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EXPLAINING RISING INCOME AND WAGE INEQUALITY AMONG THE COLLEGE-EDUCATED

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ABSTRACT

The incomes and wages of college-educated Americans have become significantly more dispersed since 1970. This paper attempts to decompose this growing dispersion into three possible sources of growth. The first source, or "extensive margin," is the increasing demographic diversity of people who attend college. The second is an increasing return to aptitude. The third, or "intensive margin," combines the increasing self-segregation (on the basis of aptitude) of students among colleges and the increasing correlation between the average aptitude of a college's student body and its expenditure on education inputs. These tendencies are the result of changes in the market structure of college education, as documented elsewhere. We find that about 70% of the growth in inequality among recipients of baccalaureate degrees can be explained with observable demographics, measures of aptitude, and college attributes. About 50% of the growth in inequality among people who have 2 years of college education can be similarly explained. Of the growth that can be explained, about 1/4th is associated with the extensive margin, 1/3rd with an increased return to measured aptitude, and 5/12ths with the intensive margin. If the intensive margin is not taken into account, the role of increasing returns to aptitude is greatly overstated.

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I. Introduction

Income and wage inequality among adults with at least some college education has risen in the U.S. since 1970, so that the difference between a male in this group who is at the 90th percentile of the income distribution and a male at the 10th percentile has risen from about $13,275 in 1972 to about $49,000 in 1995 (both in 1995 dollars). In this paper, we attempt to decompose the increase in income and wage inequality into three components. The first is the "extensive margin," or the increase due to the increasingly diverse backgrounds of people who attend college.[1] The second is an increasing rate of return to aptitude, so that a given distribution of aptitude among the college-educated generates an increasingly wide income distribution.[2] The third component is the change in the market structure of college education such that a person of a given aptitude interacts differently with colleges. As shown in Hoxby (1997a,b), colleges have become increasingly segregated on the basis of students' aptitude, so that aptitude differentials within each college are falling and aptitude differentials between colleges are rising. Also, colleges' per-student expenditures have become increasing correlated with the aptitude of their student bodies. We call these phenomena the "intensive margin" because they affect the peers and other inputs that a student experiences once he has joined the ranks of college students.

We are particularly interested in the intensive margin, partly because it is a phenomena that has not been studied and partly because it is a *mechanism* by which a given distribution of aptitude can play out differently over time as education supply changes. Moreover, it is the only one of the three components

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[1] The terms "extensive margin" is used to avoid confusion. Alternative terms would be "selection into the group" or "composition of the group," but the concepts of selection and composition are also needed to explain the "intensive margin" of college education.

[2] We use "aptitude" to refer to the combination of ability and achievement that forms the "aptitude to succeed in college," the standard used in college admissions tests and similar examinations. Our references to aptitude should not be interpreted as though they referred to innate, cognitive ability.

Several other authors have suggested that an increasing return to aptitude explains a significant amount of the increase in income and wage inequality. See Blackburn and Neumark (1993), Heckman (1995), Levy, Murnane, and Willett (1995), Heckman *et al* (1996), Cawley, Heckman, and Vytlacil (1998), and Murnane *et al* (1998).

that is both real and probably permanent. The increasing integration of the market for college appears to be due to decreased information costs (multilateral information exchanges between students, colleges, and sources of financial aid) and decreased mobility costs (transportation, long-distance communication, long-distance media and culture). See Hoxby (1997a). These factors–especially the information exchange mechanisms that now characterize college searches–are likely to be permanent. In contrast, changes in within-group income inequality that are due to moving the group boundary (the extensive margin) are mainly of practical policy interest. They suggest that groups may need to be redefined if policies are to retain their intended meaning. Also, a rising rate of return to aptitude may be the result of a recent tendency for technological innovations to be complementary to skills. This tendency may continue for some years to come, but there have been past periods in which technological innovations tended to substitute for skills.

We decompose the increase in income and wage dispersion among the college educated by comparing the incomes, wages, backgrounds, and college experiences of males who are approximately age 32 in 1972, 1986, and 1995. The males are selected on the basis of age from three data sets: Occupational Changes in a Generation (OCG, 1972 incomes), the National Longitudinal Study of the Class of 1972 (NLS72, 1986 incomes), and the National Longitudinal Survey of Youth (NLSY, 1995 incomes). We matched these data, which we hereafter call "the combined surveys," to detailed information about each college's student body, selectivity, expenditures, and inputs. The college data come from institutional surveys and many other sources.

Our results suggest that each of the three components has contributed substantially to the increase in income and wage inequality. Within the increase in inequality that can be explained by observable factors, we find that about 1/4th is associated with the extensive margin, about 1/3rd with an increased rate of return to aptitude, and about 5/12^{ths} with the intensive margin. Naive estimates that do not account for the intensive margin greatly overstate the pure increase in the rate of return to aptitude. That is, aptitude would not earn as much as it currently does if it continued to interact with the college market as it did in

1970.

In this paper, we may state that a student of a given aptitude earns more if the market changes in such a way that he experiences a college that has a higher concentration of high aptitude peers and higher per-student expenditures. This is a treatment effect of the general changes in the college market. We would not argue that these are *individual* treatment effects. That is, we would not argue that we could drop high aptitude peers and high expenditures on other students and expect to see a similar effect on their earnings. In this paper, we cannot differentiate between an intensive margin that works because high quality peers and expenditures generate actual human capital and an intensive margin that works because high quality peers and expenditures are necessary components of an elaborate signaling mechanism that signals aptitude. In either case, the intensive margin is *necessary* for aptitude to be associated with greater earnings, so we will say that the increased earnings are associated with the increasing role of the intensive margin. We return to this point in the conclusion.

A preview of the empirical strategy is as follows. We first use the Current Population Survey (CPS) to establish the time trends in income and wage inequality that we are attempting to explain. We examine males who are college-educated and have either 5 or 25 years of experience. They are comparable to other estimates of within-college income quantiles from the literature based on the CPS. Next, we show income and wage quantiles for 1972, 1986, and 1995, based on males who are about age 32 in the combined surveys. For each year, we examine two groups: those who completed at least two years of college, and and those who have at least a baccalaureate degree. We also show mean incomes and wages for individuals grouped by their colleges and by their aptitude. In the parametric part of the paper, we use regression and analysis of variance to decompose each year's variance in incomes and wages into variance attributable to individual attributes other than aptitude (family background), aptitude, the intensive margin (peer concentration, per-student expenditure), and residual inequality. We use Oaxaca-type decompositions to attribute the changes in variance to changes in the variance of attributes (such as increased demographic diversity or increased diversity of per-student expenditure), changes in the return to attributes (such as the return to aptitude), and changes in the residual. We consider a number of alternative specifications. In particular, we try different methods of estimating the extensive margin, and we use simulated instrumental variables to ensure that the attributes of an individual's college do not pick up unmeasured aptitude. Overall, when our choice of an estimation strategy is likely to bias the results, we consistently choose the strategy that will favor the conventional explanations of increasing inequality (the extensive margin, then the return to aptitude) over the intensive margin explanation.

II. Background: Wage Inequality Measures from the CPS 1969-96

The increase in income and wage dispersion in the U.S. since 1970 has been well documented by numerous authors, for instance Katz and Murphy (1992), Juhn, Murphy, and Pierce (1993), Levy and Murnane (1992), and Gottschalk (1997). About one-third of this increase is associated with increasing differentials between groups, such as the differential between people with a college education and just a high school education. The other two-thirds of the increased dispersion has been *within* groups. The group that concerns us, the college-educated, have shown an increase in the variance of their wages that is about 16% larger than the overall increase in variance.[3]

Figures 1 through 4 show log wages at various percentiles of the income distribution from 1969 to 1996 for white males who report having completed at least 16 years of education.[4] Figure 1 shows time paths of the difference between the 90th and 10th percentiles, the difference between the 90th and 50th, and the difference between the 50th and 10th for men with 25 years of experience. Figure 2 repeats the exercise substituting the 75th percentile for the 90th percentile, and the 25th percentile for the 10th percentiles.

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[3] Authors' calculations, based on combined surveys.

[4] For all four surveys used in this paper, hourly wages are constructed from periodic earnings (for instance, weekly earnings) and usual weekly hours for those men who do not report hourly wages.

(Experience is measured as age minus education minus six, so the men are aged about 57.) Figures 3 and 4 show the corresponding time paths for men with 5 years of experience (who are aged about 27). The estimates for 1969 through 1977 are taken from Buchinsky (1995) and are based on the March CPS. We estimated the incomes at various percentiles for 1978 to 1996 using the Merged Outgoing Rotation Groups of the CPS. Our method otherwise replicates that described by Buchinsky (1995) so that the updated series continues smoothly. Appendix Tables 1-4 present the estimates that are displayed in Figures 1-4.

Figures 1 and 2 show steady upward trends in wage inequality among men with 25 years of experience. In 1969, wages at the 90^{th} and 10^{th} percentiles are separated by 1.070 log points, and wages at the 75^{th} and 25^{th} percentiles are separated by 0.540 log points. The corresponding 1996 differences are 1.385 log points and 0.691 log points. The paths show relatively steady rates of increase over the entire period, with the exception of a dip in the 90^{th}-50^{th} difference from 1983 to 1987. Even though the men whose wages are shown in Figures 1 and 2 are significantly older than the men we examine in the combined surveys, it is useful to begin with them. Their wages paths are more steady, reflecting more of the trend in wage inequality than short term labor market fluctuations. Also, wage inequality among men younger than 30 understates the true inequality in their current earning potential (because schooling activities depress some men's earnings) and grossly understates the inequality in the lifetime earning potential.[5] As Heckman *et al* (1996) show, an examination of the incomes of men who are just a few years out of their 20s is much more informative than an examination of the same men a few years previously.

Figures 3 and 4 show that men with 5 years of experience also displayed increasing wage inequality over the 1969 to 1996 period. However, the time paths of the percentiles of their income distribution are much less steady and display plateaus (1971-77, 1981-87, 1990 onwards) and rather abrupt increases (1970-71, 1977-81, 1987-90). It is difficult to state with confidence whether their wage

[5] See Murphy and Welch (1990).

inequality has recently stopped growing or whether it is just currently on a plateau and will soon resume the upward trend shown by the income inequality of men with 25 years of experience. The1969 wages of men with 5 years of experience differed by 0.930 log points between the 90th and 10th percentiles and by 0.420 log points between the 75th and 25th percentiles. Their 1996 wages differed by 1.311 log points between the 90th and 10th percentiles and by 0.648 log points between the 75th and 25th percentiles.

It is useful to compare the combined survey data to the CPS data just shown. The combined survey men are about age 32, so they have approximately 10 years of experience (calculated using the age-education-6 method). They belong between the figures for men with 5 years and 25 of experience. Also, all of the CPS males in Figures 1-4 reported that they had completed at least 16 years of education, supposed to be equivalent to a baccalaureate degree. Unlike the combined surveys, however, the CPS does not provide other information we might use to confirm the existence of a baccalaureate degree (such as attending a college that actually grants baccalaureate degrees). Based on our experience with the other surveys, we expect that a minority of men (15 to 20%) in the CPS group have completed some college but do not actually have a baccalaureate degree.

The combined surveys' data are shown for the appropriate years as isolated "X"s on Figures 1 through 4. The wage differentials are, as expected, between those of men with 25 years of experience than for those of men with 5 years of experience. For baccalaureate holders in the combined surveys, wages at the 90th and 10th percentiles differ by 1.043 log points in 1972 (compare 1.100 log points for CPS men with 25 years of experience and 0.970 log points for CPS men with 5 years of experience) and by 1.288 log points in 1995 (compare 1.397 log points for CPS men with 25 years of experience and 1.338 log points for CPS men with 5 years of experience). The corresponding numbers for the 75th and 25th percentiles are 0.547 log points in 1972 (compare 0.540 log points for CPS men with 25 years of experience and 0.470 log points for CPS men with 5 years of experience) and 0.658 log points in 1995 (compare 0.695 log points for CPS men with 25 years of experience and 0.660 log points for CPS men 5 years of experience).

Thus, the combined survey data exhibit a time pattern in wage inequality that is consistent with that shown by CPS data. Figures 1 through 4 also show that inequality in the combined survey data continues to grow after the 1972-86 period. For instance, the average annual growth of the 90-10 wage differential is about the same (0.01 log points) both before and after 1986, according to the combined survey data. This implies that we should be able to learn as much from comparing NLSY data (1995 wages) to NLS72 data (1986 wages) as we can from comparing NLS72 data (1986 wages) to OCG data (1972 wages). This implication is useful because the NLSY and NLS72 contain measures of scholastic aptitude that the OCG does not contain.

III. The Combined Surveys Data

The first principle of our empirical strategy was to choose data from the beginning, middle, and end of the 1970 to 1995 period that were as comparable as possible *before* econometric analysis. The second principle was to choose wage data that would strongly reflect current trends in inequality, yet not reflect too many competing phenomena–such as job search activities undertaken by young labor market participants or the changing labor supply behavior of young women.

In practice, these data requirements pose the principal obstacle to empirical work like that we attempt in this study. We need survey data on wages, incomes, and family background that are nationally representative (or are provided with appropriate weights to generate nationally representative statistics). The data must span the period of interest–approximately 1970 to the present–and must identify each individual's actual college. The data must allow us to compare men who are out of their 20s, yet young enough to have wages that strongly reflect current trends in inequality and young enough to have attended college in a period for which college data are available. We must match the survey data to data about each institution of higher education, drawn for the relevant year. Data on the universe of colleges (not just those attended by someone in the survey) must be assembled so that colleges may be ranked and we can assess what behavior is typical for a student of given aptitude in a given year. Information on colleges' selectivity and student bodies is particularly difficult to assemble, because it is scattered in a variety of sources and comes in a variety of formats. Early (pre-1970) financial information on colleges is also onerous to assemble.

This section describes the key features of our data. The Data Appendix Table contains sample information and descriptive statistics for each data set.

A. A Description of the Data

The NLS72 provides us with 1986 wage and income data on X men, whose high school and college experiences were recorded in earlier waves of the survey (1972-86). Because the NLS72 began with a sample of people who high school seniors in 1972, the vast majority of the men are age 32 in 1986. We therefore use 32 as the focal age for drawing samples from the OCG and NLSY surveys. The NLS72 has clustered sampling based on high schools, and we take account of this clustering in the empirical analysis.[6] We use the weights, provided by the survey, that are designed to make the 1986 data nationally representative. Men are dropped from the sample if they have zero or missing earnings information. This is true for the other two surveys as well, so that it is appropriate to interpret all the results as "conditional on having positive earnings." In practice, this is not an onerous restriction because the men whom we analyze, those with at least some college education, are more likely to have positive earnings. For instance, among men in the NLS72 who have baccalaureate degrees, only 10.4 percent of the observations must be dropped because earnings are non-positive or non-interpretable.[7]

The NLSY provides us with 1995 wage and income data on X men, whose high school and college

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[6] *Stata* contains a set of survey or "svy" procedures that account for clustering. These procedures compute group means, group proportions, regression coefficients, and so on. We define the school as the cluster or probaptitude sampling unit for the NLS72, and we find that using the "svy" procedures with the school cluster is important for correct computation of variances and quantiles in the NLS72.

[7] This computation does not include men who have already left the sample previous to the 1986 wave.

experiences are recorded in waves of the survey dating from 1979 to 1996.[8] The men in the NLSY were aged 30 to 38 in 1995, and we kept observations on those men who were aged 30 to 35. Thus, the sample is roughly centered on age 32–though there is an asymmetry. In choosing these ages, we considered the trade-off between the explanatory power we would gain from increasing sample size and the explanatory power we would need to estimate age effects convincingly enough that the NLSY could be compared to the NLS72. We use the weights provided by the survey for 1995 data. The NLSY contains an oversample of people from minority and disadvantaged backgrounds. We found that keeping or excluding this sample did not affect our results significantly, so long as we used the appropriate weights.[9]

Men from the NLS72 and NLSY are associated with the college from which they obtained a baccalaureate degree, if they obtained one. Men who remain unmatched after this procedure are associated with the college from which they obtained an associates degree, if they obtained one. Men who remain unmatched after this procedure are associated with the college they attended the longest in an undergraduate capacity. We create a category for men who claim to have attended college, but whose reported colleges could not be matched with any accredited institution of higher education by the United States Department of Education.

So far as we are aware, the OCG is the only nationally representative survey that provides early 1970s wages, incomes, and background data on a large number of men *and* records the specific college that each individual attended. The OCG was a CPS supplement, so it has the same sample structure as the CPS. We use the X men who were aged 30 to 35 in 1972.[10] The OCG contains less family background information than either the NLS72 or the NLSY, so it was the limiting factor in our choice of background

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[8] NLSY earnings and hours data for 1995 were collected in the 1996 survey.

[9] The NLSY also originally contained a military sub-sample, but these men were perforce dropped because the survey stopped following them before the 1996 wave.

[10] The sample was conducted in 1973, but the earnings and hours data apply to 1972. The OCG is not longitudinal, so some information is retrospective.

variables. For all three surveys, however, we were able to obtain the background variables that have substantial explanatory power for earnings and college attendance: race, ethnicity, parents' completed education, family income at the time the respondent was in high school, family size, birth order, foreign birth of parents, and state in which the respondent attended high school. Men in the OCG are associated with their most recent college. We use the weights provided by the OCG, although these do not make much difference in practice owing to the sample design.

Colleges' financial and institutional data for 1969 onwards is derived from CASPAR, a panel version of the data gathered by the U.S. Department of Education in its Higher Education General Information System (HEGIS) and Integrated Postsecondary Education Data System (IPEDS) surveys. The variables include expenditures per student, revenues per student, tuition revenue per student, tuition, in-state and out-of-state tuition (for colleges that differentiate tuition by state of residence), average faculty salary, faculty-student ratio, and total enrollment. For the years prior to 1968, the same variables were coded from a variety of college guides, but especially the American Council on Education's guide entitled *American Universities and Colleges*, which includes every accredited institution.[11]

Each individual was matched with information about the college he attended, where the information was drawn from the approximate year in which he would have been applying to college if he had applied in his senior year of high school. Thus NLS72 men are matched with college information from 1971-72, NLSY men with college information from 1980-81, and OCG men with college information from 1958-60. We chose this matching procedure partly because of data availability, and partly because we would have otherwise had to instrument each individual's college information with the college information that would have pertained if he had applied at the normal time. (Otherwise, the effects of his college characteristics

[11] Other guides that provided us with a substantial number of observations on financial and institutional variables for this period were *Lovejoy's Guide to Colleges* and *Cass and Birmbaum's Comparative Guide to American Colleges*.

would be contaminated by the effects of his decision to attend college at an unusual time in his life.) In any case, the information for a college does not change so rapidly that a mis-match of one or two years would affect the results.[12]

Information on colleges' student bodies and selectivity was taken from a variety of college guides, including *Peterson's*, *Barrons*, *Cass and Birmbaum's Comparative Guide*, *Lovejoys*, and *American Universities and Colleges*. For any given college in any year, multiple sources of information were used. For instance, general admissions information (admissions tests required, required grade point average, and so on) might be confirmed by three sources, while *Barrons* might provide median Scholastic Aptitude Test (SAT) and/or American College Test (ACT) scores, *Peterson's* might provide cumulative densities for various points on the SAT and/or ACT distribution, and *Lovejoys* might provide mean SAT and/or ACT scores. Some colleges are nonselective, meaning that they do not have any admissions requirements beyond a high school diploma or the equivalent. These colleges are identified by a nonselective dummy variable. Other colleges' student bodies are described by the distribution of their admissions test scores, with ACT scores translated into SAT scores using the tables provided by the College Board. We then translated SAT scores translated into 1982 national percentiles using the distribution information published by the College Board. Since we are interested in how diverse a college's student body is, this translation is important. For instance, the 100 point difference between 700 and 800 on the SAT verbal test is only 1 percentile, but the 100 point difference between 450 and 550 is 27 percentiles. In addition, the SAT verbal test is considerably more sensitive than the SAT math test above 550 points, so that a 100 point difference on the verbal test contains fewer percentiles than a 100 point difference on the math test.[13]

We estimated the standard deviation of admissions test scores for each college using the method of

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[12] This is one reason why we use surveys that record earnings in years that are about a decade apart.

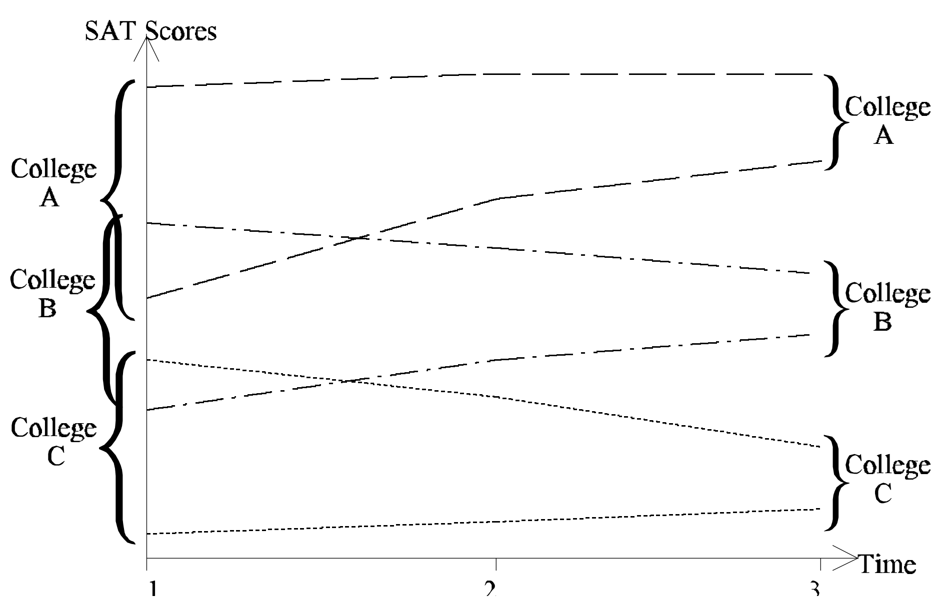
[13] All of these comments refer to the pre-1994 SAT verbal and math tests, which are relevant for our analysis. Each test has since been separately recentered.

moments on the multiple moments that we typically had for each college and assuming that the distribution for each college was normal. (Reported means and medians were usually within 10 points of one another for each college.) For instance, a college's mean SAT verbal score and its percentage of students with SAT verbal scores above 600 (both translated into national percentile scores first) would generate one method of moments estimate of the standard deviation of its verbal scores. We then took the mean of each college's method of moments estimates of the standard deviation of verbal scores (though the median of the estimates worked similarly). We performed the same procedure for SAT math scores.

B. Two Measurement Issues

We would like a measure of each college's peer influences that indicates how likely a student is, in an encounter with a fellow student, to meet person who is a beneficial academically. We attempt to form such a measure by interacting the standard deviation of colleges' admissions test scores with their mean admissions test scores. For a college with a given mean level of aptitude, peer effects are affected by the dispersion of aptitude. If we believe, for example, that interactions with much less able peers are unproductive or bad for a student's achievement, then we would expect that, conditional on attending a college with high mean SAT scores, a tighter distribution of SAT scores (a smaller standard deviation of SAT scores) generates better peer effects. On the other hand, if the aptitude of the most able student in the college is all that matters, excellent peer effects are possible even at a college with low mean SAT scores so long as the distribution of scores is not tight (the standard deviation in large). It is important to emphasize, however, that without knowing how peer effects work, we *cannot* take a stand on the sign of the interaction term. For instance, homogeneous classes may be good for all students. Or, homogeneous classes may be good only for students who are of high aptitude and are thereby segregated from low aptitude students. Or, colleges' dispersion of aptitude may matter very little because there are many means by which students can self-segregate within colleges. We do not wish to constrain the mechanism by which peer effects work. We will simply associate peer effects with the effects of the interaction between a college's average SAT score and the standard deviation of its scores, and our preferred specification (see below) allows many different peer mechanisms to reveal themselves.

The figure below may clarify the intuition. It shows a stylized version of what has happened to the college market over time. The vertical axis shows SAT scores, arranged so that students are uniformly distributed over the axis. Each college's student body is represented as a part of this distribution. For instance, college A's students have SAT scores that are uniformly distributed between the dashed lines.



In all 3 colleges, the standard deviation of students' SAT scores shrinks over time. Each college's mean SAT score (not shown, but obviously at the center of each college's range) also changes. The income of a student who attends college A is not just a function of his own aptitude (measured both by his individual score and the college's mean score), but also a function of the students he meets in college A. If he attends college A at time 1, he is more likely to meet a low aptitude student than if he attends college A at time 3. Conversely, a student who attends college C is more likely to meet a high aptitude student if he attends at time 1 than at time 3. Students at all colleges are more likely to experience classes with heterogenous students if they attend at time 1 rather than time 3.

In summary, we associate an individual's aptitude scores and the main effect of his college's average SAT scores with his individual aptitude. That is, we assume that a college's average SAT scores are another measure of individual aptitude that has descriptive power even when we control for individual measures of aptitude. Only the interaction between colleges' average SAT scores and the standard deviations of the scores are associated with the intensive margin. This pattern of association overstates the role of aptitude and understates the role of the intensive margin. This is one example of how we chose methods that would understate the intensive margin. Note that the previous literature has conventionally called the effect of a college's average SAT scores "peer effects" when an individual's own SAT score was controlled for. If we were to adopt this convention, the role of aptitude in explaining inequality would shrink and the role of the intensive margin would expand.

Both the NLS72 and NLSY administered tests of math and verbal skills to their entire survey population. These provide useful measures of scholastic aptitude. The NSL72 test was created by the United States Department of Education for use in the survey and was administered to all the respondents when they were high school seniors. We use its mathematics and language/reading components. In the NLSY, the universally administered test was the ASVAB, from which we use the parts on numerical analysis, vocabulary, and reading comprehension. Respondents' scores on all these tests are expressed as percentile scores and have distributions (see the Data Appendix Table). We hereafter give these scores the generic names of "Verbal Aptitude" and "Math Aptitude," and we claim that these scores measure attributes in which colleges admissions officers are interested. The NLS72 and NLSY contain respondents' scores on the Preliminary Scholastic Aptitude Test (PSAT), SAT, and ACT.[14] The Verbal Aptitude and Math Aptitude scores are correlated with PSAT, SAT, and ACT scores with correlation coefficients that consistently exceed 0.90.

No aptitude test was administered as part of the OCG, so the only measure of a student's aptitude is his college's average SAT score. We use colleges' average SAT scores and the standard deviations of the colleges' SAT scores in a second empirical strategy that is a small variation on the strategy described in the preceding paragraph. This second strategy (which is described in detail below) has a few advantages: (1) it allows use of the OCG and, thus, comparison over a longer period of time; (2) it allows peer effects to be modeled flexibly, and (3) it eliminates some attenuation bias that might be caused by error in the aptitude measures.

IV. Descriptive Analysis of the Income and Wage Distributions

In this section, we show that the combined surveys data suggest some role for each of three possible sources of within-college inequality: the extensive margin, aptitude, and the intensive margin. Our strategy is to first examine earnings quantiles of the whole sample, then eliminate individuals who are likely to contribute to inequality through the extensive margin and reexamine the earnings quantiles in the reduced sample, and finally show how much of income and wage inequality is associated with aptitude or college rank.

Each figure in this section has a corresponding appendix table that presents the same data numerically. Thus, all the statistics in Figure 5 are shown in Appendix Tables 5a and 5b, and all the calculations presented in this section are based on numbers available in the appropriate appendix table. We prepared statistics for each of four definitions of college-going: attended any college, completed at least 2

[14] *If* a respondent took an admissions or pre-admissions test, the score is recorded on his transcript and becomes part of the survey record.

years of college, attended a baccalaureate-granting college, and earned a baccalaureate degree. Statistics based on the first three definitions tend to be similar, so, for brevity, we usually present only statistics based on the second and fourth definitions. Most of the income and wage statistics are expressed in natural logs, but a few figures show statistics in real dollars because it is instructive to see the analysis both ways.[15]

Figure 5 shows income for 1972, 1986 and 1995 at the 95th, 90th, 75th, 50th, 25th, 10th, and 5th percentiles of the income distribution. The set of all men with a least 2 years of college are shown in one part of the figure, and the subset of men who have a baccalaureate degree are shown in the other part. The income distribution is clearly widening over time. Among those who have at least two years of college, the upper and lower halves of the distribution each account for about an equal share of the widening. Among the baccalaureate-holders, however, the upper half of the distribution accounts for a slightly disproportionate share. For them, the 90-10 differential was 34,478 dollars in 1972 and 50,050 dollars in 1995. The 90-50 differential rose from 19,050 dollars to 28,027 dollars over the same period, implying that the upper half of the distribution accounted for 57.6% of the increase in the 90-10 differential. For both groups of college-goers, earnings at the 5th and 10th percentile are flat or declining over the period, while earnings at the 50th percentile and above are rising.

Figure 6 shows the same analysis as Figure 5, except that hourly wages are presented instead of income. Figure 6 shows increasing dispersion, like Figure 5, but wages increase more on average over the period than incomes do. Nevertheless, wages at the 5th and 10th percentiles are nearly flat. Among those with at least 2 years of colleges, the 90-10 differential is 13.47 dollars in 1972 and 18.55 dollars in 1995. For the same group, the 90-50 differential is 8.45 dollars in 1972 and 10.70 dollars in 1995, implying that the lower half of the distribution accounts for 55.7% of the increase in dispersion. Among the

[15] All results that are mentioned but are not shown are available from the authors.

baccalaureate holders, the 90-10 differential grows from 14.39 dollars in 1972 to 19.25 dollars in 1995, and the two halves of the distribution account for roughly equal shares of the increase in dispersion. In both groups of men, the increase in dispersion decelerates slightly in the 1986-95 period relative to the 1986-72 period. This deceleration is not observable in the income data shown in Figure 5.

Figures 7a through 8b attempt to show what Figures 5 and 6 would have looked like if the backgrounds of people going to college had remained the same over the whole period. That is, we attempt to eliminate the increase in inequality due to the extensive margin in background–especially the increased access to college among students from socio-economically disadvantaged backgrounds. (There is also an extensive margin in aptitude, but we do not attempt to estimate it until we do parametric analysis in the next section.) We wish to overstate rather than understate the increase in inequality due to the extensive margin in background, so we adopt the following procedure for culling the sample.[16] Using the OCG sample, we estimated probit equations for at-least-two-years-of-college and baccalaureate-degree using all of the background variables and various interactions among them.[17] We calculated a propensity score for each individual to be a member of each group and we calculated the mean propensity within each group–for instance, the mean propensity to be a baccalaureate holder, conditional on actually belonging to the baccalaureate-holding group. We classified the people in the OCG who were above the mean propensity for each group as "very likely to belong." We used the estimated coefficients from the OCG probit equations to generate propensity scores for men in the NLS72 and NLSY, and we classified them as "very likely to belong" to each group if they were above the mean propensity scores calculated using the OCG data (as

[16] We do this to emphasize how much of the increase in dispersion remains to be explained even when the extensive margin has been given (more than) its due. In the next section, we adopt a more balanced method of computing the increase in variance due to the extensive margin.

[17] The variables are number of siblings, number of older siblings, black, hispanic, asian, native american, maximum of parents' highest grade completed, log(family income) when respondent was in high school, foreign-born parents or major household language is foreign, and indicator variables for state of residence while in high school.

described above). The outcome of the procedure is a sample of men from each of the surveys who would have been very likely to have at least two years of college or to have baccalaureate degrees if they had lived when the men in the OCG lived. A by-product of the procedure is a demonstration that selection into college on the basis of good background characteristics was stronger in the OCG than in the other two surveys.[18]

Figure 6a shows what happens to the distribution of income among predicted-baccalaureate-holders between 1972 and 1995. The distribution among actual baccalaureate-holders is also shown for comparison. Careful visual comparisons or, even better, a few calculations using the numbers in Appendix Table 7a demonstrate that eliminating the extensive margin in background wipes out only a minority of the increase in income inequality. (Recall that the method employed tends to overstate the role of the extensive margin.) For instance, the 90-10 differential grew by 15,572 dollars (from 34.378 dollars in 1972 to 50,050 dollars in 1995) among actual baccalaureate-holders. It grew by 14,164 dollars (from 37,888 dollars in 1972 to 52,052 dollars in 1995) among men who were always likely to be baccalaureate-holders. These numbers imply that the extensive margin in background accounts for about 10% of the increase in income inequality. We get a larger estimate, 19%, if we examine the 75-25 differential instead of the 90-10 differential.

Figure 7b is the same as Figure 7a, except that hourly wages are shown instead of income. If we make the same calculations as we made in the preceding paragraph for Figure 7a, we find that the extensive margin accounts for between 8% and 26% of the increase in wage inequality. The former number is based on the 90-10 wage differential; the latter number is based on the 75-25 differential.

Figures 8a and 8b repeat the exercise of Figures 7a and 7b, except that at-least-2-years-of-college is the group of interest, rather than baccalaureate holders. Careful visual comparisons or calculations like

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[18] Coefficient estimates that show this point are presented in the next section.

those above (based on Appendix Tables 8a and 8b) reveal that the extensive margin can account for as much as 18-30% of the increase in income inequality and 11-47% of the increase in wage inequality among men with at least 2 years of college. In all cases, the lower estimate of extensive margin's contribution comes from calculations based on the 90-10 differential, and the higher estimate comes from calculations based on the 75-25 differential. Having shown that even an exaggerated extensive margin accounts for only a minority of the increase in inequality, we use regression analysis in the next section to get more better estimates of the contribution made by the extensive margin. The parametric analysis imposes more structure, but it also uses all of the available data to calculate each contribution.

In Figures 9a through 10b, we abandon percentiles of the income and wage distributions, and we instead show incomes and wages for people who attended colleges of differing selectivity. In the figures, we group colleges into 6 ranks based on their selectivity (for visual clarity, the 12 rank groups used in the parametric analysis are contracted into 6). Rank group 1 contains nonselective and minimally selective colleges, and rank group 6 contains the most selective colleges. The first thing we observe about Figure 8a is that individuals who attend more selective colleges tend to earn higher wages. The second thing we observe is that the income differentials associated with college rank have grown over time. The increase in dispersion has occurred especially because the incomes of individuals from colleges with extreme ranks (1 and 6) have moved away from the center.

In Figures 11 and 12, individuals are grouped by their Verbal Aptitude and Math Aptitude scores into 5 convenient groups, where individuals placed in group 5 have high scores on both the Verbal and Math tests and those placed in group 1 have low scores on both tests. The groups were constructed so that the weighted proportion of people in each aptitude group would be the same in both surveys. In other words, the actual scoring of the tests should not affect the figures. (In any case, both tests are scored in terms of national percentiles and have quite similar weighted distributions of test scores, as we would expect.) The figures show only 1986 and 1995 earnings because only the NLS72 and the NLSY contained

Verbal Aptitude and Math Aptitude scores.

There is an increase in income and wage dispersion associated with higher aptitude. For instance, consider the baccalaureate holders in Figure 12. The difference in wages between group 5 (most able) and group 1 (least able) is 0.17 log points in 1986, but 0.33 log points in 1995.

V. Parametric Decomposition of the Variance of Income and Wages

In this section, we use regression methods to decompose the increase in the variance of income and wages among the college-going into the extensive margin, the return to aptitude, and the intensive margin. We want to learn, to the extent possible, how much of the increase in earnings variance is due to the extensive margin, the return to aptitude, and the intensive margin. We also want to know how the estimated effects of aptitude change when we add measures of college peers and inputs to an earnings regression. This will help us sort out the contribution of pure increases in the return to aptitude from the contribution of the intensive margin (increased variance in college attributes associated with aptitude). Along the way, we can examine issues such as whether selection into the college-going group has become less demanding in terms of good background characteristics and aptitude.

The First Empirical Strategy

Our first strategy uses the following earnings regression:

$$\ln(y_{it}) = X_{it}\beta_t + Z_{it}\delta_t + W_{it}\gamma_t + \epsilon_{it} \tag{1}$$

where i indexes individuals, t indexes the survey year, and y is the measure of earnings (either income or wages). The vector Z contains the individual's own Verbal Aptitude or Math Aptitude and his college's mean SAT scores. The vector W contains measures of the intensive margin. These include college inputs and college peer effects--that is, interactions between an individual's aptitude measures and his college's standard deviation of SAT scores. The vector X contains background variables that might affect the extensive margin–for instance, selection into the group of men with two years of college education. An alternative to including the background variables themselves would be to include a propensity score based on those background variables and aptitude, weight by a propensity score, or use some other selection correction technique. We consider these alternatives in the next section, but we find that including the X variables themselves is the procedure that is, at once, the least restrictive and the most generous towards the extensive margin. Since we are not interested in identifying the effect of being black, say, on income separately from its effect on the propensity to go to college, we simply call *all* of the variation associated with X and the return to X "the extensive margin." This naturally maximizes the contribution of the extensive margin, which is acceptable for our purposes.

Before estimating equation (1) itself, we first estimate two restricted versions of the equation. The first restricted equation contains only the background variables–that is, δ and γ are set equal to zero. The second restricted equation contains only the background and aptitude variables–that is, γ is set equal to zero. Finally, we estimate equation (1). Each of the above regressions is estimated separately, using weights, on each of the three surveys. We add explanatory variables sequentially because we are interested in knowing how the effects of background are affected by aptitude, and how the effects of aptitude are affected by college attributes.

Having estimated these regressions, we do a standard analysis of the variance of earnings, showing how much of the total variance is explained by the model and how much is residual variance. We then compute the partial variance due to each group of variables: the X, Z, and W vectors. That is, we compute the partial sum of squares for each vector and divide it by the model degrees of freedom. Each of these partial variances is a rough estimate of the amount that that group of variables contributes to the explained variance.[19] For instance, the partial sum of squares for X in the above model is:

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[19] If there were no covariances among the blocks of the explanatory variables, it would be an accurate estimate. In the process of computing the partial variances, we also computed the partial covariances. These were relatively small for the results we examine in the text (perhaps because so many of the variables in the regression are indicator variables), and it did not appear that they would be informative if presented. The equation

(2) $$\hat{\beta}_t'(X_t'M_{X_t^-}X_t)\,\hat{\beta}_t \quad \textit{where}\ X_t^- = [Z_t\,W_t]\ \textit{and}\ M_{X_t^-} = I - X_t^-(X_t^{-\prime}X_t^-)^{-1}X_t^{-\prime}$$

This is a rough measure of the contribution of X to the explained variance, since we have partialed out Z and W. However, we can learn how the contribution of X changes as we add Z and W, since we add them sequentially.

We can also see how much each of the partial variances increases from survey to survey. That is, when the total variance of earnings increases from 1972 to 1986, how much of the increase is contributed by the increases in the partial variances due to X, or Z, and W?

Up to this point, the analysis does not differentiate between changes in the variance of earnings that are due to changes in the variance of explanatory variables and changes in the returns to those explanatory variables. Applying an Oaxaca decomposition to our partial variances, we find we need to compute the following difference:

(3)
$$\hat{\beta}_t'(X_t'M_{X_t^-}X_t)\,\hat{\beta}_t - \hat{\beta}_{t-1}'(X_{t-1}'M_{X_{t-1}^-}X_{t-1})\,\hat{\beta}_{t-1} =$$
$$\left[\hat{\beta}_t'(X_t'M_{X_t^-}X_t)\hat{\beta}_t - \hat{\beta}_{t-1}'(X_t'M_{X_t^-}X_t)\hat{\beta}_{t-1}\right] + \left[\hat{\beta}_{t-1}'(X_t'M_{X_t^-}X_t)\hat{\beta}_{t-1} - \hat{\beta}_{t-1}'(X_{t-1}'M_{X_{t-1}^-}X_{t-1})\hat{\beta}_{t-1}\right]$$

Alternatively, we could compute the following:

(4)
$$\hat{\beta}_t'(X_t'M_{X_t^-}X_t)\,\hat{\beta}_t - \hat{\beta}_{t-1}'(X_{t-1}'M_{X_{t-1}^-}X_{t-1})\,\hat{\beta}_{t-1} =$$
$$\left[\hat{\beta}_t'(X_t'M_{X_t^-}X_t)\hat{\beta}_t - \hat{\beta}_t'(X_{t-1}'M_{X_{t-1}^-}X_{t-1})\hat{\beta}_t\right] + \left[\hat{\beta}_t'(X_{t-1}'M_{X_{t-1}^-}X_{t-1})\hat{\beta}_t - \hat{\beta}_{t-1}'(X_{t-1}'M_{X_{t-1}^-}X_{t-1})\hat{\beta}_{t-1}\right]$$

In equations (3) and (4), we decompose the change in the variance into the part due to the change in the variance of X and the part due to the change in β (the return to X). Each of these parts is enclosed in square brackets. In equation (3), the change in the partial variance of the explanatory variables is weighted by the "old" return and the change in the return is weighted by the "new" partial variance of the explanatory

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shown for the partial sum of squares is for exposition. It does not include the weights or cluster design that we used variables. If returns are increasing and the partial variance of the explanatory variables is also increasing, this procedure tends to minimize the estimated contribution of the change in the partial variance of the explanatory variables. It tends to maximize the estimated contribution of the change in the return. In equation (4), the change in the partial variance of the explanatory variables is weighted by the "new" return and the change in the return is weighted by the "old" partial variance of the explanatory variables. If returns are increasing and the variance of the explanatory variables is also increasing, this procedure tends to maximize the estimated contribution of the change in the partial variance of the explanatory variables and tends to minimize the estimated contribution of the change in the return.

We computed the decomposition using both equation (3) and equation (4). The two methods produce similar patterns, but we present the decomposition based on equation (3) in order to maximize the apparent contribution of the return to aptitude and minimize the apparent contribution of the intensive margin (which depends on increased partial variation in W). That is, we present the decomposition that lends itself to the more conventional explanation. Since we sweep both X and the return to X into the extensive margin, the choice of equation (3) or (4) does not affect our assessment of the importance of that source of inequality.

The Second Empirical Strategy

There are a few problems with the first empirical strategy. The OCG does not contain individual measures of aptitude, apart from the average SAT score of an individual's college. Also, there is fair amount of measurement error in a college's average SAT score, which might cause estimates of the effect of aptitude to be attenuated. Finally, the independent variables do not easily orthogonalize. This makes the decomposition less effective and more difficult to interpret--essentially because the covariances among *groups* of variables (between W and Z, for instance) must be assigned. The covariances can be assigned to one group of variables, split between the relevant groups of variables, or assigned to the residual (this is what we do), but none of these choices is clearly best. If the measures of aptitude are, instead, indicator variables for aptitude groups, the amount of covariance decreases greatly and assignment of covariance is less of an issue.[20]

Our second empirical strategy addresses all three problems by grouping colleges into 12 aptitude rank groups, based on their selectivity. The grouping standards are the same for all years of data. The regression is a modified version of equation (1), where the vector Z contains indicator variables for the rank groups instead of individuals' aptitude scores and colleges' average SAT scores. The vector W contains interactions between each college's rank group indicators and its standard deviation of SAT scores, rather than interactions between each college's average SAT scores and its standard deviation of scores. The interpretation is still the same. Z, or the main effect of colleges' aptitude rank, is associated with aptitude. W is associated with the intensive margin, and X with the extensive margin.

The first empirical strategy produces coefficient estimates that are easier to read and interpret--simply because there are fewer of them--than the coefficient estimates from the second strategy. The second strategy, however, is more flexible, uses more data, and produces better decompositions. On the whole, we prefer the second strategy and we present its results as the main results, despite the awkwardness of presenting so many coefficients. We then show the results of the first strategy.

Table 1 shows the regression of baccalaureate holders' income on their backgrounds, colleges' aptitude rank, and colleges' peers and inputs. The first three columns of table contain regressions based on 1972 (OCG) data; the next three columns contain regressions based on 1986 (NLS72) data; and the last three columns contain regressions based on 1995 (NLSY) data. The first column for each survey is the regression in which only background variables (X) are included. The second column for each survey adds indicator variables for college selectivity (Z), and the third column for each survey adds the peer measures and per-student expenditure (W). The coefficients on the background variables mainly have the

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[20] The analysis of variance section in most statistics textbooks explains this logic.

coefficients we expect. It is important to recall that they combine the effects of selection and their own treatment effects. Computations we make below inform us that the returns to good backgrounds and penalties for bad backgrounds are generally falling over time, but this pattern is hard to discern from the individual coefficients on the background variables.

More noteworthy is the pattern of coefficients on the aptitude rank indicators, when these variables are added in the second column of each survey's set of results. (Aptitude rank=1 is the excluded category. Colleges in this category are nonselective.) An individual's income increases steadily with the aptitude rank of his college, but the rate of increase is greater as the survey data become more recent. For instance, in 1972 there is a 0.528 log point difference between the incomes associated with aptitude rank group 12 (the most selective) and aptitude rank group 1 (nonselective colleges, the omitted category). In 1986, the difference is 0.645 log points; and, in 1995, the difference is 0.778 log points. Much of this growth in income differentials takes place in the extreme categories. For instance, the income differential associated with having a baccalaureate degree from a college that is ultimately selective but minimally so (aptitude rank=2) versus a college that is ultimately nonselective grows from 0.021 log points in 1972 to 0.082 log points in 1986 to 0.184 log points in 1995. The income differential associated with having a degree from a college that has an aptitude rank of 12 versus a college that has an aptitude rank index of 8 grows from 0.200 log points in 1972 to 0.289 log points in 1986 to 0.306 log points in 1995. In summary, the second regression for each survey suggests that there is a return to a college's aptitude rank and that this return increased significantly from 1972 to 1995.

Examining the third column for each survey, we see the effect of adding college attributes. (Note that the nonselective colleges that form the omitted category do not have standard deviations of SAT scores–by definition. Thus, the main effect of a standard deviation in SAT scores is implicitly included in the interaction terms.) Attending a college that has a larger standard deviation of SAT verbal scores is associated with higher individual incomes *if* that college has low aptitude rank. In contrast, attending a college that has a smaller standard deviation of SAT verbal scores is associated with higher individual incomes if that college has high aptitude rank. The log of per-student expenditure has a positive effect on income in all three surveys. A log point difference in per-student expenditure generates a 0.060 log point difference in income in 1972 , a 0.111 log point difference in 1986, and a 0.119 difference in 1995.

Moreover, adding the college attributes makes the return to aptitude rank increase much less rapidly over time. In fact, the return to aptitude rank appears to be only slightly higher in 1995 than in 1972, once we control for college attributes. It is still true that higher aptitude rank is associated with higher income in all years of the survey, but the *increase* in the return to aptitude rank is small (only really notable for colleges in aptitude rank groups 9 and 10).

Since the regression estimates for wages and for men with at least 2 years of college display similar patterns, we do not discuss these results in detail. Appendix Tables 13-15 show results like those in Table 1, substituting wages as the earnings variable (Appendix Table 13) and then examining income and wages for men who completed at least two years of college (Appendix Tables 14 and 15). However, we do examine the by-products of those regression estimates: the variance decompositions of Tables 3-5. First, consider Table 2, which presents the variance decomposition that corresponds to the regressions shown in Table 1.

In its top panel, Table 2 shows *changes* in the total variance of income between surveys and attempts to explain those changes in variance. For reference, the bottom panel displays the variances for each survey year. "Method 1" indicates the regressions that only include background variables; "method 2" indicates the regressions that include background and aptitude rank variables; and "method 3" indicates the regressions that include background, aptitude rank, and college attribute variables. The first row of the table shows the change in the total variance in log(income) between 1986 and 1972, between 1995 and 1986, and between 1995 and 1972. The next row shows, for method 1, the change in the partial variance due to background variables. The next two rows split this change into the change in returns to background and the change in the partial variance of background variables. The table also shows residual variance (plus, in methods 2 and 3, covariances that are not shown elsewhere).

Table 2 has several noteworthy implications. The partial variance due to background accounts for a smaller share of total variance in income when the aptitude rank variables are added to the regression. The partial variance due to background grows over time and explains about 12% of the increase in total variance, but *not* because the return to background grows. Instead, the returns to background shrink over time, but the variance in background characteristics among the baccalaureate-holding group grows. When we do not include college attributes in the regression, the increase in partial variance due to the aptitude rank variables explains about 48% of the total increase in the variance of income. The increase in the partial variance due to aptitude rank is mainly due to increases in the *returns* to aptitude rank. However, when college attributes are included in the equation, the increase in partial variance due to aptitude rank is more modest–about 27% of the total increase in the variance of income. Most of the shrinkage in the contribution of aptitude rank comes from the estimated contribution of its return. This suggests that college attributes explain a good portion of the increase in the return to aptitude rank. The increase in the partial variance due to college peers and per-student expenditure accounts for about 32% of the total increase in the variance of income. The remaining 27% of the total increase in the variance of income comes from an increase in the sum of the residual and covariances.

Summing up, the extensive margin in background accounts for about 15% of the total increase in the variance of income and this is because baccalaureate holders' backgrounds are becoming more diverse over time. The decreasing return to background is making a negative contribution towards the increase in the total variance of income. Colleges' aptitude rank accounts for another 27% of the total increase in the variance of income. Most of this is due to an apparent increase in the return to aptitude rank, which can interpreted as an increase in the return to aptitude (broadly construed as aptitude for college). The intensive margin accounts for about 32% of total increase in the variance of income. Most of this is due to an increase in the variance of college attributes, not an increase in the return to those attributes. If college attributes are not included in the analysis, the role of pure increasing returns to aptitude is greatly overstated (nearly double).

Table 3 is like Table 2, but presents an analysis of the *wages* of baccalaureate holders. Most of the implications of Table 3 are the same as those of Table 2. However, it is noteworthy that the increase in variance due to background accounts for a larger share (about 21%) of the increase in the total variance of wages.

Tables 4 and 5 are the parallels of Tables 2 and 3, but all men with at least 2 years of college are included. The first thing to note about these tables is that the model explains a smaller share of the increase in the total variance of the incomes and wages of these men. Only about 50% of the increase in variance can be attributed to one of the three measured sources of variance. Background still accounts for between 10% and 20% of the increases in the total variance of earnings, and the returns to background still make a negative contribution. Thus, the difference is that, among men with at least 2 years of college, colleges' aptitude rank, college peers, and college spending makes smaller contributions to the increase in the total variance of earnings. The return to aptitude rank accounts for only a small share of the increase in total variance. For income, the final breakdown is 18% associated with background, 9% associated with colleges' aptitude rank (of which 1% is due to increased returns), and 15% associated with college peers and per-student expenditures. For wages, the final breakdown is 9% associated with background, 16% associated with colleges' aptitude rank (of which 6% is due to increased returns), and 25% associated with college peers and per-student expenditures.

The full extensive margin includes the increase in variance due to the increased variance of aptitude among college students. If we include that piece in the extensive margin, we get the following totals for log income of baccalaureate holders over the entire 1972-95 period (Table 2, last column): 17.7% of the increase in total variance associated with the extensive margin, 23.6% associated with the return to aptitude rank (aptitude), and 31.9% associated with the intensive margin.

VI. Direct Measures of Aptitude and Other Alternative Specifications

Table 6 shows the results of regressing log income on background, college attributes, and the individual's own measured aptitude. Aptitude rank is everywhere replaced by aptitude–with the proviso that aptitude enters linearly rather than as a series of indicator variables.[21] Table 6 displays only the coefficients of interest–the estimated coefficients on the background variables are similar to those in Table 1–and only shows 1986 and 1995 since the OCG does not contain measures of aptitude.

People with higher aptitude scores earn substantially more income. An improvement of 1 national percentile point on the Verbal Aptitude test is associated with a 0.0168 log point increase in income in 1986. In addition, attending a college with a mean SAT verbal score that is 1 national percentile point higher is associated with a 0.0116 log point increase in income. The corresponding numbers for 1995 are 0.0182 log points and 0.0131 log points. Thus, without controlling for college attributes, own aptitude has a strong positive effect on wages and the effect appears to be increasing over time. This result is consistent with those of previous studies on aptitude and the return to education (cited in footnote 2). Once we control for college peers and expenditure per student, however, the increase in the return to aptitude shrinks. Income is still increasing in an individual's own Verbal Aptitude and the mean SAT verbal score of his college, and the returns appear to be increasing over time (though not by statistically significant amount). An improvement of 1 national percentile point on Verbal Aptitude is now associated with a 0.0095 log point increase in income in 1986 and a 0.0111 log point increase in 1995. Attending a college with a mean SAT verbal score that is 1 national percentile point higher is associated with a 0.0083 log point increase in

[21] If aptitude rank is made to enter linearly, the results are generally similar to those shown in Tables 1 and 2. The breakdown of the increase in the total variance of log income is as follows: 15.3% (total associated with X), -7.9% (return to X), 23.2% (partial variance of X); 19.4% (total associated with Z), 16.6% (return to Z), 2.8% (partial variance of Z); 27.1% (total associated with W), 2.8% (return to W), 24.3% (partial variance of W).

income in 1986 and a 0.0097 log point increase in 1995.

Moreover, college attributes play an important role. A person who attends a college with a low mean SAT verbal score is better off if his college has a high standard deviation of SAT scores. A person who attends a college with high mean SAT verbal score ends up with the highest income if that college's SAT scores were highly concentrated. An additional log point of expenditure per student generates an increase in income of about 0.1 log points.

Finally, Table 7 shows the accounting for the change in the variance of income for a number of specifications that are alternatives to the baseline specification presented in Tables 1 and 2. The first column restates the results of Table 2, for comparison. The next two columns show the accounting for the increase in variance when actual aptitude measures are used. One of these columns is the counterpart of Table 6; the other column use math tests rather than verbal tests but is otherwise identical to the regressions shown in Table 6. It is noteworthy that measured aptitude accounts for a smaller share of the increase in the total variance of income than the aptitude rank dummies accounted for. This is probably because the aptitude measures are limited in scope so that they are an erroneous redaction of the full set of aptitude data that college admissions officers perceive. The next column adds several additional variables to the college attributes: the log average faculty salary, the faculty-student ratio, and the percentile of expenditures devoted to instruction. The addition of these variables does increase the contribution of college attributes slightly, but it is apparent that per-student expenditure was a adequate measure of institutional inputs for many colleges.

Strictly speaking, it is a poor idea to match each individual with his actual college's characteristics, since an individual who is matched to a college that appears to unexpectedly selective (given his characteristics) is likely to have positive traits that we do not observe. These unobserved positive traits could bias the return to aptitude rank and college attributes upwards. A reasonable way to treat this problem is simulated instruments–that is, instrumenting for a person's actual college characteristics with the college characteristics he would be predicted to experience. We formed simulated instruments by creating a prediction equation for each state that was based on all the observations outside that state and its adjoining states. In practice, we did not expect that instrumenting would reveal that the least squares coefficients on college characteristics had suffered from positive bias. The reason is that college characteristics are rather crudely measured, so that instrumenting might so improve attenuation bias that any reduction in omitted variables bias would be fully offset. This expectation proved true: using the simulated instruments raises the contribution of college characteristics very slightly.

The final column of Table 7 illustrates an alternative approach to estimating the contribution of the extensive margin. We controlled for the propensity score directly–the score was computed based on probit regressions using the OCG. Regardless of whether we included other background variables directly in the log income equation, the propensity score accounted for only a small share of the increase in the total variance of income. This is probably because the prediction of the score imposes numerous restrictions on relationship between the background variables and income. We also tried other, related methods of controlling for the extension margin explicitly: the Heckman selection correction, censored regression, weighting by the propensity score. Since we have no particularly convincing way to identify the selection decision and we do not care to interpret the returns to background variables, our preferred method is including all the background variables and assigning all partial variance due to them to the extensive margin.

VI. Conclusions

In this paper, we attempt to explain the rising income and wage inequality among college educated people. We find that we can explain about 70% of the increase in inequality among baccalaureate holders and about 50% among people who have completed at least 2 years of college. Although we do not present the results above, it is worth noting that we can explain only about 38% of the increase among people who have attended *any* college. As we move towards more marginal college attendees, our measures of aptitude rank and college attributes fall off in quality. This quality degradation probably accounts for the fact that our weakening aptitude to explain the increase in inequality among people with slight college experience.

We find that the socio-economic and scholastic achievement backgrounds of people who are going to college are becoming more diverse over time. However, we estimate that the income reward associated with a good socio-economic background is falling over time so that the overall contribution of the extensive margin to within-college income and wage inequality is significant but not large: about 1/4 of the total increase in inequality.

Like other researchers, we find evidence of an increased return to aptitude over the period. This increased return is associated with about 1/3rd of the increase in income and wage inequality. However, we also find that the estimated contribution of an increasing return to aptitude is almost doubled if we do not allow the intensive margin to affect earnings.

We find that the intensive margin explains about 5/12ths of the increase in the return to aptitude. College peers and expenditures both make important contributions to the intensive margin. It is, perhaps, slightly confusing to interpret the intensive margin, so it may be worthwhile to recall that the intensive margin is identified (separately from aptitude) only because the way in which more and less able people have been matched to college experiences has changed over time. If colleges were not becoming more segregated on the basis of aptitude, it would be impossible to identify the interaction terms that make up the peer effects. If colleges' per-student expenditures were not becoming more correlated with aptitude over time, adding expenditures to the equation would not diminish the coefficient on aptitude–at an increasing rate over time. This is not to say that the intensive margin can function separately from aptitude. A reasonable interpretation of the results is that intensive margin represents the market equilibrium distribution of human capital inputs to people, based on their aptitude. Perhaps market equilibrium in previous years associated fewer peer and institutional inputs with highly able students–because mobility or other information costs prevented the current equilibrium from evolving. Since signaling equilibria are also market equilibria, nothing in this paper enables one to easily dismiss the argument that the intensive margin represents, at least in part, an elaborate mechanism for credibly signaling aptitude.

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Table 1 - Dependent Variable is Log(Wage and Salary Income) of Male who is approximately Age 32 and has at least a BA Degree -- all covariates shown except for indicator variables for state of high school --

		1972			1986			1995	
Individual Attributes (selection into BA Degree group)									
Number of Siblings	-0.0420	-0.0380	-0.0370	-0.0060	-0.0040	-0.0030	-0.0120	-0.0190	-0.0120
	(0.0170)	(0.0170)	(0.0170)	(0.0110)	(0.0120)	(0.0120)	(0.0256)	(0.0261)	(0.0271)
Number of Older Siblings	0.0360	0.0340	0.0340	-0.0140	-0.0180	-0.0220	0.0190	0.0300	0.0320
	(0.0200)	(0.0200)	(0.0200)	(0.0190)	(0.0190)	(0.0190)	(0.0256)	(0.0261)	(0.0267)
Black	-0.1740	-0.1970	-0.2270	-0.0990	-0.0950	-0.0580	0.0000	0.0300	-0.0130
	(0.1610)	(0.1610)	(0.1670)	(0.0860)	(0.0810)	(0.0730)	(0.1199)	(0.1222)	(0.1244)
Hispanic	0.2060	0.1690	0.1700	-0.1140	-0.1260	-0.1590	-0.3330	-0.3020	-0.3650
	(0.3070)	(0.3060)	(0.3120)	(0.1160)	(0.1220)	(0.1350)	(0.5053)	(0.5086)	(0.5073)
Asian	-0.6160	-0.6300	-0.6680	0.2230	0.2180	0.2460	0.3310	0.2660	0.3500
	(0.5760)	(0.5730)	(0.5810)	(0.0640)	(0.0780)	(0.0870)	(0.2449)	(0.2523)	(0.2674)
Native American				-1.0610	-1.1040	-1.2170	0.2590	0.2620	0.3350
				(0.4440)	(0.4280)	(0.4470)	(0.1750)	(0.1763)	(0.1782)
Parents' Highest Grade Completed	0.1890	0.1410	0.1520	0.1890	0.2270	0.2780	0.0510	0.0060	0.0870
	(0.1180)	(0.1190)	(0.1220)	(0.1450)	(0.1450)	(0.1420)	(0.1566)	(0.1603)	(0.1658)
Log(Fam Income) when in high school	0.0930	0.0440	0.0590	0.1060	0.1660	0.2060	0.0570	0.1220	0.2050
	(0.1430)	(0.1430)	(0.1470)	(0.1920)	(0.1900)	(0.1860)	(0.2149)	(0.2192)	(0.2232)
Parents' High Grd x Log(Fam Income)	0.0180	0.0130	0.0140	0.0180	0.0220	0.0260	0.0050	0.0010	0.0080
	(0.0110)	(0.0110)	(0.0110)	(0.0140)	(0.0140)	(0.0130)	(0.0145)	(0.0148)	(0.0153)
Foreign-Born Parents	0.0590	0.0540	0.0480	-0.0310	-0.0260	-0.0180	-0.1740	-0.1860	-0.2300
	(0.0770)	(0.0770)	(0.0790)	(0.0640)	(0.0650)	(0.0680)	(0.1212)	(0.1223)	(0.1243)
Foreign-Born Parents x Hispanic	-0.3920	-0.4010	-0.4560	-0.0110	-0.0120	-0.0380	0.5560	0.5290	0.4990
	(0.4690)	(0.4670)	(0.4760)	(0.1590)	(0.1670)	(0.1890)	(0.5465)	(0.5507)	(0.5521)
Urban Residence at Age 32?	0.1830	0.1540	0.1580	0.0600	0.0490	0.0460	0.1290	-0.1290	-0.1150
	(0.0540)	(0.0550)	(0.0570)	(0.0510)	(0.0510)	(0.0520)	(0.0897)	(0.0910)	(0.0923)
Age 30	-0.1120	-0.1130	-0.1160	na	na	na	-0.0670	-0.0650	-0.0670
	(0.0750)	(0.0750)	(0.0770)	na	na	na	(0.0721)	(0.0756)	(0.0737)
Age 31	-0.0510	-0.0500	-0.0570	na	na	na	-0.0320	-0.0330	-0.0320
	(0.0750)	(0.0760)	(0.0780)	na	na	na	(0.0752)	(0.0734)	(0.0739)
Age 33	0.0510	0.0520	0.0520	na	na	na	0.0320	0.0320	0.0300
	(0.0860)	(0.0860)	(0.0890)	na	na	na	(0.0655)	(0.0735)	(0.0756)
Age 34	0.0870	0.0880	0.0900	na	na	na	0.0620	0.0610	0.0550
	(0.0810)	(0.0810)	(0.0830)	na	na	na	(0.0649)	(0.0716)	(0.0735)
Age 35	0.1170	0.1200	0.0120	na	na	na	0.0910	0.0950	0.0920
	(0.0790)	(0.0800)	(0.0820)	na	na	na	(0.0721)	(0.0720)	(0.0710)
College Selectivity Effects and College Attributes									
Aptitude rank Index=2		0.0210	0.0600		0.0820	0.1460		0.1840	0.2560
		(0.1490)	(0.1090)		(0.1690)	(0.1680)		(0.1790)	(0.1244)
Aptitude rank Index=3		0.1810	0.1390		0.1160	0.2010		0.3390	0.1870
		(0.1400)	(0.1090)		(0.1960)	(0.1780)		(0.1717)	(0.1270)
Aptitude rank Index=4		0.1930	0.1640		0.1500	0.1930		0.4060	0.2130
		(0.1350)	(0.1090)		(0.1610)	(0.1700)		(0.1787)	(0.1297)
Aptitude rank Index=5		0.2840	0.2280		0.1720	0.2170		0.4680	0.2410
		(0.1360)	(0.1090)		(0.1600)	(0.1750)		(0.1768)	(0.1325)
Aptitude rank Index=6		0.2650	0.1860		0.2520	0.2180		0.3720	0.2890
		(0.1400)	(0.1140)		(0.1640)	(0.1790)		(0.1729)	(0.1303)

Aptitude rank Index=7	0.3070	0.2610	0.2840	0.2170	0.4570	0.2970
	(0.1370)	(0.1650)	(0.1750)	(0.1680)	(0.1724)	(0.1314)
Aptitude rank Index=8	0.3280	0.2740	0.3560	0.2690	0.4720	0.3390
	(0.1790)	(0.1630)	(0.1680)	(0.1690)	(0.1825)	(0.1376)
Aptitude rank Index=9	0.3560	0.2090	0.4350	0.3790	0.4640	0.3680
	(0.1480)	(0.1610)	(0.2080)	(0.1870)	(0.1828)	(0.1348)
Aptitude rank Index=10	0.4320	0.3050	0.5280	0.3690	0.5420	0.3770
	(0.1700)	(0.1620)	(0.2270)	(0.1900)	(0.1798)	(0.1450)
Aptitude rank Index=11	0.4730	0.3220	0.6310	0.3980	0.6680	0.3960
	(0.1510)	(0.1670)	(0.2280)	(0.2030)	(0.1962)	(0.1539)
Aptitude rank Index=12	0.5280	0.3910	0.6450	0.3980	0.7780	0.3980
	(0.1950)	(0.1630)	(0.2290)	(0.2010)	(0.1950)	(0.1712)
StdDev in SAT Verbal x Selectivity=2		0.0710		0.0770		0.0440
		(0.0270)		(0.0290)		(0.0246)
StdDev in SAT Verbal x Selectivity=3		0.0680		0.0580		0.0390
		(0.0260)		(0.0290)		(0.0185)
StdDev in SAT Verbal x Selectivity=4		0.0520		0.0320		0.0330
		(0.0270)		(0.0310)		(0.0187)
StdDev in SAT Verbal x Selectivity=5		0.0210		0.0150		0.0260
		(0.0250)		(0.0260)		(0.0200)
StdDev in SAT Verbal x Selectivity=6		-0.0030		0.0020		0.0160
		(0.0220)		(0.0260)		(0.0205)
StdDev in SAT Verbal x Selectivity=7		-0.0040		-0.0090		0.0080
		(0.0270)		(0.0250)		(0.0223)
StdDev in SAT Verbal x Selectivity=8		-0.0110		-0.0160		-0.0180
		(0.0250)		(0.0290)		(0.0210)
StdDev in SAT Verbal x Selectivity=9		-0.0210		-0.0260		-0.0280
		(0.0250)		(0.0270)		(0.0207)
StdDev in SAT Verbal x Selectivity=10		-0.0280		-0.0380		-0.0470
		(0.0260)		(0.0270)		(0.0218)
StdDev in SAT Verbal x Selectivity=11		-0.0470		-0.0490		-0.0580
		(0.0230)		(0.0230)		(0.0241)
StdDev in SAT Verbal x Selectivity=12		-0.0530		-0.0550		-0.0600
		(0.0240)		(0.0260)		(0.0199)
Log(Expenditure Per Student $1995)		0.0600		0.1110		0.1190
		(0.0310)		(0.0400)		(0.0258)
College is Selective but does not use Admissions Tests		-0.0080		-0.1870		-0.1510
		(0.1410)		(0.1900)		(0.2449)
College is Not Accredited		-0.1530		-0.0950		-0.0200
		(0.2140)		(0.3230)		(0.6666)

See notes on following page.

Standard error in parentheses. See Data Appendix Table for the number of observations in each regression, variable means and standard deviations. No age effects are included in 1986 (NLS72) regressions because the survey is based on a single high school class. Family income (when respondent was in high school) and college expenditure per student are in 1995 dollars. Both of these variables are in logs. Selectivity index combines information from college's average admissions test scores and admissions procedures indexed by Barron's, Peterson's, and Cass and Birmbaum's college guides. Standard deviations in SAT verbal scores are measured in *10s* of percentile points (based on the national distribution of SATscores). The omitted category is a college that is accredited but nonselective (aptitude rank index=1). Such colleges do not have SAT score distributions, so the "main effect" of the standard deviation in SAT scores is included.

Table 2
Decomposition of the Change in the Variance of Log(Wage and Salary Income)
of Males who are approximately age 32 and have a Baccalaureate Degree

		Change in the Variance of Log (Wage and Salary Income) between....					
		1972 and 1986		1986 and 1995		1972 and 1995	
total variance to be explained		0.0691		0.0452		0.1143	
method 1	background	0.0183	26.5%	0.0169	37.4%	0.0352	30.8%
change in the variance that is due to...	[Δ in r to background]	[-0.0120]	[-17.4%]	[-0.0123]	[-27.2%]	[-0.0212]	[-18.5%]
	[Δ in var(background)]	[0.0303]	[43.8%]	[0.0292]	[64.6%]	[0.0564]	[49.3%]
	residual	0.0508	73.5%	0.0283	62.6%	0.0791	69.2%
method 2	background	0.0119	17.2%	0.0049	10.8%	0.0168	14.7%
change in the variance that is due to...	[Δ in r to background]	[-0.0067]	[-9.7%]	[-0.0060]	[-13.3%]	[-0.0143]	[-12.5%]
	[Δ in var(background)]	[0.0186]	[26.9%]	[0.0109]	[24.1%]	[0.0311]	[27.2%]
	college selectivity dummies	0.0288	41.7%	0.0259	57.3%	0.0547	47.9%
	[Δ in r to select. dummies]	[0.0267]	[38.6%]	[0.0242]	[53.5%]	[0.0513]	[44.9%]
	[Δ in var(select. dummies)]	[0.0021]	[3.0%]	[0.0017]	[3.8%]	[0.0034]	[3.0%]
	residual + covariances	0.0284	41.1%	0.0144	31.9%	0.0428	37.4%
method 3	background	0.0119	17.2%	0.0051	11.3%	0.0167	14.6%
change in the variance that is due to...	[Δ in r to background]	[-0.0071]	[-10.3%]	[-0.0064]	[-14.2%]	[-0.0086]	[-7.5%]
	[Δ in var(background)]	[0.0190]	[27.5%]	[0.0115]	[25.4%]	[0.0253]	[22.1%]
	college selectivity dummies	0.0151	21.9%	0.0155	34.3%	0.0306	26.8%
	[Δ in r to select. dummies]	[0.0129]	[18.7%]	[0.0136]	[30.1%]	[0.0270]	[23.6%]
	[Δ in var(select. dummies)]	[0.0022]	[3.2%]	[0.0019]	[4.2%]	[0.0036]	[3.1%]
	college peers & spending	0.0194	28.1%	0.0171	37.8%	0.0365	31.9%
	[Δ in r to peers & spending]	[0.0025]	[3.6%]	[0.0024]	[5.3%]	[0.0053]	[4.6%]
	[Δ in var(peers & spending)]	[0.0169]	[24.5%]	[0.0147]	[32.5%]	[0.0312]	[27.3%]
	residual + covariances	0.0227	32.9%	0.0075	16.6%	0.0305	26.7%

Variance of Log (Wage and Salary Income) –from which the above changes were calculated				
		1972	1986	1995
total variance to be explained		0.3155	0.3846	0.4298
method 1	background	0.0440	0.0623	0.0792
	residual	0.2715	0.3223	0.3506
method 2	background	0.0412	0.0531	0.0580
	college selectivity dummies	0.0192	0.0480	0.0739
	residual + covariances	0.2551	0.2835	0.2979
method 3	background	0.0409	0.0528	0.0596
	college selectivity dummies	0.0178	0.0329	0.0484
	college peers & spending	0.0132	0.0326	0.0497
	residual + covariances	0.2436	0.2663	0.2721

See notes following Table 1, which contains the regressions that underlie the above table.

Table 3
Decomposition of the Change in the Variance of Log(Hourly Wage)
of Males who are approximately age 32 and have a Baccalaureate Degree

		Change in the Variance of Log (Hourly Wage) between....					
		1972 and 1986		1986 and 1995		1972 and 1995	
total variance to be explained		0.0374		0.0148		0.0522	
method 1	background	0.0099	26.5%	0.0060	40.5%	0.0159	30.5%
change in the variance that is due to...	[Δ in r to background]	-0.0020	-5.3%	-0.0028	-18.9%	-0.0068	-13.0%
	[Δ in var(background)]	0.0119	31.8%	0.0088	59.5%	0.0227	43.5%
	residual	0.0275	73.5%	0.0088	59.5%	0.0363	69.5%
method 2	background	0.0084	22.5%	0.0024	16.2%	0.0108	20.7%
change in the variance that is due to...	[Δ in r to background]	-0.0036	-9.6%	-0.0021	-14.2%	-0.0068	-13.0%
	[Δ in var(background)]	0.0120	32.1%	0.0045	30.4%	0.0176	33.7%
	college selectivity dummies	0.0207	55.3%	0.0093	62.8%	0.0300	57.5%
	[Δ in r to select. dummies]	0.0148	39.6%	0.0073	49.3%	0.0218	41.8%
	[Δ in var(select. dummies)]	0.0059	15.8%	0.0020	13.5%	0.0082	15.7%
	residual + covariances	0.0083	22.2%	0.0031	20.9%	0.0114	21.8%
method 3	background	0.0109	29.1%	0.0031	20.9%	0.0140	26.8%
change in the variance that is due to...	[Δ in r to background]	-0.0037	-9.9%	-0.0024	-16.2%	-0.0062	-11.9%
	[Δ in var(background)]	0.0146	39.0%	0.0055	37.2%	0.0202	38.7%
	college selectivity dummies	0.0073	19.5%	0.0045	30.4%	0.0118	22.6%
	[Δ in r to select. dummies]	0.0016	4.3%	0.0027	18.2%	0.0040	7.7%
	[Δ in var(select. dummies)]	0.0057	15.2%	0.0018	12.2%	0.0078	14.9%
	college peers & spending	0.0113	30.2%	0.0046	31.1%	0.0159	30.5%
	[Δ in r to peers & spending]	0.0008	2.1%	0.0012	8.1%	0.0021	4.0%
	[Δ in var(peers & spending)]	0.0105	28.1%	0.0034	23.0%	0.0138	26.4%
	residual + covariances	0.0079	21.1%	0.0026	17.6%	0.0105	20.1%

Variance of Log (Hourly Wage) –from which the above changes were calculated

		1972	1986	1995
total variance to be explained		0.2009	0.2383	0.2531
method 1	background	0.0288	0.0387	0.0447
	residual	0.1721	0.1996	0.2084
method 2	background	0.0292	0.0376	0.0400
	college selectivity dummies	0.0208	0.0415	0.0508
	residual + covariances	0.1509	0.1592	0.1623
method 3	background	0.0261	0.0370	0.0401
	college selectivity dummies	0.0206	0.0279	0.0324
	college peers & spending	0.0191	0.0304	0.0350
	residual + covariances	0.1351	0.1430	0.1456

See notes following Table 1. See also Appendix Table 13, which contains the regressions that underlie the above table.

Table 4
Decomposition of the Change in the Variance of Log(Wage and Salary Income)
of Males who are approximately age 32 and have Attended at least 2 years of College

		Change in the Variance of Log (Wage and Salary Income) between....					
		1972 and 1986		1986 and 1995		1972 and 1995	
total variance to be explained		0.1221		0.1129		0.2350	
method 1	background	0.0195	16.0%	0.0175	15.5%	0.0370	15.7%
change in the variance that is due to...	[Δ in r to background]	-0.0107	-8.8%	-0.0133	-11.8%	-0.0229	-9.7%
	[Δ in var(background)]	0.0302	24.7%	0.0308	27.3%	0.0599	25.5%
	residual	0.1026	84.0%	0.0954	84.5%	0.1980	84.3%
method 2	background	0.0225	18.4%	0.0097	8.6%	0.0322	13.7%
change in the variance that is due to...	[Δ in r to background]	-0.0089	-7.3%	-0.0111	-9.8%	-0.0155	-6.6%
	[Δ in var(background)]	0.0314	25.7%	0.0208	18.4%	0.0477	20.3%
	college selectivity dummies	0.0295	24.2%	0.0272	24.1%	0.0567	24.1%
	[Δ in r to select. dummies]	0.0204	16.7%	0.0189	16.7%	0.0375	16.0%
	[Δ in var(select. dummies)]	0.0091	7.5%	0.0083	7.4%	0.0192	8.2%
	residual + covariances	0.0701	57.4%	0.0760	67.3%	0.1461	62.2%
method 3	background	0.0247	20.2%	0.0184	16.3%	0.0431	18.3%
change in the variance that is due to...	[Δ in r to background]	-0.0075	-6.1%	-0.0122	-10.8%	-0.0085	-3.6%
	[Δ in var(background)]	0.0322	26.4%	0.0306	27.1%	0.0516	22.0%
	college selectivity dummies	0.0127	10.4%	0.0084	7.4%	0.0211	9.0%
	[Δ in r to select. dummies]	0.0038	3.1%	0.0005	0.4%	0.0023	1.0%
	[Δ in var(select. dummies)]	0.0089	7.3%	0.0079	7.0%	0.0188	8.0%
	college peers & spending	0.0165	13.5%	0.0176	15.6%	0.0341	14.5%
	[Δ in r to peers & spending]	0.0013	1.1%	0.0009	0.8%	0.0022	0.9%
	[Δ in var(peers & spending)]	0.0152	12.4%	0.0167	14.8%	0.0319	13.6%
	residual + covariances	0.0682	55.9%	0.0685	60.7%	0.1367	58.2%

Variance of Log (Wage and Salary Income) –from which the above changes were calculated				
		1972	1986	1995
total variance to be explained		0.3377	0.4598	0.5727
method 1	background	0.0429	0.0624	0.0799
	residual	0.2948	0.3974	0.4928
method 2	background	0.0337	0.0562	0.0659
	college selectivity dummies	0.0106	0.0401	0.0673
	residual + covariances	0.2934	0.3635	0.4395
method 3	background	0.0339	0.0586	0.0770
	college selectivity dummies	0.0078	0.0205	0.0289
	college peers & spending	0.0052	0.0217	0.0393
	residual + covariances	0.2908	0.3590	0.4275

See notes following Table 1. See also Appendix Table 14, which contains the regressions that underlie the above table.

Table 5
Decomposition of the Change in the Variance of Log(Hourly Wage)
of Males who are approximately age 32 and have Attended at least 2 years of College

		Change in the Variance of Log (Hourly Wage) between....					
		1972 and 1986		1986 and 1995		1972 and 1995	
total variance to be explained		0.0517		0.0222		0.0739	
method 1	background	0.0049	9.5%	0.0011	5.0%	0.0060	8.1%
change in the variance that is due to...	[Δ in r to background]	-0.0019	-3.7%	-0.0014	-6.3%	-0.0033	-4.5%
	[Δ in var(background)]	0.0068	13.2%	0.0025	11.3%	0.0093	12.6%
	residual	0.0480	92.8%	0.0199	89.6%	0.0679	91.9%
method 2	background	0.0067	13.0%	0.0020	9.0%	0.0087	11.8%
change in the variance that is due to...	[Δ in r to background]	-0.0023	-4.4%	-0.0015	-6.8%	-0.0042	-5.7%
	[Δ in var(background)]	0.0090	17.4%	0.0035	15.8%	0.0129	17.5%
	college selectivity dummies	0.0187	36.2%	0.0066	29.7%	0.0253	34.2%
	[Δ in r to select. dummies]	0.0136	26.3%	0.0045	20.3%	0.0189	25.6%
	[Δ in var(select. dummies)]	0.0051	9.9%	0.0021	9.5%	0.0064	8.7%
	residual + covariances	0.0263	50.9%	0.0136	61.3%	0.0399	54.0%
method 3	background	0.0063	12.2%	0.0017	7.7%	0.0080	10.8%
change in the variance that is due to...	[Δ in r to background]	-0.0014	-2.7%	-0.0019	-8.6%	-0.0035	-4.7%
	[Δ in var(background)]	0.0077	14.9%	0.0036	16.2%	0.0115	15.6%
	college selectivity dummies	0.0121	23.4%	0.0036	16.2%	0.0157	21.2%
	[Δ in r to select. dummies]	0.0022	4.3%	0.0014	6.3%	0.0046	6.2%
	[Δ in var(select. dummies)]	0.0099	19.1%	0.0022	9.9%	0.0111	15.0%
	college peers & spending	0.0124	24.0%	0.0061	27.5%	0.0185	25.0%
	[Δ in r to peers & spending]	0.0012	2.3%	0.0010	4.5%	0.0024	3.2%
	[Δ in var(peers & spending)]	0.0112	21.7%	0.0051	23.0%	0.0161	21.8%
	residual + covariances	0.0209	40.4%	0.0108	48.6%	0.0317	42.9%

Variance of Log (Hourly Wage) –from which the above changes were calculated

		1972	1986	1995
total variance to be explained		0.1924	0.2441	0.2663
method 1	background	0.0249	0.0298	0.0309
	residual	0.1675	0.2155	0.2354
method 2	background	0.0197	0.0264	0.0284
	college selectivity dummies	0.0075	0.0262	0.0328
	residual + covariances	0.1652	0.1915	0.2051
method 3	background	0.0194	0.0257	0.0274
	college selectivity dummies	0.0106	0.0186	0.0222
	college peers & spending	0.0065	0.0199	0.0260
	residual + covariances	0.1590	0.1799	0.1907

See notes following Table 1. See also Appendix Table 15, which contains the regressions that underlie the above table.

Table 6 - Dependent Variable is Log(Wage and Salary Income) of Male who is approximately Age 32 and has at least a BA Degree -- only selected coefficients shown

	1986		1995	
Individual Attributes (selection into BA Degree group) –not shown				
Ability				
Own Verbal Ability on High School Test	0.0168	0.0095	0.0182	0.0111
	(0.0036)	(0..0038)	(0.0042)	(0.0044)
College's Mean SAT Verbal Score	0.0126	0.0083	0.0131	0.0097
	(0.0034)	(0.0037)	(0.0043)	(0.0046)
College Peers and College Inputs				
College's StdDev in SAT Verbal		0.0163		0.0182
		(0.0090)		(0.0095)
College's StdDev in SAT Verbal x College's Mean SAT Verbal Score		-0.0011		-0.0013
		(0.0004)		(0.0005)
Log(Expenditure Per Student $1995)		0.0837		0.1192
		(0.0355)		(0.0654)

The table shows selected coefficients from a regression with all of the covariates shown in Table 1. The only differences are (1) that the two above measures of ability are substituted for the 11 indicator variables for colleges' aptitude rank and (2) that the college's standard deviation in SAT verbal and the interaction of the standard deviation with the mean SAT verbal score are substituted for the 11 interaction terms between aptitude rank and standard deviation of the SAT verbal. Standard deviations of SAT scores are measured in *10s* of national percentile points. See Table 1 and notes to Table 1.

Table 7 - Accounting for the Change in the Variance of Log(Wage and Salary Income)
–Males who are approximately age 32 and have a Baccalaureate Degree–

	Specification					
	Table 1 specification for reference	ability measures	ability measures using math tests	additional college input variables faculty-student ratio etc.	IV for college attributes with simulated instruments	control for the propensity score
period under consideration	1972-95	1986-95	1986-95	1972-95	1972-95	1972-95
total	100%	100%	100%	100%	100%	100%
background	14.6%	24.1%	24.4%	14.3%	14.4%	2.7%
[Δ in r to background]	[-7.5%]	[-14.2%]	[-14.5%]	[-7.4]	[-7.4%]	[-0.6%]
[Δ in var(background)]	[22.1%]	[38.3%]	[38.9%]	[21.7%]	[21.8%]	[3.3%]
coll selectivity or ability	26.8%	14.8%	11.9%	24.9%	26.3%	30.8%
[Δ in r to select or ability]	[23.6%]	[12.2%]	[9.6%]	[21.8%]	[23.1%]	[26.4%]
[Δ in var(select or ability)]	[3.1%]	[2.6%]	[2.3%]	[3.1%]	[3.2%]	[4.4%]
college peers & spending	31.9%	23.1%	22.6%	34.5%	34.9%	32.6%
[Δ in r to peers & spending]	[4.6%]	[2.1%]	[2.0%]	[5.8%]	[5.4%]	[4.8%]
[Δ in var(peers & spending)]	[27.3%]	[20.0%]	[20.6%]	[28.7%]	[29.5%]	[27.9%]

residual + covariances	26.7%	39.0%	41.1%	26.2%	24.4%	33.9%

Figure 1

Log(Hourly Wage) Differentials of White Males with 16+ Years and Education and 25 Years of Experience

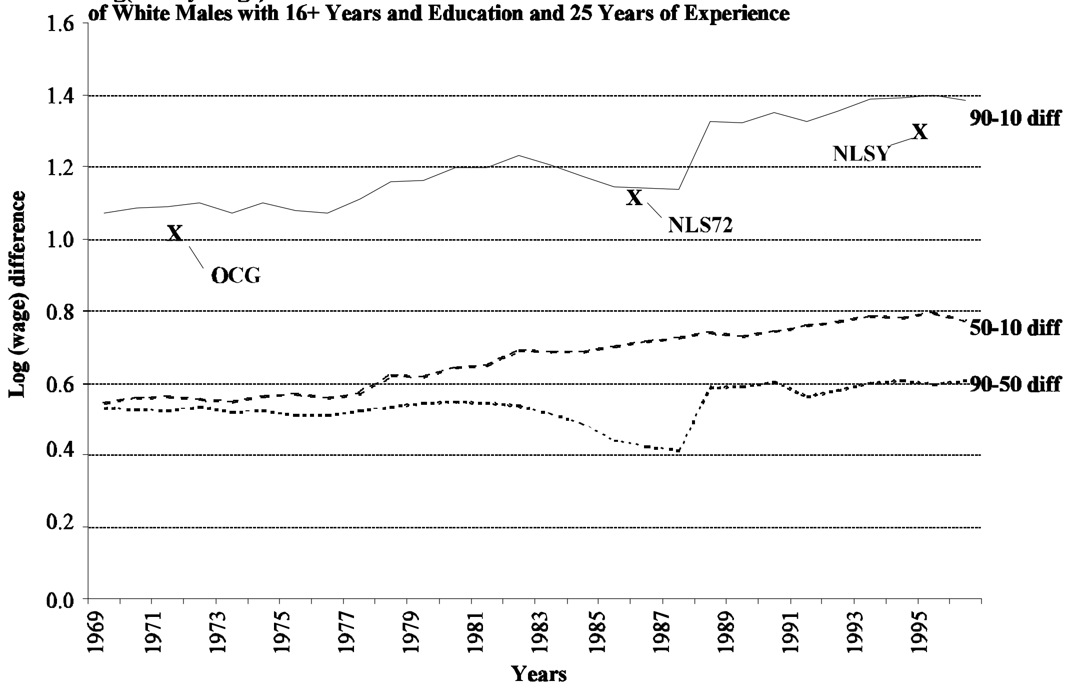


Figure 2

Log(Hourly Wage) Differentials of White Males with 16+ Years of Education and 25 Years of Experience

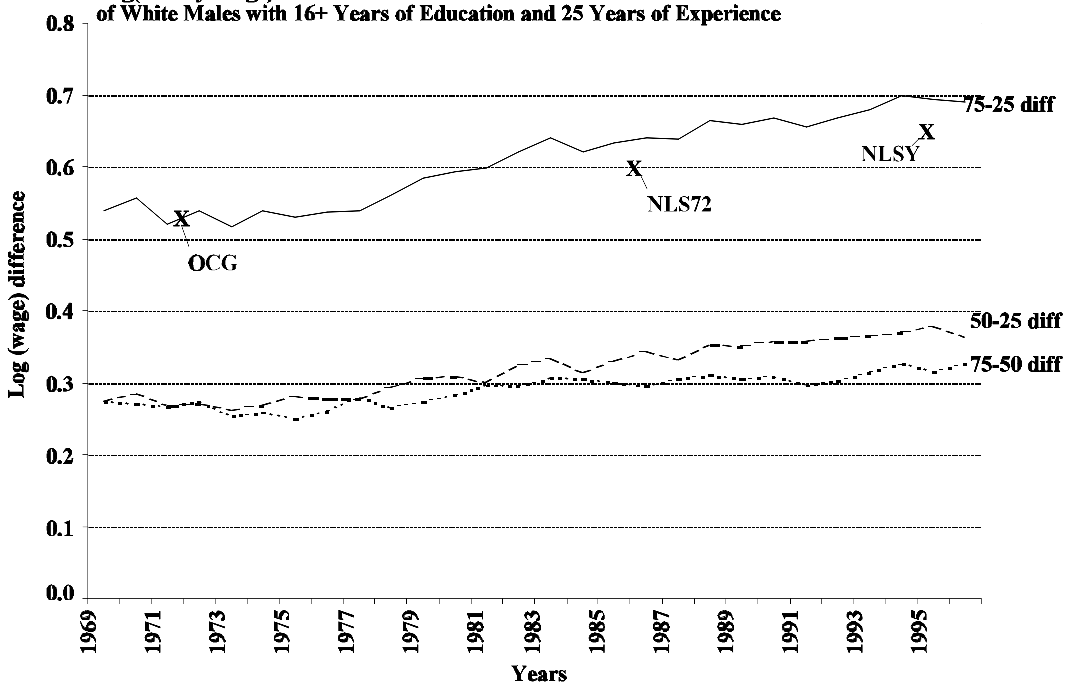


Figure 3

Log(Hourly Wage) Differentials
of White Males with 16+ Years of Education and 5 Years of Experience

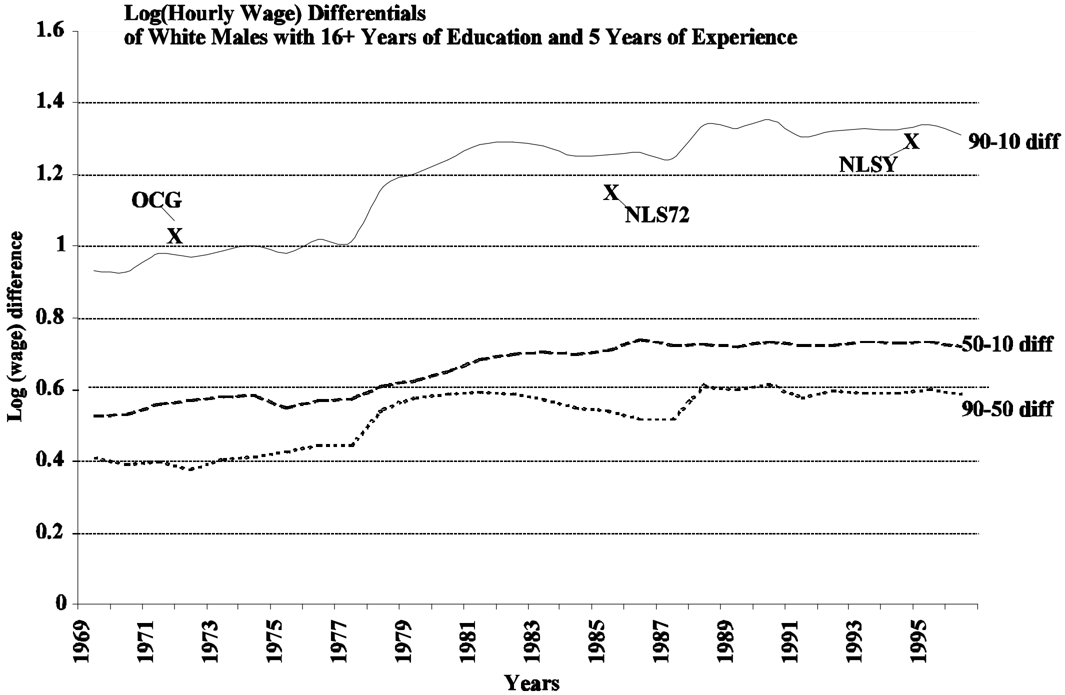


Figure 4

Log (Hourly Wage) Differentials
of White Males with 16+ Years of Education and 5Years of Experience

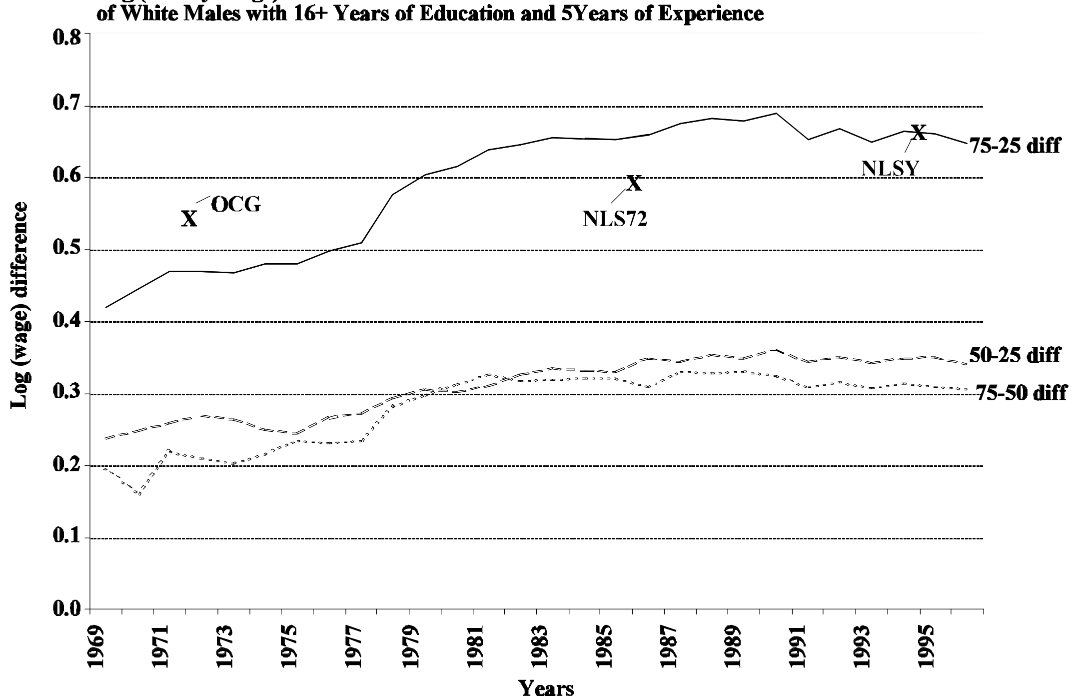
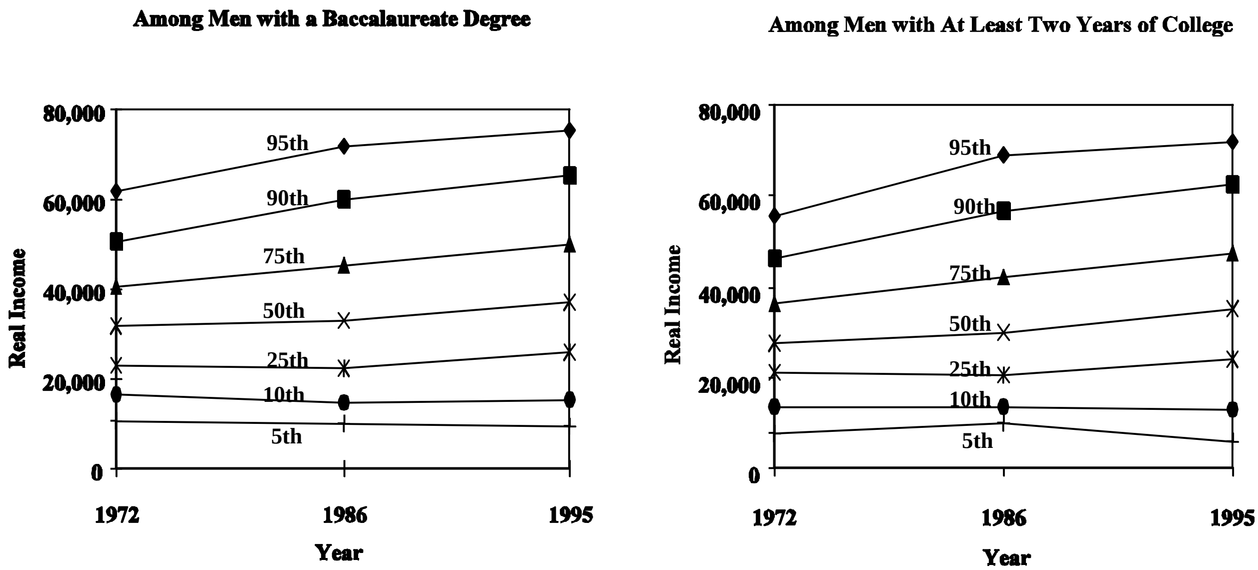


Figure 5: The Distribution of Real Income



Notes: The lines show percentiles of the distribution. The samples contain males of about 32 years of age in the year shown. Incomes are in 1995 dollars (inflated using DGP index).

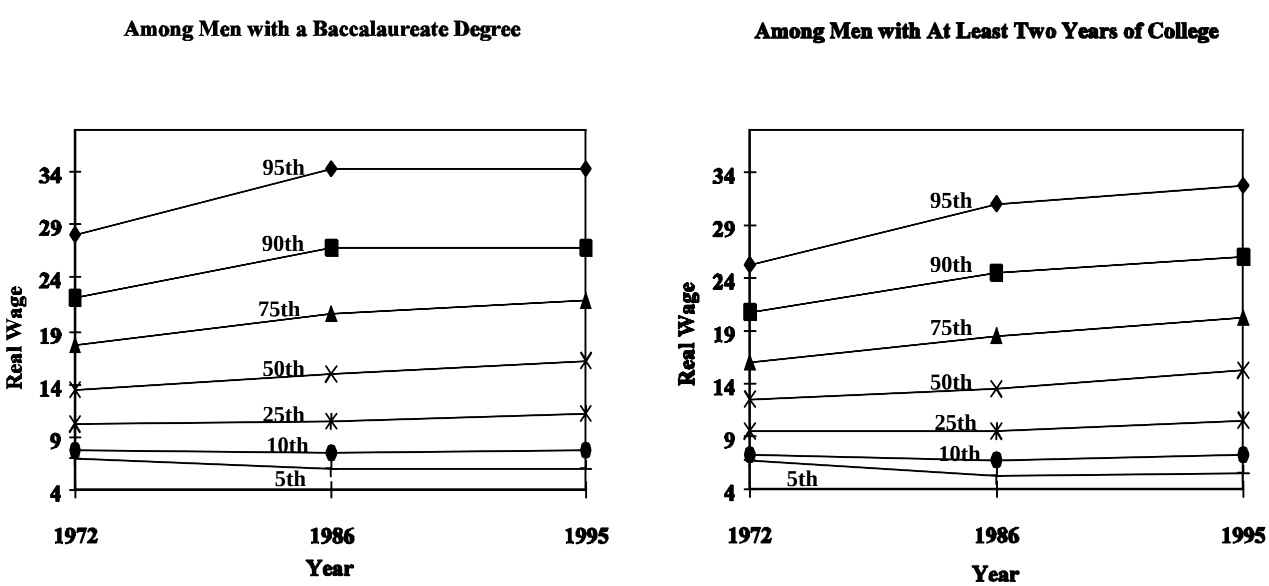
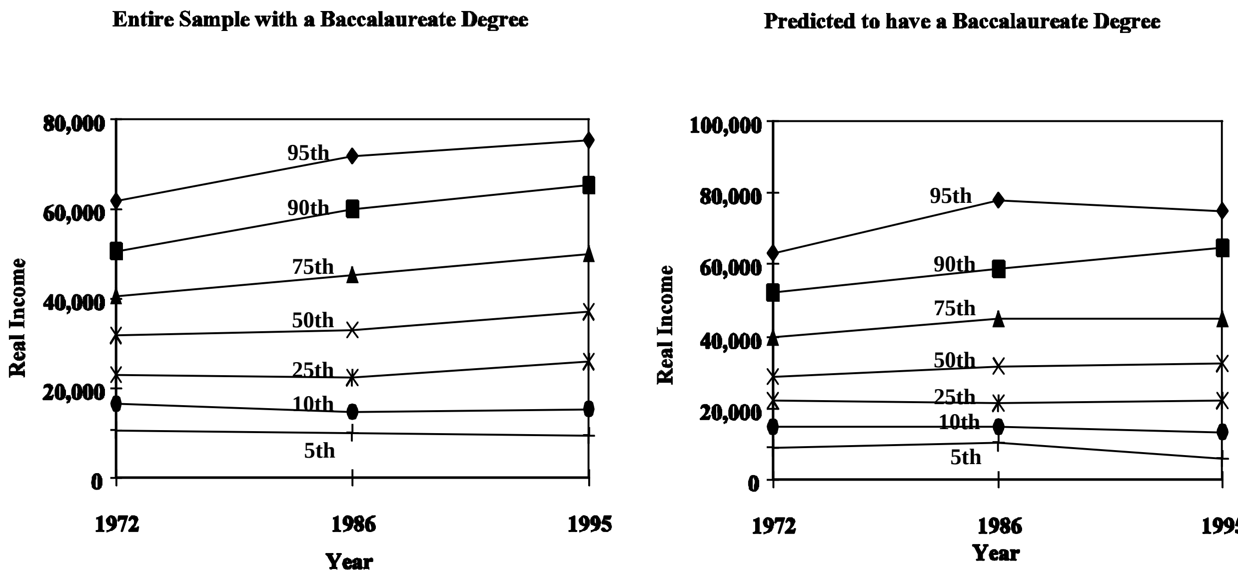


Figure 6: The Distribution of Real Wages

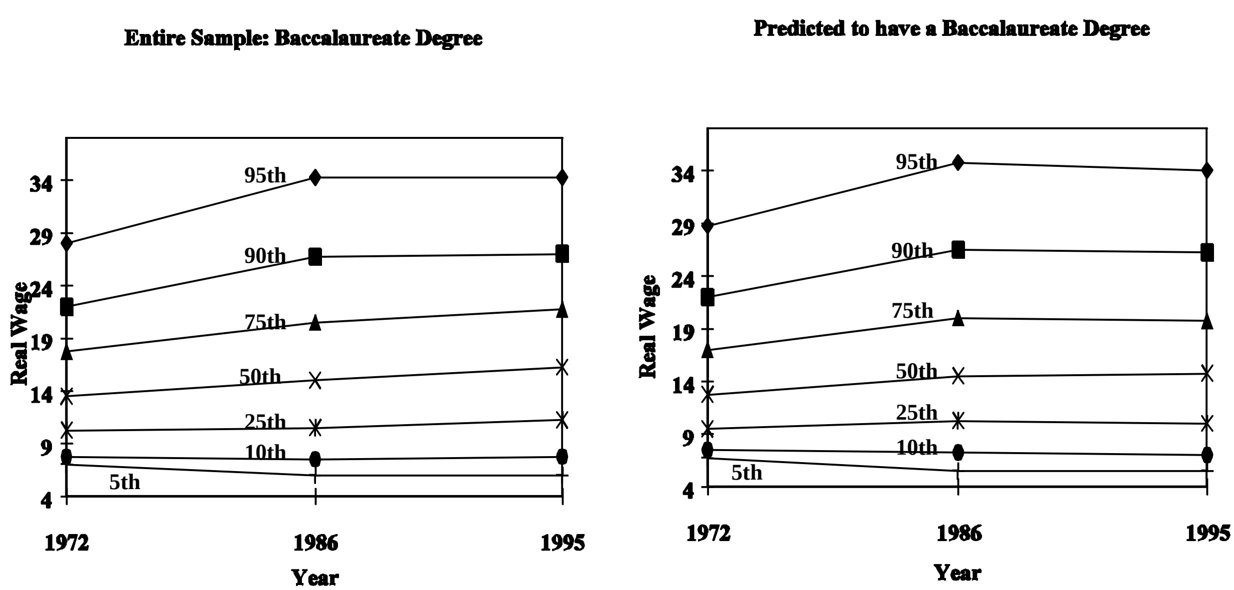
Notes: The lines show percentiles of the distribution. The samples contain males of about 32 years of age in the year shown. Wages are in 1995 dollars (inflated using DGP index).

Figure 7a: Real Income for the Sample versus Predicted College Graduates



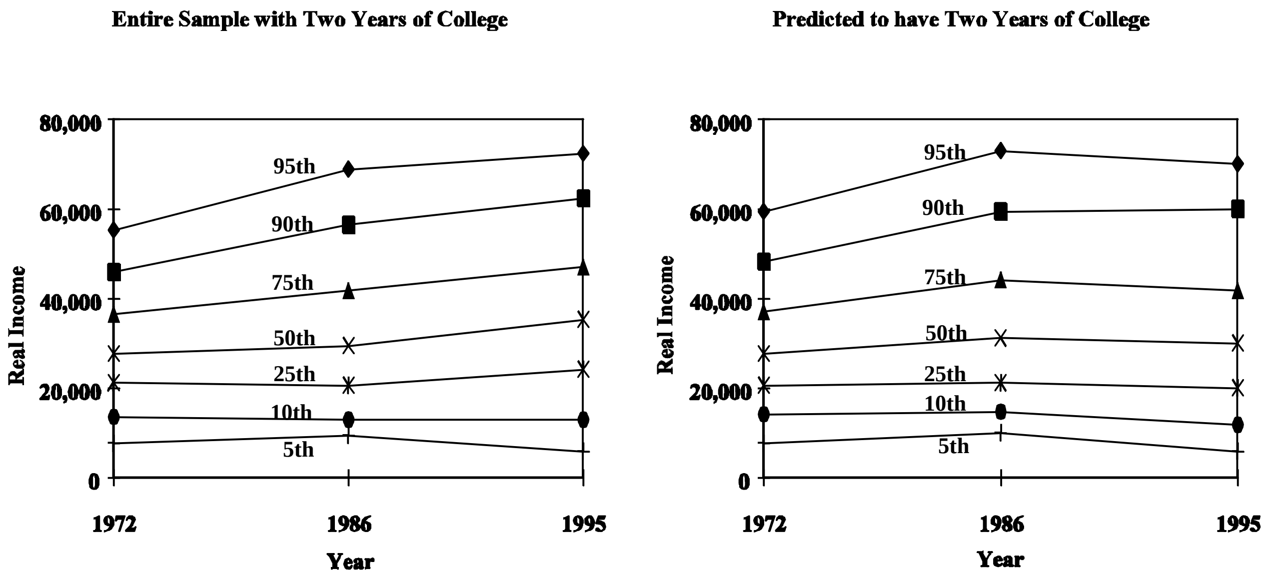
Notes: The predicted group is composed of individuals who had a propensity score to have a baccalaureate degree above the average propensity score of college students in the original sample (OCG).

Figure 7b: Real Wages for the Sample versus Predicted College Graduates



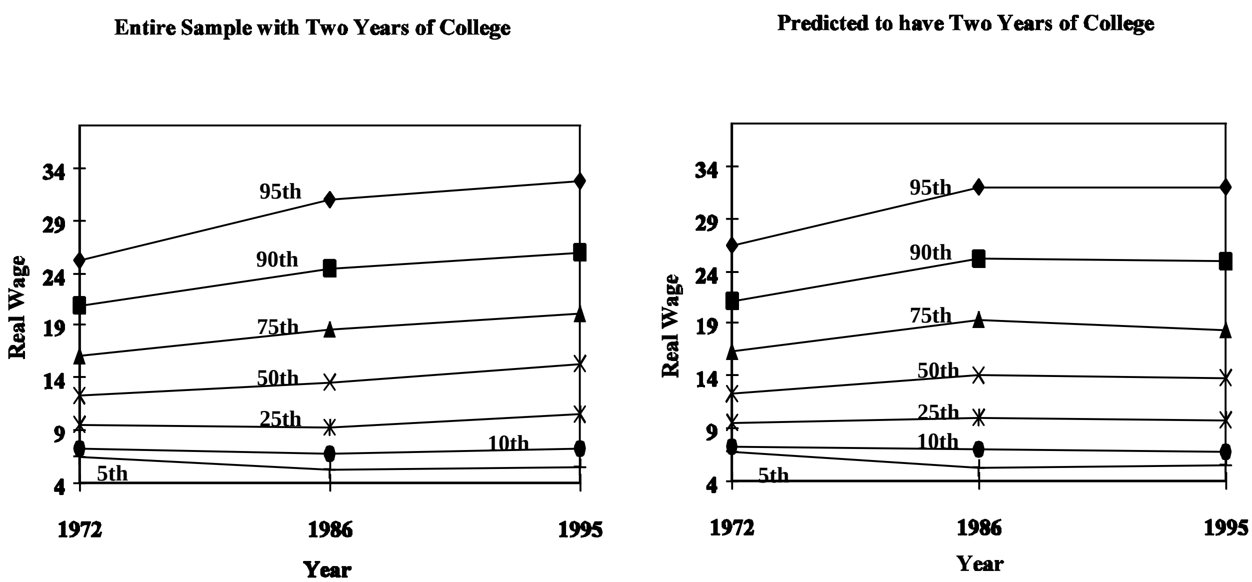
Notes: The predicted group is composed of individuals who had a propensity score to have a baccalaureate degree above the average propensity score of college students in the original sample (OCG).

Figure 8a: Real Income for the Sample versus Men Predicted to have Two Years of College



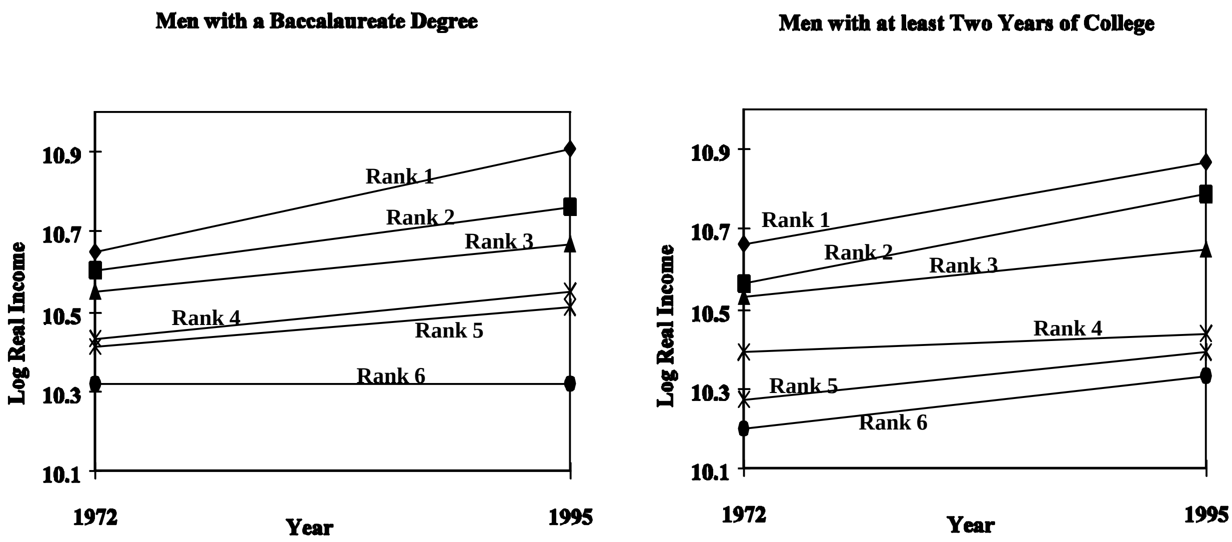
Notes: The predicted group is composed of individuals who had a propensity score to have two years of college above the average propensity score of college students in the original sample (OCG).

Figure 8b: Real Wages for the Sample versus Men Predicted to have Two Years of College



Notes: The predicted group is composed of individuals who had a propensity score to have two years of college above the average propensity score of college students in the original sample (OCG).

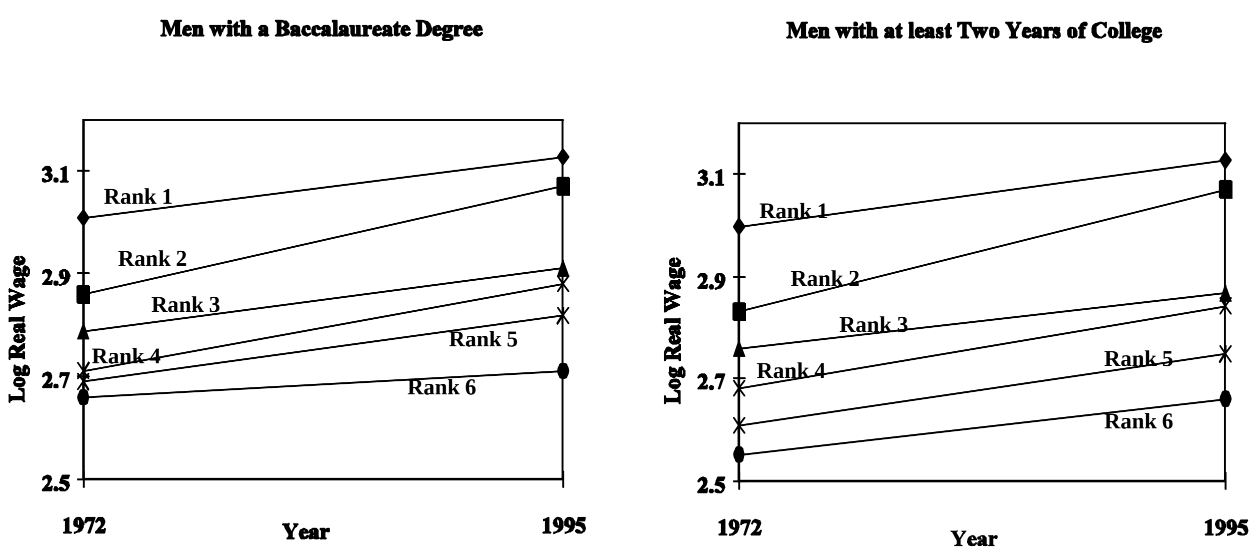
Figure 9: Real Income by College Rank Group (College Selectivity)



Notes: Colleges are divided into six rank groups, based on their admissions selectivity.

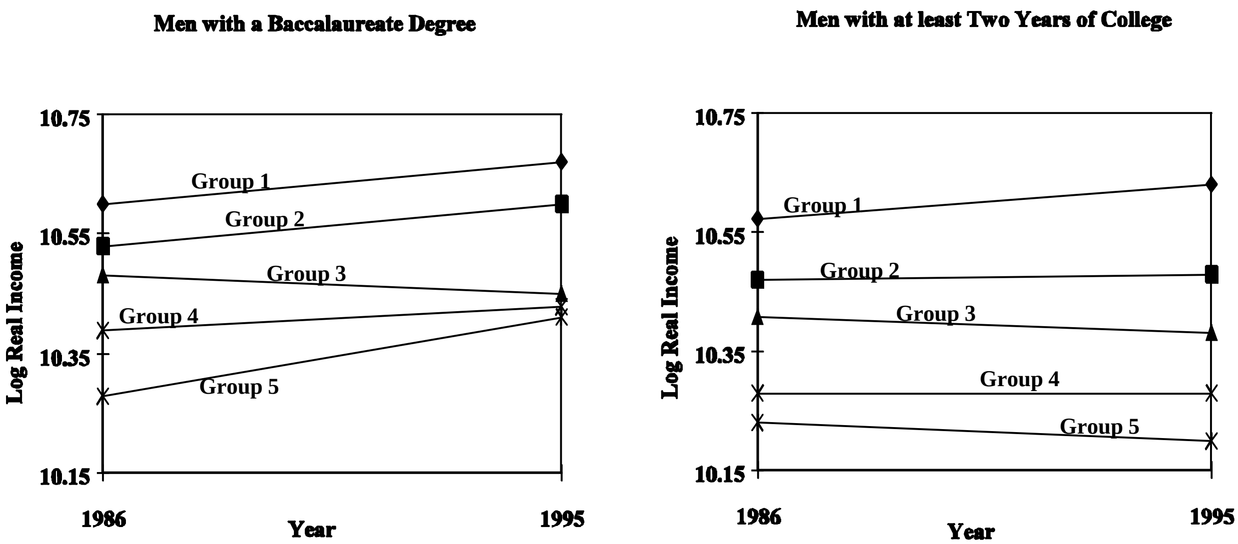
Figure 10: Real Wages by College Rank Group (College Selectivity)

Notes: Colleges are divided into six rank groups, based on



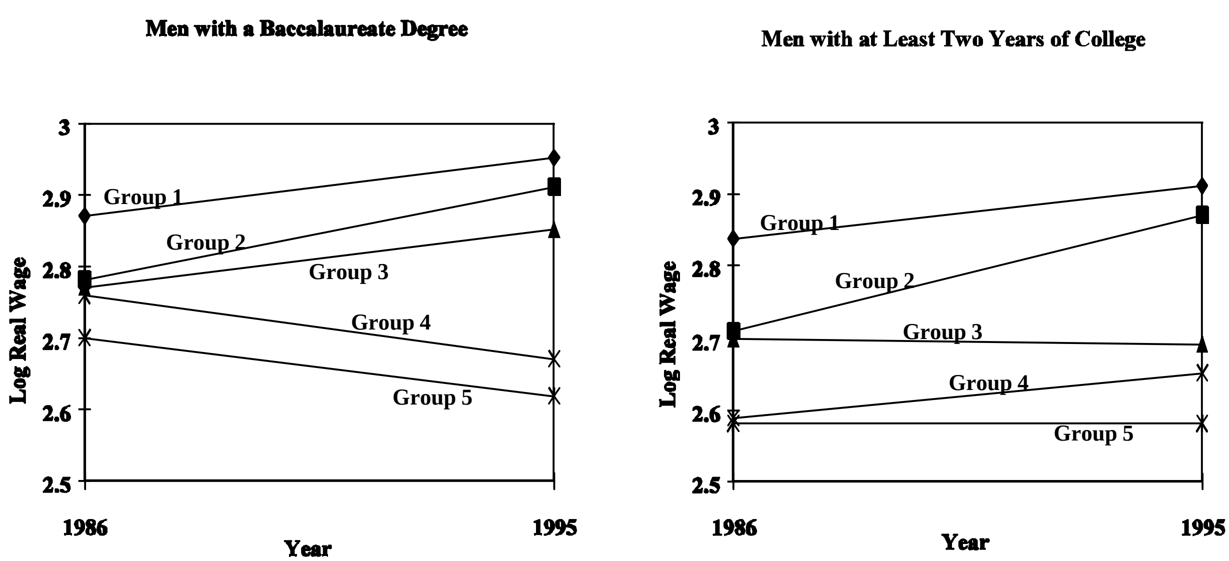
their admissions selectivity.

Figure 11: Real Income by Aptitude Group



Notes: A lower group number indicates higher measured aptitude on mathematics and verbal tests.

Figure 12: Real Wages by Ability Group



Notes: A lower group number indicates higher measured aptitude on mathematics and verbal tests.

Data Appendix

	OCG	NLS72	NLSY
total sample (males, correct age, no missing background variables or earnings, etc.)	5807	8629	3865
sample with any college	2944 [50.7%] (54.2%)	5886 [68.2%] (57.8%)	1886 [48.8%] (60.5%)
sample with at least 2 years of college	2023 [34.8%] (37.3%)	4894 [56.7%] (47.3%)	1570 [40.6%] (47.9%)
sample who attended a BA granting college	1194 [20.6%] (24.9%)	4279 [49.5%] (36.1%)	1339 [34.6%] (39.4%)
sample with a BA degree	854 [14.7%] (17.9%)	2524 [29.3%] (24.0%)	970 [22.5%] (27.0%)

OCG Sample	mean	std. dev.	minimum	maximum
log(wage and salary income) - 1972 dollars	9.1697	0.6637	7.8637	11.5119
log(hourly wage) - 1972 dollars	1.5852	0.4370	0.4097	4.0275
number of siblings	3.5602	2.9368	0	18
number of older siblings	1.7096	2.1520	0	14
black	0.0937			
hispanic	0.0273			
asian	0.0019			
native american	0.0000			
max highest grade completed by a parent	10.5617	3.4205	0	17
log(family income) - 1995 dollars	10.2621	0.7557	8.2822	11.4889
parents foreign-born or hh used foreign language	0.0849			
lived in a metro area when earnings recorded	0.6763			
age 30	0.1937			
age 31	0.1810			
age 33	0.1565			
age 34	0.1605			
age 35	0.1482			
college ultimate selectivity index=1	0.6001			
college ultimate selectivity index=2	0.0810			
college ultimate selectivity index=3	0.0598			
college ultimate selectivity index=4	0.1094			
college ultimate selectivity index=5	0.0547			
college ultimate selectivity index=6	0.0277			
college ultimate selectivity index=7	0.0328			
college ultimate selectivity index=8	0.0144			
college ultimate selectivity index=9	0.0140			
college ultimate selectivity index=10	0.0130			
college ultimate selectivity index=11	0.0088			
college ultimate selectivity index=12	0.0041			
std. dev. of college's SAT verbal %ile scores	12.3423	6.1110	2.6340	25.0000
std. dev. of college's SAT math %ile scores	17.7693	6.0770	4.4814	25.0000
log(expenditure per student) - 1995 dollars	8.6508	0.5791	8.0603	11.1190

NLS72 Sample	mean	std. dev.	minimum	maximum
log(wage and salary income) - 1986 dollars	10.1078	0.7990	8.0781	12.3118
log(hourly wage) - 1986 dollars	2.4187	0.4590	1.2528	4.4466
number of siblings	3.0871	2.3459	0	20
number of older siblings	1.4521	1.6795	0	20
black	0.0525			
hispanic	0.0390			
asian	0.0081			
native american	0.0084			
max highest grade completed by a parent	13.3307	2.7051	8	20
log(family income) - 1995 dollars	10.6087	0.5405	9.1177	11.2924
parents foreign-born or hh used foreign language	0.0712			
lived in a metro area when earnings recorded	0.7609			
college ultimate selectivity index=1	0.1030			
college ultimate selectivity index=2	0.2541			
college ultimate selectivity index=3	0.1218			
college ultimate selectivity index=4	0.2148			
college ultimate selectivity index=5	0.1251			
college ultimate selectivity index=6	0.0517			
college ultimate selectivity index=7	0.0613			
college ultimate selectivity index=8	0.0121			
college ultimate selectivity index=9	0.0200			
college ultimate selectivity index=10	0.0113			
college ultimate selectivity index=11	0.0200			
college ultimate selectivity index=12	0.0045			
std. dev. of college's SAT verbal %ile scores	6.4497	3.8497	2.0000	25.0000
std. dev. of college's SAT math %ile scores	9.0285	4.6123	2.0000	25.0000
log(expenditure per student) - 1995 dollars	9.0025	0.7032	8.1611	11.8519

NLSY Sample	mean	std. dev.	minimum	maximum
log(wage and salary income) - 1995 dollars	9.9835	0.9029	8.3012	11.9184
log(hourly wage) - 1995 dollars	2.4958	0.5204	1.3863	4.4592
number of siblings	3.3190	2.1211	0	17
number of older siblings	1.9195	1.8714	0	17
black	0.1286			
hispanic	0.0598			
asian	0.0082			
native american	0.0564			
max highest grade completed by a parent	12.4515	3.0484	8	20
log(family income) - 1995 dollars	10.4617	0.7513	9.1969	11.9668
parents foreign-born or hh used foreign language	0.1259			
lived in a metro area when earnings recorded	0.7883			
age 30	0.1453			
age 31	0.1564			
age 33	0.1660			
age 34	0.1702			
age 35	0.1670			
college ultimate selectivity index=1	0.1190			
college ultimate selectivity index=2	0.2556			
college ultimate selectivity index=3	0.1499			
college ultimate selectivity index=4	0.1600			
college ultimate selectivity index=5	0.1293			
college ultimate selectivity index=6	0.0637			
college ultimate selectivity index=7	0.0442			
college ultimate selectivity index=8	0.0186			
college ultimate selectivity index=9	0.0166			
college ultimate selectivity index=10	0.0134			
college ultimate selectivity index=11	0.0162			
college ultimate selectivity index=12	0.0135			
std. dev. of college's SAT verbal %ile scores	7.1909	3.2380	2.0000	25.0000
std. dev. of college's SAT math %ile scores	9.6248	3.7957	2.0000	25.0000
log(expenditure per student) - 1995 dollars	9.3704	0.8308	8.5170	11.8613

Appendix Table 1
CPS-based Estimates of Wage Inequality – White Men with 25 Years of Experience

	Difference between log(wage) at the 90th and 10th percentiles	Cumulative Increase	Difference between log(wage) at the 90th and 50th percentiles	Difference between log(wage) at the 50th and 10th percentiles
1969	1.070		0.533	0.545
1970	1.086	1.600	0.527	0.559
1971	1.090	2.000	0.525	0.565
1972	1.100	3.000	0.535	0.555
1973	1.071	0.100	0.521	0.550
1974	1.100	3.000	0.525	0.563
1975	1.080	1.000	0.510	0.570
1976	1.072	0.200	0.513	0.559
1977	1.110	4.000	0.525	0.570
1978	1.159	8.900	0.537	0.622
1979	1.163	9.298	0.545	0.618
1980	1.195	12.530	0.551	0.644
1981	1.197	12.730	0.545	0.652
1982	1.232	16.179	0.538	0.694
1983	1.202	13.214	0.515	0.687
1984	1.173	10.263	0.485	0.687
1985	1.146	7.586	0.443	0.703
1986	1.140	7.021	0.425	0.715
1987	1.138	6.819	0.413	0.726
1988	1.327	25.685	0.587	0.740
1989	1.321	25.135	0.591	0.731
1990	1.350	28.024	0.605	0.745
1991	1.326	25.642	0.565	0.761
1992	1.353	28.344	0.580	0.774
1993	1.388	31.826	0.603	0.785
1994	1.392	32.155	0.607	0.784
1995	1.397	32.700	0.599	0.798
1996	1.385	31.477	0.609	0.775

The values for 1969-77 are taken from Buchinsky (1995) and are based on the March Current Population Survey (CPS). The values for 1978-96 are based on the Merged Outgoing Rotations files of the CPS.

Appendix Table 2
CPS-based Estimates of Wage Inequality – White Men with 25 Years of Experience

	Difference between log(wage) at the 75th and 25th percentiles	Cumulative Increase	Difference between log(wage) at the 75th and 50th percentiles	Difference between log(wage) at the 50th and 25th percentiles
1969	0.540		0.274	0.274
1970	0.557	1.700	0.272	0.285
1971	0.520	-2.000	0.268	0.270
1972	0.540	0.000	0.275	0.272
1973	0.517	-2.300	0.254	0.263
1974	0.540	0.000	0.260	0.269
1975	0.530	-1.000	0.250	0.282
1976	0.538	-0.200	0.261	0.278
1977	0.540	0.000	0.280	0.279
1978	0.560	2.000	0.266	0.294
1979	0.584	4.366	0.275	0.309
1980	0.592	5.226	0.284	0.309
1981	0.598	5.842	0.298	0.301
1982	0.621	8.090	0.296	0.325
1983	0.641	10.085	0.308	0.333
1984	0.621	8.076	0.307	0.314
1985	0.633	9.269	0.301	0.331
1986	0.640	10.042	0.296	0.344
1987	0.639	9.907	0.306	0.333
1988	0.665	12.494	0.312	0.353
1989	0.659	11.865	0.307	0.352
1990	0.669	12.866	0.310	0.359
1991	0.655	11.504	0.298	0.357
1992	0.668	12.835	0.304	0.364
1993	0.679	13.950	0.315	0.364
1994	0.698	15.850	0.327	0.371
1995	0.695	15.478	0.316	0.378
1996	0.691	15.077	0.327	0.364

The values for 1969-77 are taken from Buchinsky (1995) and are based on the March Current Population Survey (CPS). The values for 1978-96 are based on the Merged Outgoing Rotations files of the CPS.

Appendix Table 3
CPS-based Estimates of Wage Inequality – White Men with 5 Years of Experience

	Difference between log(wage) at the 90th and 10th percentiles	Cumulative Increase	Difference between log(wage) at the 90th and 50th percentiles	Difference between log(wage) at the 50th and 10th percentiles
1969	0.930		0.410	0.530
1970	0.928	-0.200	0.395	0.533
1971	0.980	5.000	0.400	0.560
1972	0.970	4.000	0.380	0.570
1973	0.988	5.800	0.407	0.581
1974	1.000	7.000	0.415	0.585
1975	0.980	5.000	0.430	0.550
1976	1.017	8.700	0.446	0.571
1977	1.010	8.000	0.445	0.575
1978	1.163	23.293	0.548	0.614
1979	1.204	27.393	0.578	0.626
1980	1.239	30.937	0.589	0.650
1981	1.284	35.412	0.597	0.687
1982	1.290	35.976	0.589	0.700
1983	1.281	35.051	0.573	0.707
1984	1.253	32.267	0.550	0.702
1985	1.254	32.433	0.544	0.710
1986	1.262	33.213	0.519	0.743
1987	1.244	31.438	0.518	0.727
1988	1.337	40.691	0.608	0.728
1989	1.327	39.660	0.605	0.722
1990	1.353	42.288	0.616	0.737
1991	1.303	37.293	0.579	0.724
1992	1.322	39.204	0.598	0.724
1993	1.328	39.756	0.592	0.735
1994	1.324	39.359	0.592	0.731
1995	1.338	40.819	0.603	0.736
1996	1.311	38.071	0.589	0.722

The values for 1969-77 are taken from Buchinsky (1995) and are based on the March Current Population Survey (CPS). The values for 1978-96 are based on the Merged Outgoing Rotations files of the CPS.

Appendix Table 4
CPS-based Estimates of Wage Inequality – White Men with 5 Years of Experience

	Difference between log(wage) at the 75th and 25th percentiles	Cumulative Increase	Difference between log(wage) at the 75th and 50th percentiles	Difference between log(wage) at the 50th and 25th percentiles
1969	0.420		0.196	0.238
1970	0.445	2.500	0.160	0.248
1971	0.470	5.000	0.220	0.260
1972	0.470	5.000	0.210	0.270
1973	0.468	4.800	0.203	0.265
1974	0.480	6.000	0.215	0.250
1975	0.480	6.000	0.235	0.245
1976	0.498	7.800	0.231	0.267
1977	0.510	9.000	0.235	0.273
1978	0.575	15.540	0.281	0.294
1979	0.604	18.397	0.298	0.306
1980	0.616	19.592	0.313	0.303
1981	0.638	21.781	0.326	0.312
1982	0.645	22.526	0.318	0.327
1983	0.655	23.481	0.319	0.336
1984	0.653	23.328	0.322	0.332
1985	0.653	23.302	0.322	0.331
1986	0.660	23.970	0.309	0.350
1987	0.675	25.465	0.330	0.345
1988	0.682	26.232	0.328	0.354
1989	0.679	25.882	0.330	0.349
1990	0.688	26.783	0.326	0.362
1991	0.653	23.292	0.309	0.344
1992	0.667	24.697	0.317	0.350
1993	0.649	22.900	0.307	0.342
1994	0.665	24.513	0.315	0.350
1995	0.660	24.035	0.309	0.351
1996	0.648	22.771	0.307	0.341

The values for 1969-77 are taken from Buchinsky (1995) and are based on the March Current Population Survey (CPS). The values for 1978-96 are based on the Merged Outgoing Rotations files of the CPS.

Appendix Table 5: The Distribution of Real Income
by Educational Group (1995 Dollars)

		1972	1986	1995
Baccalaureate Degree	95th Percentile	61,749	71,482	75,074
	90th Percentile	50,581	59,803	65,064
	75th Percentile	40,509	45,264	50,050
	50th Percentile	31,531	32,730	37,037
	25th Percentile	23,211	22,083	26,026
	10th Percentile	16,204	14,425	15,015
	5th Percentile	10,729	9,919	9,610
	95-5 Diff	51,019	61,563	65,465
	90-10 Diff	34,378	45,378	50,050
	75-25 Diff	17,298	23,179	24,024
Two Years of College	95th Percentile	55,383	68,711	72,071
	90th Percentile	45,983	56,612	62,562
	75th Percentile	36,349	41,851	47,047
	50th Percentile	27,371	29,601	35,035
	25th Percentile	21,214	20,632	24,024
	10th Percentile	13,664	13,215	13,013
	5th Percentile	7,883	9,665	6,006
	95-5 Diff	47,500	59,046	66,065
	90-10 Diff	32,320	43,397	49,549
	75-25 Diff	15,135	21,218	23,023

Notes: The respondents are males approximately 32 years of age in the designated year. The figures are from the following data sets: *Occupational Changes in a Generation* (for the 1972 group), *National Longitudinal Survey, Class of 1972* (for the 1986 group), *National Longitudinal Survey of Youth* (for the 1995 group). Incomes were adjusted into 1995 constant dollars using the Durable Goods Price Index (Source: The Department of Commerce).

Appendix Table 6: The Distribution of Real Wages
by Educational Group (1995 Dollars)

		1972	1986	1995
Baccalaureate Degree	95th Percentile	28.07	34.33	34.26
	90th Percentile	22.11	26.86	26.95
	75th Percentile	17.68	20.61	21.78
	50th Percentile	13.47	14.94	16.18
	25th Percentile	10.21	10.56	11.23
	10th Percentile	7.72	7.39	7.70
	5th Percentile	6.89	5.92	5.97
	95-5 Diff	21.18	28.40	28.30
	90-10 Diff	14.39	19.47	19.25
	75-25 Diff	7.48	10.05	10.55
Two Years of College	95th Percentile	25.26	31.06	32.72
	90th Percentile	20.84	24.41	25.91
	75th Percentile	16.01	18.60	20.21
	50th Percentile	12.39	13.56	15.21
	25th Percentile	9.53	9.39	10.56
	10th Percentile	7.37	6.70	7.36
	5th Percentile	6.63	5.30	5.56
	95-5 Diff	18.63	25.75	27.16
	90-10 Diff	13.47	17.72	18.55
	75-25 Diff	6.48	9.21	9.65

Notes: The respondents are males approximately 32 years of age in the designated year. The figures are from the following data sets: *Occupational Changes in a Generation* (for the 1972 group), *National Longitudinal Survey, Class of 1972* (for the 1986 group), *National Longitudinal Survey of Youth* (for the 1995 group). Wages were adjusted into 1995 constant dollars using the Durable Goods Price Index (Source: The Department of Commerce).

Appendix Table 7a: The Distribution of Real Income (1995 Dollars)
Men with a Baccalaureate Degree: Actual versus Predicted Groups

		1972	1986	1995
Actual Group	95th Percentile	61,749	71,482	75,074
	90th Percentile	50,581	59,803	65,064
	75th Percentile	40,509	45,264	50,050
	50th Percentile	31,531	32,730	37,037
	25th Percentile	23,211	22,083	26,026
	10th Percentile	16,204	14,425	15,015
	5th Percentile	10,729	9,919	9,610
	95-5 Diff	51,019	61,563	65,465
	90-10 Diff	34,378	45,378	50,050
	75-25 Diff	17,298	23,179	24,024
Predicted Group	95th Percentile	63,500	77,973	75,074
	90th Percentile	52,552	59,038	65,064
	75th Percentile	39,414	44,619	45,045
	50th Percentile	28,904	31,954	32,032
	25th Percentile	21,845	21,594	22,022
	10th Percentile	14,665	14,463	13,013
	5th Percentile	8,978	10,061	6,006
	95-5 Diff	54,523	67,912	69,068
	90-10 Diff	37,888	44,574	52,052
	75-25 Diff	17,569	23,034	23,023

Notes: The respondents are males approximately 32 years of age in the designated year. The figures are from the following data sets: *Occupational Changes in a Generation* (for the 1972 group), *National Longitudinal Survey, Class of 1972* (for the 1986 group), *National Longitudinal Survey of Youth* (for the 1995 group). Incomes were adjusted into 1995 constant dollars using the Durable Goods Price Index (Source: The Department of Commerce). The Predicted group is composed of individuals who went to college and had a propensity to attend college above the average propensity of college students in the original sample (OCG).

Appendix Table 7b: The Distribution of Real Wages (1995 Dollars)
Men with a Baccalaureate Degree: Actual versus Predicted Groups

		1972	1986	1995
Actual Group	95th Percentile	28.07	34.33	34.26
	90th Percentile	22.11	26.86	26.95
	75th Percentile	17.68	20.61	14.05
	50th Percentile	13.47	14.94	16.18
	25th Percentile	10.21	10.56	11.23
	10th Percentile	7.72	7.39	7.70
	5th Percentile	6.89	5.92	5.97
	95-5 Diff	21.18	28.40	28.30
	90-10 Diff	14.39	19.47	19.25
	75-25 Diff	7.48	10.05	10.55
Predicted Group	95th Percentile	28.77	34.78	34.01
	90th Percentile	22.11	26.57	26.18
	75th Percentile	17.06	20.02	19.73
	50th Percentile	12.64	14.57	14.68
	25th Percentile	9.53	10.14	9.94
	10th Percentile	7.52	7.15	7.11
	5th Percentile	6.63	5.44	5.56
	95-5 Diff	22.13	29.34	28.44
	90-10 Diff	14.59	19.43	19.07
	75-25 Diff	7.53	9.88	9.79

Notes: The respondents are males approximately 32 years of age in the designated year. The figures are from the following data sets: *Occupational Changes in a Generation* (for the 1972 group), *National Longitudinal Survey, Class of 1972* (for the 1986 group), *National Longitudinal Survey of Youth* (for the 1995 group). Wages were adjusted into 1995 constant dollars using the Durable Goods Price Index (Source: The Department of Commerce). The Predicted group is composed of individuals who went to college and had a propensity to attend college above the average propensity of college students in the original sample (OCG).

Appendix Table 8a: The Distribution of Real Income (1995 Dollars)
Men with Two Years of College: Actual versus Predicted Groups

		1972	1986	1995
Actual Group	95th Percentile	55,383	68,711	72,071
	90th Percentile	45,983	56,612	62,562
	75th Percentile	36,349	41,851	47,047
	50th Percentile	27,371	29,601	35,035
	25th Percentile	21,214	20,632	24,024
	10th Percentile	13,664	13,215	13,013
	5th Percentile	7,883	9,665	6,006
	95-5 Diff	47,500	59,046	66,065
	90-10 Diff	32,320	43,397	49,549
	75-25 Diff	15,135	21,218	23,023
Predicted Group	95th Percentile	59,121	73,045	70,069
	90th Percentile	48,173	59,479	60,060
	75th Percentile	37,224	44,109	42,042
	50th Percentile	27,371	31,117	30,030
	25th Percentile	20,684	21,179	20,020
	10th Percentile	14,233	14,626	12,012
	5th Percentile	7,883	10,136	6,006
	95-5 Diff	51,238	62,910	64,063
	90-10 Diff	33,940	44,853	48,048
	75-25 Diff	16,540	22,931	22,022

Notes: The respondents are males approximately 32 years of age in the designated year. The figures are from the following data sets: *Occupational Changes in a Generation* (for the 1972 group), *National Longitudinal Survey, Class of 1972* (for the 1986 group), *National Longitudinal Survey of Youth* (for the 1995 group). Incomes were adjusted into 1995 constant dollars using the Durable Goods Price Index (Source: The Department of Commerce). The Predicted group is composed of individuals who went to college and had a propensity to attend college above the average propensity of college students in the original sample (OCG).

Appendix Table 8b: The Distribution of Real Wages (1995 Dollars)
Men with Two Years of College: Actual versus Predicted Groups

		1972	1986	1995
Actual Group	95th Percentile	25.26	31.06	32.72
	90th Percentile	20.84	24.41	25.91
	75th Percentile	16.01	18.60	20.21
	50th Percentile	12.39	13.56	15.21
	25th Percentile	9.53	9.39	10.56
	10th Percentile	7.37	6.70	7.36
	5th Percentile	6.63	5.30	5.56
	95-5 Diff	18.63	25.75	27.16
	90-10 Diff	13.47	17.72	18.55
	75-25 Diff	6.48	9.21	9.65
Predicted Group	95th Percentile	26.32	31.90	32.08
	90th Percentile	21.05	25.15	25.02
	75th Percentile	16.42	19.46	18.42
	50th Percentile	12.36	14.19	13.90
	25th Percentile	9.48	9.97	9.81
	10th Percentile	7.39	6.99	6.85
	5th Percentile	6.73	5.20	5.56
	95-5 Diff	19.60	26.69	26.53
	90-10 Diff	13.66	18.16	18.17
	75-25 Diff	6.94	9.48	8.61

Notes: The respondents are males approximately 32 years of age in the designated year. The figures are from the following data sets: *Occupational Changes in a Generation* (for the 1972 group), *National Longitudinal Survey, Class of 1972* (for the 1986 group), *National Longitudinal Survey of Youth* (for the 1995 group). Wages were adjusted into 1995 constant dollars using the Durable Goods Price Index (Source: The Department of Commerce). The Predicted group is composed of individuals who went to college and had a propensity to attend college above the average propensity of college students in the original sample (OCG).

Appendix Table 9: Log Mean Income by College Rank
Grouped by Educational Attainment

	Baccalaureate Degree		At Least Two Years of College	
	1972	1995	1972	1995
Rank 6	10.65	10.91	10.66	10.87
Rank 5	10.60	10.76	10.56	10.79
Rank 4	10.55	10.67	10.53	10.65
Rank 3	10.43	10.55	10.39	10.44
Rank 2	10.41	10.51	10.27	10.39
Rank 1	10.32	10.32	10.20	10.33
Diff 6 - 1	0.33	0.59	0.45	0.54
Diff 5 - 2	0.19	0.25	0.29	0.39

Notes: The respondents are males approximately 32 years of age in the designated year. The figures are from the following data sets: *Occupational Changes in a Generation* (for the 1972 group), *National Longitudinal Survey, Class of 1972* (for the 1986 group), *National Longitudinal Survey of Youth* (for the 1995 group). Incomes were adjusted into 1995 constant dollars using the Durable Goods Price Index (Source: The Department of Commerce). A higher college rank constitutes a higher-quality college.

Appendix Table 10: Log Mean Wage by College Rank
Grouped by Educational Attainment

	Baccalaureate Degree		At Least Two Years of College	
	1972	1995	1972	1995
Rank 6	3.01	3.13	3.00	3.13
Rank 5	2.86	3.07	2.83	3.07
Rank 4	2.79	2.91	2.76	2.87
Rank 3	2.71	2.88	2.68	2.84
Rank 2	2.69	2.82	2.61	2.75
Rank 1	2.66	2.71	2.55	2.66
Diff 6 - 1	0.35	0.42	0.46	0.48
Diff 5 - 2	0.17	0.25	0.22	0.32

Notes: The respondents are males approximately 32 years of age in the designated year. The figures are from the following data sets: *Occupational Changes in a Generation* (for the 1972 group), *National Longitudinal Survey, Class of 1972* (for the 1986 group), *National Longitudinal Survey of Youth* (for the 1995 group). Incomes were adjusted into 1995 constant dollars using the Durable Goods Price Index (Source: The Department of Commerce). A higher college rank constitutes a higher-quality college.

Appendix Table 11: Log Mean Income by Ability

	Baccalaureate Degree		Two Years of College	
	1986	1995	1986	1995
Group 5	10.60	10.67	10.57	10.63
Group 4	10.53	10.60	10.47	10.48
Group 3	10.48	10.45	10.41	10.38
Group 2	10.39	10.43	10.28	10.28
Group 1	10.28	10.41	10.23	10.20
Diff: Groups 5-1	0.32	0.27	0.33	0.43
Diff: Groups 4-2	0.15	0.17	0.18	0.20

Notes: The respondents are males approximately 32 years of age in the designated year. The figures are from the following data sets: *Occupational Changes in a Generation* (for the 1972 group), *National Longitudinal Survey, Class of 1972* (for the 1986 group), *National Longitudinal Survey of Youth* (for the 1995 group). Incomes were adjusted into 1995 constant dollars using the Durable Goods Price Index (Source: The Department of Commerce). Group 5 contains the individuals with the highest ability while Group 1 has the individuals with the least level of ability as measured by the tests.

Appendix Table 12: Log Mean Wage by Ability

	Baccalaureate Degree		Two Years of College	
	1986	1995	1986	1995
Group 5	2.87	2.95	2.84	2.91
Group 4	2.78	2.91	2.71	2.87
Group 3	2.77	2.85	2.70	2.69
Group 2	2.76	2.67	2.59	2.65
Group 1	2.70	2.62	2.58	2.58
Diff: Groups 5-1	0.17	0.33	0.26	0.33
Diff: Groups 4-2	0.02	0.23	0.12	0.22

Notes: The respondents are males approximately 32 years of age in the designated year. The figures are from the following data sets: *Occupational Changes in a Generation* (for the 1972 group), *National Longitudinal Survey, Class of 1972* (for the 1986 group), *National Longitudinal Survey of Youth* (for the 1995 group). Incomes were adjusted into 1995 constant dollars using the Durable Goods Price Index (Source: The Department of Commerce). Group 5 contains the individuals with the highest ability while Group 1 has the individuals with the least level of ability as measured by the tests.

Appendix Table 13 - Dependent Variable is Log(Hourly Wage) of Male who is approximately Age 32 and has at least a BA Degree -- all covariates shown except for indicator variables for state of high school --

	1972			1986			1995		
Individual Attributes (selection into BA Degree group)									
Number of Siblings	-0.0138	-0.0094	-0.0074	-0.0059	-0.0044	-0.0038	-0.0096	-0.0164	-0.0114
	(0.0108)	(0.0107)	(0.0108)	(0.0097)	(0.0101)	(0.0101)	(0.0204)	(0.0208)	(0.0215)
Number of Older Siblings	0.0150	0.0129	0.0139	-0.0151	-0.0179	-0.0190	0.0273	0.0301	0.0348
	(0.0129)	(0.0128)	(0.0129)	(0.0132)	(0.0134)	(0.0130)	(0.0203)	(0.0208)	(0.0212)
Black	-0.0934	-0.1276	-0.1495	-0.0124	-0.0029	-0.0145	0.0633	0.0997	0.0438
	(0.1025)	(0.1023)	(0.1042)	(0.0758)	(0.0735)	(0.0745)	(0.0965)	(0.0987)	(0.1003)
Hispanic	0.0207	-0.0164	-0.0475	-0.0854	-0.1005	-0.0890	-0.2931	-0.2576	-0.2486
	(0.1953)	(0.1938)	(0.1938)	(0.1067)	(0.1107)	(0.1187)	(0.3925)	(0.3962)	(0.3955)
Asian	na	na	na	0.0385	0.0424	0.0430	0.3989	0.4197	0.4380
	na	na	na	(0.0628)	(0.0638)	(0.0707)	(0.1915)	(0.1981)	(0.2104)
Native American	na	na	na	-0.4075	-0.4268	-0.5401	0.3320	0.3378	0.4041
	na	na	na	(0.1873)	(0.1793)	(0.1961)	(0.1433)	(0.1444)	(0.1464)
Parents' Highest Grade Completed	-0.0461	-0.0011	0.0020	-0.1704	-0.1781	-0.2401	-0.2126	-0.2208	-0.0753
	(0.0764)	(0.0765)	(0.0771)	(0.1097)	(0.1138)	(0.1146)	(0.1248)	(0.1280)	(0.1322)
Log(Fam Income) when in high school	-0.0070	0.0391	0.0499	-0.1200	-0.1385	-0.2080	-0.2461	-0.2492	-0.1133
	(0.0924)	(0.0923)	(0.0932)	(0.1450)	(0.1482)	(0.1501)	(0.1721)	(0.1762)	(0.1791)
Parents' High Grd x Log(Fam Income)	0.0060	0.0014	0.0008	0.0164	0.0170	0.0226	0.0205	0.0210	0.0073
	(0.0071)	(0.0072)	(0.0072)	(0.0102)	(0.0106)	(0.0107)	(0.0115)	(0.0118)	(0.0122)
Foreign-Born Parents	-0.0293	-0.0414	-0.0455	0.0144	0.0146	0.0003	-0.0708	-0.0719	-0.0783
	(0.0500)	(0.0501)	(0.0501)	(0.0549)	(0.0558)	(0.0570)	(0.0971)	(0.0985)	(0.1002)
Foreign-Born Parents x Hispanic	-0.1218	-0.1002	-0.1051	0.0101	0.0219	-0.0234	0.3449	0.2974	0.2405
	(0.2984)	(0.2956)	(0.2957)	(0.1424)	(0.1432)	(0.1531)	(0.4256)	(0.4300)	(0.4305)
Urban Residence at Age 32?	0.1717	0.1372	0.1545	0.0722	0.0648	0.0692	-0.0363	-0.0240	-0.0132
	(0.0351)	(0.0357)	(0.0364)	(0.0357)	(0.0361)	(0.0364)	(0.0712)	(0.0724)	(0.0731)
Age 30	-0.1038	-0.1074	-0.1224	na	na	na	-0.0615	-0.0614	-0.0634
	(0.0482)	(0.0483)	(0.0485)	na	na	na	(0.0715)	(0.0722)	(0.0725)
Age 31	-0.0560	-0.0565	-0.0529	na	na	na	-0.0301	-0.0325	-0.0312
	(0.0486)	(0.0486)	(0.0493)	na	na	na	(0.0722)	(0.0718)	(0.0730)
Age 33	0.0461	0.0481	0.0341	na	na	na	0.3390	0.0338	0.0323
	(0.0552)	(0.0553)	(0.0560)	na	na	na	(0.0691)	(0.0706)	(0.0737)
Age 34	0.0920	0.0609	0.0578	na	na	na	0.0599	0.0623	0.0620
	(0.0518)	(0.0517)	(0.0522)	na	na	na	(0.0725)	(0.0738)	(0.0760)
Age 35	0.1231	0.1028	0.0948	na	na	na	0.0908	0.0911	0.0903
	(0.0504)	(0.0507)	(0.0511)	na	na	na	(0.0736)	(0.0743)	(0.0766)
College Selectivity Effects and College Attributes									
Ultimate Selectivity Index=2		0.0524	0.0331		0.0400	0.0279		0.0942	0.0675
		(0.1125)	(0.1155)		(0.1591)	(0.1192)		(0.1757)	(0.1442)
Ultimate Selectivity Index=3		0.1097	0.0655		0.0538	0.0486		0.1402	0.0835
		(0.1123)	(0.1148)		(0.1595)	(0.1191)		(0.1360)	(0.1442)
Ultimate Selectivity Index=4		0.1565	0.0905		0.1345	0.1132		0.1784	0.1129
		(0.1121)	(0.1149)		(0.1595)	(0.1189)		(0.1291)	(0.1441)
Ultimate Selectivity Index=5		0.1988	0.1076		0.1805	0.1369		0.2646	0.1386
		(0.1124)	(0.1150)		(0.1595)	(0.1188)		(0.1316)	(0.1443)
Ultimate Selectivity Index=6		0.2370	0.1245		0.2792	0.1371		0.3623	0.1687
		(0.1120)	(0.1145)		(0.1591)	(0.1200)		(0.1388)	(0.1439)

Ultimate Selectivity Index=7	0.2679	0.1339	0.1772	0.1968	0.4327	0.1711
	(0.1119)	(0.1151)	(0.1591)	(0.1201)	(0.1355)	(0.1445)
Ultimate Selectivity Index=8	0.3268	0.1604	0.3740	0.2353	0.4700	0.2114
	(0.1126)	(0.1184)	(0.1582)	(0.1342)	(0.1379)	(0.1450)
Ultimate Selectivity Index=9	0.2904	0.1743	0.4630	0.2731	0.5186	0.2327
	(0.1123)	(0.1190)	(0.1603)	(0.1377)	(0.1539)	(0.1458)
Ultimate Selectivity Index=10	0.3697	0.1906	0.4369	0.3612	0.6163	0.2752
	(0.1125)	(0.1171)	(0.1642)	(0.1419)	(0.1935)	(0.1812)
Ultimate Selectivity Index=11	0.4105	0.2063	0.5609	0.3635	0.6721	0.3581
	(0.1121)	(0.1196)	(0.1593)	(0.1705)	(0.1828)	(0.1611)
Ultimate Selectivity Index=12	0.4427	0.2485	0.6200	0.3900	0.7699	0.3740
	(0.1125)	(0.1169)	(0.1611)	(0.1731)	(0.1557)	(0.1445)
StdDev in SAT Verbal x Selectivity=2		0.0612		0.0632		0.0641
		(0.0164)		(0.0246)		(0.2100)
StdDev in SAT Verbal x Selectivity=3		0.0282		0.0297		0.0414
		(0.0153)		(0.0209)		(0.0187)
StdDev in SAT Verbal x Selectivity=4		0.0080		0.0172		0.0258
		(0.0159)		(0.0212)		(0.0205)
StdDev in SAT Verbal x Selectivity=5		-0.0178		0.0417		-0.0059
		(0.0169)		(0.0215)		(0.0212)
StdDev in SAT Verbal x Selectivity=6		-0.0007		-0.0096		-0.0159
		(0.0171)		(0.0234)		(0.0224)
StdDev in SAT Verbal x Selectivity=7		-0.0136		-0.0197		-0.0234
		(0.0170)		(0.0232)		(0.0218)
StdDev in SAT Verbal x Selectivity=8		-0.0265		-0.0268		-0.0230
		(0.0175)		(0.0207)		(0.0205)
StdDev in SAT Verbal x Selectivity=9		-0.0458		-0.0453		-0.0469
		(0.0190)		(0.0196)		(0.0213)
StdDev in SAT Verbal x Selectivity=10		-0.0510		-0.0524		-0.0589
		(0.0202)		(0.0212)		(0.0208)
StdDev in SAT Verbal x Selectivity=11		-0.0634		-0.0569		-0.0657
		(0.0185)		(0.0201)		(0.0208)
StdDev in SAT Verbal x Selectivity=12		-0.0671		-0.0673		-0.0736
		(0.0224)		(0.0212)		(0.0216)
Log(Expenditure Per Student $1995)		0.0470		0.0699		0.0841
		(0.0195)		(0.0235)		(0.0250)
College is Selective but does not use Admissions Tests		-0.0239		-0.0486		-0.0765
		(0.0554)		(0.0686)		(0.0359)
College is Not Accredited		-0.0632		-0.1061		-0.1276
		(0.0704)		(0.0772)		(0.0656)

See notes to Table 1. See also Data Appendix Table for number of observations in each regression, variable means and standard deviations.

Appendix Table 14 - Dependent Variable is Log(Wage and Salary Income) of Male who is approximately Age 32 and has at least 2 years of college -- all covariates shown except for indicator variables for state of high school --

		1972			1986			1995	
Individual Attributes (selection into 2-years-of-college group)									
Number of Siblings	-0.0345	-0.0288	-0.0286	-0.0025	0.0004	0.0014	-0.0319	-0.0335	-0.0350
	(0.0100)	(0.0100)	(0.0101)	(0.0075)	(0.0075)	(0.0080)	(0.0212)	(0.0214)	(0.0221)
Number of Older Siblings	0.0350	0.0291	0.0302	-0.0105	-0.0145	-0.0127	0.0213	0.0249	0.0279
	(0.0132)	(0.0131)	(0.0133)	(0.0123)	(0.0122)	(0.0124)	(0.0217)	(0.0219)	(0.0225)
Black	-0.2119	-0.1476	-0.1584	-0.1585	-0.1578	-0.1599	-0.1594	-0.1267	-0.1423
	(0.0708)	(0.0715)	(0.0725)	(0.0587)	(0.0565)	(0.0599)	(0.0938)	(0.0943)	(0.0956)
Hispanic	0.1671	0.1197	0.1063	-0.1373	-0.1389	-0.1471	-0.1175	-0.0839	-0.0500
	(0.1944)	(0.1925)	(0.1949)	(0.0896)	(0.0898)	(0.0915)	(0.4498)	(0.4485)	(0.4513)
Asian	-0.3475	-0.3262	-0.3327	0.2104	0.2060	0.1500	0.4936	0.3753	0.4216
	(0.2780)	(0.2754)	(0.2776)	(0.0857)	(0.0870)	(0.0883)	(0.2289)	(0.2350)	(0.2660)
Native American	na	na	na	-0.4936	-0.5268	-0.5715	-0.2876	-0.2875	-0.2800
	na	na	na	(0.3328)	(0.3334)	(0.3393)	(0.1520)	(0.1518)	(0.1545)
Parents' Highest Grade Completed	0.0150	0.0133	0.0079	0.2693	0.2670	0.2969	0.1212	0.1700	0.2479
	(0.0712)	(0.0707)	(0.0718)	(0.1480)	(0.1471)	(0.1442)	(0.1263)	(0.1274)	(0.1305)
Log(Fam Income) when in high school	0.0430	0.0585	0.0508	0.2292	0.2341	0.2669	0.2873	0.3401	0.4227
	(0.0860)	(0.0853)	(0.0865)	(0.2058)	(0.2044)	(0.2023)	(0.1677)	(0.1687)	(0.1720)
Parents' High Grd x Log(Fam Income)	0.0030	0.0000	0.0006	0.0260	0.0255	0.0281	0.0098	0.0149	0.0226
	(0.0068)	(0.0067)	(0.0068)	(0.0139)	(0.0138)	(0.0135)	(0.0117)	(0.0119)	(0.0122)
Foreign-Born Parents	0.0180	0.0173	0.0182	-0.0226	-0.0262	-0.0373	-0.2025	-0.2017	-0.2499
	(0.0550)	(0.0546)	(0.0556)	(0.0685)	(0.0698)	(0.0706)	(0.0905)	(0.0906)	(0.0929)
Foreign-Born Parents x Hispanic	-0.2012	-0.1381	-0.1357	-0.1439	-0.1409	-0.1318	0.2472	0.1976	0.1848
	(0.2608)	(0.2582)	(0.2606)	(0.2835)	(0.2826)	(0.2879)	(0.4752)	(0.4743)	(0.4781)
Urban Residence at Age 32?	0.2250	0.2086	0.2096	0.0453	0.0411	0.0265	0.0725	0.0627	0.0670
	(0.0368)	(0.0369)	(0.0376)	(0.0351)	(0.0359)	(0.0367)	(0.0718)	(0.0720)	(0.0730)
Age 30	-0.0858	-0.0784	-0.0750	na	na	na	-0.0634	-0.0621	-0.0647
	(0.0523)	(0.0519)	(0.0526)	na	na	na	(0.0728)	(0.0728)	(0.0755)
Age 31	-0.0677	-0.0752	-0.0669	na	na	na	-0.0321	-0.0340	-0.0361
	(0.0540)	(0.0537)	(0.0546)	na	na	na	(0.0744)	(0.0744)	(0.0765)
Age 33	0.1080	0.1199	0.1249	na	na	na	0.0286	0.0281	0.0274
	(0.0574)	(0.0572)	(0.0583)	na	na	na	(0.0756)	(0.0758)	(0.0768)
Age 34	0.1179	0.1033	0.1000	na	na	na	0.0605	0.0602	0.0682
	(0.0573)	(0.0569)	(0.0580)	na	na	na	(0.0772)	(0.0775)	(0.0793)
Age 35	0.1466	0.1187	0.1184	na	na	na	0.1007	0.1068	0.1120
	(0.0572)	(0.0570)	(0.0581)	na	na	na	(0.0758)	(0.0757)	(0.0777)
College Selectivity Effects and College Attributes									
Ultimate Selectivity Index=2		0.0766	0.0643		0.0514	0.0952		0.1370	0.0857
		(0.1978)	(0.1096)		(0.1942)	(0.1162)		(0.1865)	(0.1957)
Ultimate Selectivity Index=3		0.1331	0.1217		0.1019	0.0712		0.2106	0.1296
		(0.1987)	(0.1080)		(0.1825)	(0.1145)		(0.1856)	(0.1961)
Ultimate Selectivity Index=4		0.1267	0.1420		0.1466	0.1392		0.2652	0.1654
		(0.1954)	(0.1107)		(0.2060)	(0.1161)		(0.1832)	(0.1964)
Ultimate Selectivity Index=5		0.2241	0.2076		0.2307	0.1801		0.3467	0.2051
		(0.1971)	(0.1118)		(0.1942)	(0.1177)		(0.1855)	(0.2019)
Ultimate Selectivity Index=6		0.1788	0.1493		0.2141	0.2219		0.3558	0.2088
		(0.2027)	(0.1098)		(0.2376)	(0.1278)		(0.1941)	(0.2018)

Ultimate Selectivity Index=7	0.3235	0.2050	0.3531	0.2680	0.4183	0.2174
	(0.2008)	(0.1147)	(0.2466)	(0.1249)	(0.1901)	(0.1951)
Ultimate Selectivity Index=8	0.3278	0.2233	0.3835	0.2992	0.4885	0.2176
	(0.2492)	(0.1164)	(0.2500)	(0.1282)	(0.2477)	(0.2417)
Ultimate Selectivity Index=9	0.3537	0.2508	0.4560	0.2543	0.4704	0.2258
	(0.2135)	(0.1090)	(0.2417)	(0.1364)	(0.2119)	(0.2181)
Ultimate Selectivity Index=10	0.3453	0.2655	0.5906	0.3245	0.5494	0.2507
	(0.2396)	(0.1118)	(0.2541)	(0.1318)	(0.2361)	(0.2270)
Ultimate Selectivity Index=11	0.4413	0.3069	0.6464	0.3470	0.6420	0.3427
	(0.2232)	(0.1268)	(0.3099)	(0.1480)	(0.2304)	(0.2347)
Ultimate Selectivity Index=12	0.5130	0.3583	0.7983	0.3691	0.7648	0.3745
	(0.2130)	(0.1572)	(0.3175)	(0.1598)	(0.2278)	(0.2305)
StdDev in SAT Verbal x Selectivity=2		0.0259		0.0180		0.0282
		(0.0191)		(0.0123)		(0.0171)
StdDev in SAT Verbal x Selectivity=3		0.0159		0.0193		0.0271
		(0.0130)		(0.0120)		(0.0158)
StdDev in SAT Verbal x Selectivity=4		0.0147		0.0061		0.0039
		(0.0174)		(0.0136)		(0.0118)
StdDev in SAT Verbal x Selectivity=5		0.0449		0.0150		-0.0109
		(0.0164)		(0.0161)		(0.0155)
StdDev in SAT Verbal x Selectivity=6		0.0355		-0.0023		-0.0111
		(0.0148)		(0.0145)		(0.0162)
StdDev in SAT Verbal x Selectivity=7		0.0167		-0.0122		-0.0161
		(0.0200)		(0.0178)		(0.0194)
StdDev in SAT Verbal x Selectivity=8		-0.0435		-0.0310		-0.0225
		(0.0162)		(0.0257)		(0.0264)
StdDev in SAT Verbal x Selectivity=9		-0.0390		-0.0364		-0.0350
		(0.0310)		(0.0258)		(0.0285)
StdDev in SAT Verbal x Selectivity=10		-0.0408		-0.0488		-0.0386
		(0.0281)		(0.0168)		(0.0294)
StdDev in SAT Verbal x Selectivity=11		-0.0493		-0.0550		-0.0526
		(0.0281)		(0.0179)		(0.0302)
StdDev in SAT Verbal x Selectivity=12		-0.0592		-0.0646		-0.0606
		(0.0232)		(0.0273)		(0.0322)
Log(Expenditure Per Student $1995)		0.0471		0.0668		0.0669
		(0.0232)		(0.0273)		(0.0242)
College is Selective but does not use Admissions Tests		-0.1185		-0.0846		-0.1236
		(0.2141)		(0.1811)		(0.2048)
College is Not Accredited		-0.1783		-0.2068		-0.2050
		(0.1579)		(0.2196)		(0.1890)

See notes to Table 1. See also the Data Appendix Table for variables mean and standard deviations.

Appendix Table 15 - Dependent Variable is Log(Hourly Wage) of Male who is approximately Age 32 and has at least 2 years of college -- all covariates shown except for indicator variables for state of high school --

		1972			1986			1995	
Individual Attributes (selection into 2-years-of-college group)									
Number of Siblings	-0.0161	-0.0120	-0.0118	-0.0133	-0.0107	-0.0092	-0.0236	-0.0228	-0.0166
	(0.0063	(0.0062)	(0.0062)	(0.0065)	(0.0065)	(0.0065)	(0.0148)	(0.0150)	(0.0152)
Number of Older Siblings	0.0192	0.0156	0.0169	-0.0015	-0.0057	-0.0038	0.0123	0.0121	0.0141
	(0.0082	(0.0081)	(0.0082)	(0.0092)	(0.0091)	(0.0088)	(0.0152)	(0.0154)	(0.0155)
Black	-0.1495	-0.1182	-0.1187	-0.0238	-0.0226	-0.0295	-0.1186	-0.0935	-0.1387
	(0.0433	(0.0439)	(0.0441)	(0.0496)	(0.0484)	(0.0483)	(0.0664)	(0.0670)	(0.0670)
Hispanic	-0.0539	-0.0788	-0.0870	-0.0688	-0.0665	-0.0596	-0.2066	-0.1954	-0.2233
	(0.1178	(0.1169)	(0.1169)	(0.0798)	(0.0795)	(0.0808)	(0.3074)	(0.3071)	(0.3042)
Asian	-0.3126	-0.2609	-0.2675	0.1049	0.1043	0.0833	0.4402	0.4204	0.3688
	(0.1909	(0.1896)	(0.1887)	(0.0659)	(0.0639)	(0.0658)	(0.1573)	(0.1621)	(0.1705)
Native American	na	na	na	-0.2145	-0.2456	-0.2928	-0.2791	-0.2878	-0.3010
	na	na	na	(0.1438)	(0.1488)	(0.1634)	(0.1076)	(0.1077)	(0.1080)
Parents' Highest Grade Completed	0.0213	0.0235	0.0253	0.1154	0.0935	0.1360	0.1528	0.1373	0.0343
	(0.0453)	(0.0451)	(0.0452)	(0.0850)	(0.0863)	(0.0850)	(0.0914)	(0.0925)	(0.0942)
Log(Fam Income) when in high school	0.0297	0.0458	0.0523	0.0331	0.0155	0.0614	0.1870	0.1671	0.0644
	(0.0547)	(0.0544)	(0.0545)	(0.1081)	(0.1093)	(0.1074)	(0.1228)	(0.1239)	(0.1250)
Parents' High Grd x Log(Fam Income)	0.0017	0.0008	0.0011	0.0117	0.0092	0.0129	0.0149	0.0131	0.0035
	(0.0043)	(0.0043)	(0.0043)	(0.0079)	(0.0080)	(0.0079)	(0.0085)	(0.0086)	(0.0088)
Foreign-Born Parents	0.0191	0.0140	0.0069	0.0237	0.0217	0.0165	-0.0550	-0.0578	-0.0749
	(0.0338)	(0.0337)	(0.0338)	(0.0384)	(0.0374)	(0.0378)	(0.0641)	(0.0645)	(0.0653)
Foreign-Born Parents x Hispanic	-0.0510	-0.0861	-0.0879	-0.1232	-0.1261	-0.1086	-0.1711	-0.1440	-0.1461
	(0.1576)	(0.1563)	(0.1561)	(0.1154)	(0.1143)	(0.1177)	(0.3261)	(0.3263)	(0.3235)
Urban Residence at Age 32?	0.1752	0.1595	0.1675	0.0472	0.0395	0.0299	0.0618	0.0520	0.0588
	(0.0230)	(0.0231)	(0.0233)	(0.0243)	(0.0244)	(0.0250)	(0.0503)	(0.0506)	(0.0505)
Age 30	-0.0744	-0.0742	-0.0815	na	na	na	-0.0654	-0.0633	-0.0649
	(0.0322)	(0.0320)	(0.0320)	na	na	na	(0.0529)	(0.0537)	(0.0545)
Age 31	-0.0330	-0.0404	-0.0460	na	na	na	-0.0313	-0.0304	-0.0325
	(0.0333)	(0.0331)	(0.0333)	na	na	na	(0.0536)	(0.0540)	(0.0539)
Age 33	0.0653	0.0586	0.0622	na	na	na	0.0316	0.0320	0.0339
	(0.0353)	(0.0353)	(0.0354)	na	na	na	(0.0531)	(0.0534)	(0.0546)
Age 34	0.0715	0.0584	0.0434	na	na	na	0.0625	0.0645	0.0621
	(0.0351)	(0.0350)	(0.0351)	na	na	na	(0.0543)	(0.0547)	(0.0555)
Age 35	0.0964	0.0736	0.0645	na	na	na	0.0966	0.0932	0.0902
	(0.0350)	(0.0350)	(0.0351)	na	na	na	(0.0538)	(0.0539)	(0.0553)
College Selectivity Effects and College Attributes									
Ultimate Selectivity Index=2		0.0032	0.0044		0.0069	0.0033		0.0573	0.0364
		(0.0887)	(0.0882)		(0.1178)	(0.1177)		(0.1167	(0.1156)
Ultimate Selectivity Index=3		0.0242	0.0635		0.0061	0.0168		0.1093	0.0756
		(0.0889)	(0.0882)		(0.1177)	(0.1183)		(0.1166)	(0.1157)
Ultimate Selectivity Index=4		0.0913	0.0902		0.1010	0.0704		0.2343	0.1267
		(0.0877)	(0.0881)		(0.1178)	(0.1181)		(0.1167)	(0.1158)
Ultimate Selectivity Index=5		0.1122	0.1309		0.1246	0.1115		0.2585	0.1541
		(0.0892)	(0.0881)		(0.1177)	(0.1183)		(0.1167)	(0.1157)
Ultimate Selectivity Index=6		0.1510	0.1520		0.1561	0.1407		0.3404	0.1528
		(0.0877)	(0.0884)		(0.1174)	(0.1205)		(0.1165)	(0.1145)

Ultimate Selectivity Index=7	0.1782	0.1673	0.2289	0.1719	0.3125	0.1787
	(0.0875)	(0.0882)	(0.1179)	(0.1170)	(0.1165)	(0.1177)
Ultimate Selectivity Index=8	0.2163	0.1786	0.3091	0.2320	0.4422	0.2547
	(0.0930)	(0.0941)	(0.1172)	(0.1310)	(0.1172)	(0.1163)
Ultimate Selectivity Index=9	0.2185	0.1866	0.3541	0.2532	0.5509	0.2279
	(0.0899)	(0.0932)	(0.1186)	(0.1228)	(0.1172)	(0.1171)
Ultimate Selectivity Index=10	0.2489	0.1953	0.4200	0.3146	0.5741	0.3219
	(0.0934)	(0.0902)	(0.1206)	(0.1384)	(0.1168)	(0.1187)
Ultimate Selectivity Index=11	0.3639	0.2037	0.5592	0.3643	0.6830	0.3470
	(0.0891)	(0.0956)	(0.1176)	(0.1535)	(0.1177)	(0.1197)
Ultimate Selectivity Index=12	0.3737	0.2000	0.6450	0.3724	0.7275	0.3699
	(0.0953)	(0.0958)	(0.1191)	(0.1615)	(0.1160)	(0.1202)
StdDev in SAT Verbal x Selectivity=2		0.0287		0.0285		0.0476
		(0.0258)		(0.0247)		(0.0210)
StdDev in SAT Verbal x Selectivity=3		0.0154		0.0236		0.0363
		(0.0190)		(0.0180)		(0.0261)
StdDev in SAT Verbal x Selectivity=4		0.0124		0.0140		0.0266
		(0.0188)		(0.0196)		(0.0184)
StdDev in SAT Verbal x Selectivity=5		0.0127		-0.0159		0.0103
		(0.0187)		(0.0229)		(0.0174)
StdDev in SAT Verbal x Selectivity=6		-0.0012		-0.0197		-0.0139
		(0.0215)		(0.0243)		(0.0172)
StdDev in SAT Verbal x Selectivity=7		-0.0047		-0.0239		-0.0166
		(0.0209)		(0.0224)		(0.0192)
StdDev in SAT Verbal x Selectivity=8		-0.0273		-0.0256		-0.0339
		(0.0205)		(0.0183)		(0.0200)
StdDev in SAT Verbal x Selectivity=9		-0.0300		-0.0309		-0.0471
		(0.0201)		(0.0186)		(0.0187)
StdDev in SAT Verbal x Selectivity=10		-0.0459		-0.0452		-0.0578
		(0.0227)		(0.0211)		(0.0198)
StdDev in SAT Verbal x Selectivity=11		-0.0493		-0.0518		-0.0648
		(0.0177)		(0.0187)		(0.0195)
StdDev in SAT Verbal x Selectivity=12		-0.0566		-0.0559		-0.6582
		(0.0176)		(0.0212)		(0.0253)
Log(Expenditure Per Student $1995)		0.0123		0.0624		0.0618
		(0.0177)		(0.0208)		(0.0362)
College is Selective but does not use Admissions Tests		-0.0421		-0.0856		-0.0981
		(0.0913)		(0.0943)		(0.0628)
College is Not Accredited		-0.0853		-0.1354		-0.1275
		(0.1204)		(0.1693)		(0.0837)

See notes to Table 1. See also Data Appendix Table for number of observations in each regression, variable means and standard deviations.