B* data. We have entered into an agreement with the U. S. Department of Education where we created a data set that included the percent Catholics in a county and county FIPS codes. The contractor for the *HS&B* data set then merged the data set we created with student identification numbers. In order to protect the confidentiality of the data, the percent Catholic in the county variable was grouped (0.0–4.9 percent, 5.0–9.9 percent, etc.) and top-coded at 70 percent.

22. This hypothesis is easily validated. In a first-stage probit model where *CATHOLIC SCHOOL* is the dependent variable, the coefficient on % *CATHOLIC IN THE COUNTY* is .001 with a standard error of  $3.1 \times 10^{-4}$ . To put this result into perspective, moving a student from the twenty-fifth percentile % *CATHOLIC IN THE COUNTY* to the seventy-fifth percentile increases the probability that the student will attend a Catholic school by ten percentage points.

at the internal consistency of the model; i.e., whether the variables we use as instruments can be excluded from the structural equation. In a 2SLS model the test statistic is constructed by regressing the estimated errors from the structural model of interest on all exogenous variables in the system. The number of observations times the uncentered  $R^2$  from this synthetic regression is distributed as  $\chi^2$  with degrees of freedom equal to the number of instruments minus the endogenous right-hand-side variables in the structural equation of interest. Here again, we recognize that this is not a proper formal test. Although the Angrist [1991] result allows us to accurately estimate the average treatment effect via 2SLS, it is not clear that the assumptions necessary to perform the tests of overidentifying restrictions are met when both  $Y$  and  $C$  are discrete. This class of tests, however, is the best available diagnostic.

Table VII summarizes the estimates of models that rely on these alternative instruments. All of the models include the exogenous variables that we included in the basic versions of our probits presented in Table III. In lines (1) and (7) we repeat the estimates of the Catholic school effect from lines (2) and (7) in Table VI. For the *HIGH SCHOOL GRADUATE* models, we first interact Catholic religion with the religious attendance variables. Next, we use % *CATHOLIC IN COUNTY* as an instrument. We next use both *CATHOLIC RELIGION* and % *CATHOLIC IN COUNTY* as instruments, and then add the interaction of these variables to the previous model. Finally, in line (6) we use % *CATHOLIC IN COUNTY* as our instrument and include *CATHOLIC RELIGION* as a covariate in both the Catholic school and dropout equations.

Our estimates of the Catholic school effect from the bivariate probit models in lines (1)–(5) fall between 0.114 and 0.141. The 2SLS estimates are quite similar to the bivariate probit estimates in all cases. We cannot construct a test of overidentifying restrictions for the models in lines (1) and (3) since those models are exactly identified. For the other three models, however, all test statistics are well below their 95 percent critical value. The 2SLS estimate of the Catholic school effect in line (6) is consistent with our other estimates, though this effect is measured imprecisely (the standard error is more than ten times as large as the standard errors in most of the first five models). The bivariate probit estimate of model (6) is somewhat smaller than the other estimates in the upper panel of Table VII. It thus appears that our graduation

TABLE VII  
SYSTEM ESTIMATES OF *HIGH SCHOOL GRADUATE* AND *COLLEGE ENTRANT*  
MODELS WITH ALTERNATIVE INSTRUMENTS

Instruments	Bivariate probit estimates of average treatment effect, <i>CATHOLIC SCHOOL</i>	2SLS estimate of <i>CATHOLIC SCHOOL</i>	Test of overidentifying restrictions, (d.o.f.), [95% critical value]
<i>HIGH SCHOOL GRADUATE</i> <sup>a</sup>			
(1) <i>CATHOLIC RELIGION</i>	0.141 (0.014)	0.127 (0.024)	
(2) <i>CATHOLIC RELIGION</i> × <i>ATTENDANCE AT RELIGIOUS SERVICES</i>	0.141 (0.013)	0.107 (0.022)	3.29 (2) [5.99]
(3) % <i>CATHOLIC IN COUNTY</i>	0.114 (0.033)	0.130 (0.076)	
(4) <i>CATHOLIC RELIGION</i> and % <i>CATHOLIC IN COUNTY</i>	0.139 (0.044)	0.127 (0.024)	0.10 (1) [3.84]
(5) <i>CATHOLIC RELIGION</i> , % <i>CATHOLIC IN COUNTY</i> AND <i>CATHOLIC RELI- GION</i> * % <i>CATHOLIC IN COUNTY</i>	0.137 (0.014)	0.127 (0.024)	0.84 (2) [5.99]
(6) % <i>CATHOLIC IN COUNTY</i> <sup>b</sup>	0.061 (0.038)	0.144 (0.373)	
<i>COLLEGE ENTRANT</i> <sup>a</sup>			
(7) <i>CATHOLIC RELIGION</i>	0.098 (0.028)	0.148 (0.030)	
(8) <i>CATHOLIC RELIGION</i> × <i>ATTENDANCE AT RELIGIOUS SERVICES</i>	0.122 (0.127)	0.167 (0.027)	6.3 (2) [5.99]
(9) % <i>CATHOLIC IN COUNTY</i>	0.240 (0.053)	0.656 (0.093)	
(10) <i>CATHOLIC RELIGION</i> and % <i>CATHOLIC IN COUNTY</i>	0.115 (0.037)	0.161 (0.029)	33.7 (1) [3.84]
(11) <i>CATHOLIC RELIGION</i> and <i>CATHOLIC RELIGION</i> × % <i>CATHOLIC IN COUNTY</i> <sup>c</sup>	0.071 (0.028)	0.104 (0.031)	0.81 (1) [3.84]

Asymptotic standard errors are in parentheses. The number of observations in the *HIGH SCHOOL GRADUATE* and *COLLEGE ENTRANT* models is 13,294 and 10,983, respectively.

a. Other exogenous variables include those listed in Table III.

b. *CATHOLIC RELIGION* is included as an exogenous variable in the model.

c. % *CATHOLIC IN COUNTY* is included as an exogenous variable in the model.

results are fairly robust, though the results where we depend on *CATHOLIC RELIGION* as an instrument are estimated more precisely.

The *COLLEGE ENTRANT* models in lines (7) through (10)



parallel the graduation models in lines (1) through (4). The *COLLEGE ENTRANT* models are much more sensitive to the choice of instruments than are the *HIGH SCHOOL GRADUATE* models. In particular, versions of the model that use % *CATHOLIC IN COUNTY* as an instrument sometimes lead to results that are substantially different from the results we reported earlier. For example, in line (9) where we use % *CATHOLIC IN COUNTY* as the single instrument, the 2SLS estimate of *CATHOLIC SCHOOL* is implausibly large. The tests of overidentifying restrictions in the college model where we interact *CATHOLIC RELIGION* with the religious attendance variable is slightly larger than the critical value (the  $p$ -value is approximately 0.043), but the college model in line (10) clearly rejects the null hypothesis of internal consistency.

We suspect that the problem is that Catholics are likely to live in states where large numbers of students go on to college. To test this hypothesis, we used the data files from the 1980–1982 October Current Population Surveys and calculated state-level averages of the percent of 18 to 22 year-olds who are enrolled in college. The raw correlation between these values and the percent of the population in a state that is Catholic is 0.38 ( $p$ -value of 0.006). Because % *CATHOLIC IN COUNTY* may be capturing some unobserved state characteristics in the college models, in line (11) we included it as an exogenous variable and use *CATHOLIC RELIGION* and the interaction *CATHOLIC RELIGION* and % *CATHOLIC IN COUNTY* as instruments. In that model the estimated average treatment effect is 10.4 percent, and the statistic required for the test of overidentifying restrictions is well below the 95 percent critical value.

### *C. Heterogeneity in the Catholic School Effect*

We have also explored the impact of Catholic schools on different subgroups of our sample, and thus, for example, we have estimated separate models for blacks and whites and Catholics and non-Catholics. When we divide the sample into Catholics and non-Catholics, we clearly cannot use *CATHOLIC RELIGION* as an instrument and thus must rely on % *CATHOLIC IN COUNTY* to identify those bivariate probit models. As we showed in Table VII, % *CATHOLIC IN COUNTY* led to several implausible results in the college models. We therefore focus on high school graduation in this section of the paper.

Table VIII presents estimates of the average treatment effect of a Catholic school education for various subgroups. In the

TABLE VIII  
HETEROGENEITY OF THE AVERAGE TREATMENT EFFECT,  
HIGH SCHOOL GRADUATE MODELS

Sample	Number of obs.	Mean <i>HIGH SCHOOL GRADUATE</i>	Average treatment effect, <i>CATHOLIC SCHOOL</i> <sup>a</sup>		
			Single-equation probit	Bivariate probit estimates with instructions:	
				% <i>CATHOLIC IN COUNTY</i>	<i>CATHOLIC RELIGION</i>
<i>WHITE</i>	7831	0.826	0.141 (0.007)	0.086 (0.039)	0.128 (0.016)
<i>BLACK</i>	1833	0.803	0.134 (0.019)	0.111 (0.101)	0.146 (0.044)
<i>URBAN</i> <sup>b</sup>	3150	0.774	0.172 (0.016)	0.139 (0.069)	0.184 (0.037)
<i>SUBURBAN</i>	6696	0.862	0.109 (0.008)	-0.003 (0.052)	0.120 (0.017)
<i>SOPHOMORE TEST, FIRST QUARTILE</i>	2842	0.658	0.213 (0.025)	0.113 (0.145)	0.242 (0.051)
<i>SOPHOMORE TEST, SECOND QUARTILE</i>	2842	0.829	0.105 (0.016)	0.128 (0.066)	0.110 (0.037)
<i>SOPHOMORE TEST, THIRD QUARTILE</i>	2854	0.916	0.069 (0.010)	0.176 (0.039)	0.071 (0.020)
<i>SOPHOMORE TEST, FOURTH QUARTILE</i>	2841	0.960	0.030 (0.007)	-0.217 (0.188)	0.012 (0.031)
<i>CATHOLIC</i>	5104	0.884	0.107 (0.008)	0.328 (0.033)	
<i>NON-CATHOLIC</i>	8190	0.790	0.145 (0.013)	0.072 (0.098)	

Asymptotic standard errors are in parentheses.

a. Other exogenous variables include those listed in Table III.

b. Schools in the South were deleted from this subsample because there were no urban Catholic schools.

single-equation probits and bivariate probits where we use *CATHOLIC RELIGION* as an instrument, Catholic schools have a larger impact on students who have the lowest probability of finishing high school: blacks, students in urban areas, and students with low test scores. We still find, however, a large, statistically significant Catholic school effect for white and suburban students. These results are in contrast to Neal [1994], who found that Catholic schools raise the probability that urban black students will graduate but have little impact on other groups of students.

Some of these patterns emerge in bivariate probits where we use % *CATHOLIC IN COUNTY* as an instrument, though in general, these models are estimated less precisely. The effect on black and white students is similar, but the average treatment

effect for blacks is not significantly different from zero. The pattern across test score groups is difficult to interpret, and the Catholic school effect for Catholics is implausibly large. In all, these results and the *COLLEGE ENTRANT* results in Table VII lead us to conclude that while the argument in favor of using % *CATHOLIC IN COUNTY* to identify the bivariate probit models is quite plausible, the actual gains from doing so are not as clear as we had first hoped.<sup>23</sup>

## V. SUMMARY AND CONCLUSIONS

Spurred by the work of Coleman et al., academics and policy-makers have been involved in a decade-long debate over the relative effectiveness of public and private schools. This debate has been waged largely over a single outcome measure: standardized test scores. But, as Card and Krueger [1992, p. 37] have argued, "success in the labor market is at least as important a yardstick for measuring the performance of the educational system as standardized tests." In this paper we have looked at two measures of education that are clearly linked to virtually every measure of success in the labor market: the decisions to finish high school and go to college. We find that teens enrolled in Catholic schools have a significantly higher probability of completing high school and starting college, that the results appear to be robust, and that we cannot attribute the differences between sectors to sample selection bias. Catholic schools appear to have particularly large effects for urban students. This result has some potentially important policy implications given the concern over the quality of public schools in many inner cities. Most of our conclusions are consistent with other work on this problem including Neal [1994], who uses a different data set but a similar econometric approach, and Sander and Krautmann [1995] (which we learned of only after finishing the research for this paper), who use the same data set, a somewhat different econometric approach, and different instruments.

Our research leaves open a number of questions. First, it is possible that further analysis of the *HS&B* data or other data will make the Catholic school effect go away. For example, perhaps we

23. Implicitly, we have treated % *CATHOLIC IN COUNTY* as an exogenous variable. It will be correlated with the error term in the outcome equations if, for example, families that care a great deal about education move to counties where many Catholics live in order to take advantage of the availability of Catholic schools or lower tuition as a member of the parish. This argument could explain the problems we have found when we try to use this variable as an instrument.

have missed an important omitted variables problem or possibly a different approach to selectivity bias will yield different conclusions. Second, if Catholic schools are as effective as our results suggest, then we are left with a puzzle: why do not more families (particularly lower income Catholic families) make a fairly modest investment and send their children to a Catholic school? Third, if Catholic schools are more effective than public schools, we need to know more about the source of their effectiveness. Coleman et al. attribute this success to Catholic schools' emphasis on discipline, attendance, and homework. Our research does not address this issue, but it is an obvious next step. Finally, we need to know whether it will ever be possible to apply the lessons we learn from the Catholic schools to nonreligious private schools. In some ways, Catholic schools are like other private schools—they must meet the test of the market. But in other ways they are obviously fundamentally different, and it is not clear that they succeed because of the importance of religion or the discipline of competition.<sup>24</sup>

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24. There is substantial disagreement over this issue in the literature. See, for example, Bryk, Lee, and Holland [1993] and Chubb and Moe [1990] for two very different views.

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