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Returns to Graduate and Professional Education:
The Roles of Mathematical and Verbal Skills by Major

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Students in majors with higher average quantitative GRE scores are less likely to attend graduate school while students in majors with higher average verbal GRE scores are more likely to attend graduate school. This sorting effect means that students whose cognitive skills are associated with lower earnings at the bachelor's level are the most likely to attend graduate school. As a result, there is a substantial downward bias in estimated returns to graduate education. Correcting for the sorting effect raises estimated annualized returns to a Master's or doctoral degree from about 5% to 14.5% and 12.6% respectively. Estimated returns to professional degrees rise from 14% to 20%. These findings correspond to a large increase in relative earnings received by post graduate degree holders in the United States over the past 20 years.

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I. Background

A wealth of economic research has documented an increase in the returns to education in the 1980s. Most of this research has concentrated on the relative returns to a bachelor's degree relative to lower levels of education. Since the 1980s, there has been a well-documented increase in returns to a college education relative to lower levels of schooling. The trend in relative earnings for bachelor's degree holders relative to high school graduates between 1976 and 1998 is illustrated in Figure 1. The bachelor's degree premium over a high school degree rose from 25% in 1976 to 45% in 1998 with the gains beginning in the early 1980s. Not as commonly known is that returns for those who entered or completed some post graduate training rose in a parallel fashion through the 1980s, and then began to rise even more rapidly than did returns to bachelor's degrees in the 1990s. Over the period, the premium earned by those with graduate degrees relative to bachelor's degree recipients rose from 32% to 67%.

This study has two objectives. The first is to measure the returns to post graduate training, controlling for likely joint choices of years of schooling and their associated returns. The second objective is to determine if the rise in returns to post graduate training can be explained by changes in the quality of more recent cohorts of graduate students relative to their older colleagues or if we need to seek other explanations for the rising returns to graduate education.

Skill-biased technological change is believed to have progressively raised returns to college graduates since the 1970s. Given that graduate training is a heavy user of the information technologies believed to be a major source of technological innovations, one would expect that technological factors should have had a similar, if not a stronger, impact on post-graduate earnings as on bachelor's degree earnings. The rising graduate degree premium over the bachelor's degree premium in the 1990s might be a signal that graduate training has particularly benefited by skill-biased technical changes, although one might then have expected the premium to have risen earlier in the information technology adoption process.

To assess the role of technological change in explaining rising returns to graduate training, we focus on the role of quantitative skills on observed returns. Several studies have documented changes in the returns to quantitative skills in the 1980s. Murnane, Willett and Levy (1995) found that rising returns to mathematics skills can explain a substantial fraction of the observed increase in returns to college between 1978 and 1986. The effect was stronger for women than for men. Grogger and Eide (1995) and Levine and Zimmerman (1995) also reported that standardized mathematics scores or having taken more mathematics classes had a significant positive impact on women's wages but not men's wages.

The mechanism by which mathematical skills influence wages is not clear. It is likely that stronger quantitative skills are complementary with the use of information technologies that are widely suspected to have raised worker productivity and wages. However, quantitative skills may also affect the type of training individuals receive. Willis and Rosen (1979), Murnane, Willett and Levy (1995) and Taber (2001) all found that stronger mathematical skills in high school increased the likelihood of attending college. Paglin and Rufolo (1990) found that quantitative skills influenced choice of graduate major.

There is a presumption that quantitative and verbal skills increase in importance as the education level rises, and so changes in the value of these skills would be expected to affect the market for post-graduate training as well. Our review of the literature that concentrated on lower levels of education suggests that two effects are potentially at work:

1) Rising returns to cognitive skills may have increased the opportunity costs of attending graduate school, limiting incentives to pursue post-graduate education in the areas where

the returns are rising the most rapidly. Consequently, the most able students opt not to pursue graduate education in favor of capturing returns to those skills in jobs they can acquire with a bachelor's degree.

2) The marginal product of cognitive skills may have risen atypically in post-graduate t raining, raising the returns to graduate training relative to lower education levels.

These two possibilities would have opposite effects on incentives to attend graduate school and on observed wages. The former would suggest that the observed wage differentials between graduate and undergraduate degree holders would understate the true returns to graduate education because the earnings of those stopping at the bachelor's degree exceed the opportunity costs of those who attended graduate school. The latter would suggest the most able would attend graduate school, suggesting that the observed wage differential between graduate and undergraduate degree holders is an upward biased measure of the returns to graduate school. The latter argument would also potentially explain why we see rising graduate degree premia in the 1990s relative to earnings at the bachelor's degree level.

Even before we examine why returns to graduate training may have changed, we must document the returns to that training. There are many studies that examine incentives to enter individual majors and the returns to those decisions. However, more general studies of returns to graduate education are rare.[1] The main advantage to a general study of returns to graduate education for our purposes is that if one of the phenomena we wish to examine is how quantitative skills sort individuals across degrees, we need to have the sample cover the universe of students and not just a specific field or major. In addition, it is easier to compare estimated returns to an education level to the literature on returns to high school or college that do not distinguish by field than it is to compare returns to a specific graduate degree in, say, law or sociology.

A frequent challenge for studies measuring returns to schooling is that individuals are not randomly assigned to different schooling levels. If schooling choices are driven by individual comparative advantage, then the returns will reflect, at least in part, that nonrandom sorting of individuals across education levels. A large literature has developed assessing the impact on measured returns to schooling of various procedures aimed at controlling nonrandom sorting across school levels. A common tactic has been to use measures of parental education or other family background measures as instruments for education levels. Other instruments have included distance to school or other measures of school costs. As reviewed by Card (1999), these studies routinely obtain higher estimated returns to schooling when employing instrumental variables than they obtained using ordinary least squares.

However, these instruments are often challenged. For example, commonly used family background variables (Willis and Rosen (1979), Altonji and Dunn (1996), Deschenes (2002)) may be correlated with unmeasured ability, rendering them invalid.[2] Another large body of research has utilized data on twins to better control for unmeasured ability. Interestingly, results based on twins are similar to the findings reported from instrumental variables using family background or school attributes as instruments. While this does not validate the use of instrumental variables, it at least suggests that instrumental variables can approximate the results obtained from presumably better controls for missing ability.

Sections II discusses the estimation strategy and III discusses the data. Empirical results are reported in Section IV, and Section V reviews the study's conclusions.

II. Estimation Model

Our analysis begins with the standard log-earnings framework:

1) $$\ln y_i = S_i \beta_S + X_i\, \beta_X + \mu_i\, \beta_\mu + u_i\,,$$

where $\ln y_i$ is the observed earnings of the i^{th} individual; S_i is the observed schooling level, taken as a vector of dummy variables with the value of one indicating the individual's highest degree earned; X_i is a vector of individual characteristics; μ_i is an individual-specific ability component that influences earnings; and u_i is a random error term that is uncorrelated with S_i , X_i and μ_i. The β_s and β_x represent the estimated returns to schooling levels and individual attributes, respectively.

If μ_i is not observable by the econometrician, then (1) becomes

1′) $$ln\, y_i = S_i\, \beta_s + X_i\, \beta_x + \varepsilon_i\, ; \quad \varepsilon_i = \mu_i \beta_\mu + u_i,$$

where the error term ε_i will include both purely random components and unmeasured individual ability. If that ability is correlated with schooling success, then exclusion of μ_i from the estimating equation will lead to $E(S_i \varepsilon_i) = E(S_i \mu_i \beta_\mu) \neq 0$, and so the estimates of β_s and β_x will be subject to missing variables bias.

In our application, individuals decide between stopping at the bachelor's degree or continuing on for additional schooling. The choice set at the time the individual finishes undergraduate training includes four schooling levels: Bachelor's, Master's, Doctorate and Professional degree (mainly law or medicine). These choices are denoted respectively by subscripts B, M, D, and P. For simplicity, we consider these choices mutually exclusive, and so we only consider the choice of the highest degree earned. This avoids complications related to sequential educational choices.

The schooling decision involves selecting the option that maximizes utility. This can be written as $S_i = max\ (S_{Bi}, S_{Mi}, S_{Di}, S_{Pi})$ where S_{li} is the utility from schooling choice *l*. Although the utility levels are not observable, we can observe how the elements of S_{li} affect the probability of selecting schooling choice *l*.

Suppose that the individual selects schooling level S_i at least in part on the basis of expected earnings at that education level. Then the individual will use knowledge of X_i and μ_i to forecast what he expects to earn from each of the four educational choices. Suppose also that there is a vector Z_i that contains factors that shift the individual's taste for or cost of schooling choice *l*. Then utility from each choice S_{li} can be approximated by

(2) $$S_{li} = X_{li}\,\theta_X + Z_{li}\,\theta_Z + \mu_{li}\,\theta_\mu + v_{li} \quad ; \quad l = B, M, D, P,$$

where v_{li} may include omitted variables, measurement errors, or specification errors of functional choice, and it is assumed to be independent of observed variables.

Now, even if $E(S_i\, \mu_{li}\, \beta_\mu) = 0$, direct estimation of (1) will yield biased estimates if $E(v_{li}\, u_i) \neq 0$. This endogeneity bias is caused by the joint selection of years of schooling with the expected returns from that schooling. A large literature on returns to schooling suggests that both sources of bias, missing measures of ability and endogeneity of the schooling choice, are likely to hold, although the biases are often small. However, we cannot infer from the past literature that there would be small biases in the context of estimated returns to post graduate education. Consequently, we need to derive a mechanism to address the two potential sources of bias.

To solve the problem, we follow two strategies commonly employed in the literature. First, we use graduate school tuition, medical school tuition, and the proportion of self-supporting graduate students in the year of receipt of the bachelor's degree as measures of the anticipated cost of attending graduate or professional education. These measures are included as elements of Z_i that are believed to alter the probability of continuing in school but do not affect what individuals expect to earn after completing school.

We also included measures of parental education as elements of Z_i. Card (1999) argued that parental education might not be a legitimate instrument for years of schooling because parental education is correlated with unobserved individual ability, even if parental education does not directly affect earnings. His argument suggested that when parental education is used as an instrument for years of schooling, the estimated returns would be biased upward. We also estimated equation systems that included parental education as elements of X_i that enter both the schooling and earnings equations. Those estimates showed that estimated returns were even larger when parental education was used as an instrument, although the differences were not large. In our application, use of parental education as an instrument for years of schooling does not appear to bias the coefficients upward. Because the joint test of overidentification failed to reject the use of the tuition measures and the parental background variables as instruments, we report the estimates that exclude parental education from X_i . Results from other specifications are available on request.

One reason our measures of parental education appear not to cause problems may be that we are able to incorporate measures of verbal and quantitative ability into equations (1) and (2) that are typically missing in other studies. Let individual ability be given by

(3) $$\mu_{li} = \mu_l^M + \eta_i$$

where μ_l^M is the vector of average mathematical and verbal skills associated with the individual's undergraduate major and η_i is an individual-specific ability component that does not vary in productivity across schooling levels. The η_i would not affect choice of schooling level. However, verbal and mathematical skills can have different productivities at different schooling levels. Variation in μ_l^M across majors at one point in time or across cohorts can affect the graduate school entry decision. Elements of Z_i can still serve as legitimate instruments for years of schooling provided that $E(Z_i \eta_i) = 0$.

Inserting equation (3) into equation (2), we obtain

$$(4) \quad S_{li} = X_{li}\theta_x + Z_{li}\theta_Z + (\mu_l^M + \eta_i)\theta_\mu + v_{li},$$

$$= V(X_{li}, Z_{li}, \mu_l^M) + \zeta_{li} \quad ; V(X_{li}, Z_{li}, \mu_l^M) = X_{li}\theta_x + Z_{li}\theta_Z + \mu_l^M\theta_\mu, \ \zeta_{li} = v_{li} + \eta_i\,\theta_\mu, \ l =$$

B, M, D, P.

Therefore an individual chooses an alternative l over B if $I_{li}^* \geq 0$ where

$$(5) \quad I_{li}^* = g(X_{li}, Z_{li}, \mu_l^M) - \omega_{li}\,; \ g(X_{li}, Z_{li}, \mu_l^M) = V(X_{li}, Z_{li}, \mu_l^M) - V(X_{Bi}, Z_{Bi}, \mu_B^M), \ \omega_{lu} = v_{Bi} - v_{li}\ .$$

The probability of an individual to choose a schooling level l over B is

$$(6)\ \Pr[I_{li}^* \geq 0] = \Pr[g(X_{li}, Z_{li}, \mu_l^M) - \omega_{li} \geq 0]$$

$$= \Pr[\omega_{li} \leq g(X_{li}, Z_{li}, \mu_l^M)].$$

If the ω_{li} are drawn independently from an extreme value distribution, then (4) can be estimated using multinomial logit. The parameter estimates will generate predicted probabilities that individual i will select any of the four options S_{Bi}, S_{Mi}, S_{Di}, and S_{Pi}. Three of these are inserted into (1) in place of the endogenous S_i to generate unbiased estimates of β_s under the maintained hypothesis that $E(Z_i v_{li}) = E(Z_i \eta_i) = 0$.

This two-step procedure is inefficient because it does not incorporate the sampling errors in the parameter estimation of the multinomial logit estimates of (4) into the estimation of the log earnings equation (1). We correct the second-stage standard errors using a bootstrapping procedure in which the two-step estimation was replicated 100 times, sampling with replacement, and sampling variation in the resulting estimates used to compute the second-stage standard errors.

If major-specific skills at the bachelor's degree level are increasing in market value, then they will tend to lower incentives to pursue graduate work in that field. Conversely, majors whose skills are falling in value at the bachelor's level will have disproportionately high numbers of graduate students. If this sorting effect drives lower earning bachelor's degree recipients into graduate school and drives higher earning bachelor's degree recipients out of graduate school, it would tend to depress estimated returns to graduate work. If true, then least squares estimates of the returns to graduate school that ignored the role of major-specific ability measures would tend to understate the true returns. Our empirical work provides evidence consistent with this sorting story.

III. Data

The primary data source for this study is the Scientist and Engineer Statistics Data System (SESTAT) collected by the National Science Foundation (NSF). The 1993 wave of SESTAT also incorporated the 1993 National Survey of College Graduates, a once-per-decade survey that also covered fields outside of the sciences and engineering. The universe for the 1993 SESTAT was approximately 29 million individuals who received a bachelor's degree between 1939 and 1992. Our working sample included 67,565 individuals who received a bachelor's degree between 1963 and 1986. The 1963 limit was necessitated by the lack of information on Graduate Records Exam (GRE) scores by major before 1963. The 1986 limit was imposed because we needed to give bachelor's degree recipients sufficient time to enter and complete higher degrees. Through the use of sample weights, our subsample is representative of the population of all bachelor's degree recipients in the United States between 1963 and 1986.

Table 1 includes summary statistics on the variables included in the analysis. The dependent variables include the natural logarithm of annual salary in 1993 and a series of dummy variables indicating highest degree earned. Earnings of all college graduates in 1993 averaged just under $54,000. Bachelor's recipients averaged $48,000 while Master's recipients averaged $53,000, Ph.D.s averaged $60,000 and those with professional degrees averaged $84,000. Fifty-five percent of the college graduate population did not earn a degree beyond the bachelor's level. Twenty-nine percent had a Master's degree, 10 percent held professional degrees, and 6 percent had doctorates.

Variables included in the demographic vector X_i are potential work experience (1993 – graduation year of highest degree), gender, citizenship, and racial and ethnic dummy variables. The vector Z_i includes average real medical school and graduate school tuition, and the percentage of self-supporting graduate students for the year the individual received the first undergraduate diploma. Data on tuition and availability of graduate support were collected from the National Center for Education Statistics. Higher tuition levels should lower the probability of pursuing a graduate or professional degree. The percentage of graduate students who are self-supporting indicates a lower probability of obtaining a graduate assistantship or fellowship at the time the individual received the bachelor's degree. We also included information on whether the individual was raised in a rural area and the education levels of the individual's parents as reported in SESTAT. These measures are presumed to proxy tastes for graduate education: individuals from more educated households or from more cosmopolitan settings are expected to have stronger taste for graduate training.

Measures of X_{li} include a vector of dummy variables indicating bachelor's degree major. We also know the year of graduation. This allows us to append information on the average GRE mathematics and verbal score for the college major in the year of graduation.[3] The GRE scores are used to approximate the skill content of the major. These measures are not fixed over time, as can be seen in Figure 2. Average verbal scores rose until 1975 and then fell thereafter. Average quantitative scores rose about 12 percent until 1975, retreated slightly over the next ten years, and then resumed modest growth.

These changes may reflect changes in the composition of foreign graduate students taking the GRE. We computed the proportion of foreign doctorate recipients by major for each year in the sample period, using data from the Survey of Earned Doctorates. We then regressed the GRE scores by major on the proportion of foreign doctoral graduates in the major six year earlier.[4] The residual represents changes in the skill content of college graduates holding fixed the proportion of foreign test takers. These corrected GRE time paths are also shown in Figure 2. The corrected verbal GRE path is very similar to the uncorrected path. However, the corrected quantitative GRE path shows a much steeper decline in average scores after 1975 and a much steeper rebound after 1986.[5] The time series of average GRE scores does not demonstrate a systematic improvement in the quality of GRE test takers over time, suggesting that rising quality of graduate degree holders is not the explanation for the pattern of rising returns to graduate school in Figure 1.

The GRE scores also varied across majors, genders, races, and education levels. This variation provides cross-sectional variation in the skill content of bachelor's degree recipients. As shown in Table 2, students whose highest degrees were at the bachelor's level were in majors with the highest quantitative scores and the lowest verbal scores. This is consistent with the speculation that the sorting into graduate school may be based in part on cognitive skill content of majors as proxied by GRE scores. Undergraduate majors in the sciences and engineering had markedly higher average quantitative scores while Engineering and Business had markedly lower average verbal scores. If returns to these skills have changed over time, there will be asymmetric changes in the relative incentives to seek post-graduate training across majors. Because demographic groups concentrate in different majors, there is cross-sectional variation in major GRE scores by race, ethnicity and gender. Men tended to be in majors with higher average quantitative GREs and marginally lower verbal GREs. Asians also concentrate in majors with high quantitative and low verbal scores.

Together, the time series and cross-sectional variation in GRE scores should be sufficiently large to assess whether changes in cognitive skills developed in undergraduate programs have a role in explaining changes in the returns to post-graduate education in the United States. We proceed to that exercise in the next section.

IV. Estimation Results

A. Schooling Choices

Our primary interest is in deriving estimates of equation (1), but we also have an interest in assessing how bachelor degree recipients decide to continue on in school. Results from the weighted multinomial logit estimation of the schooling choice equation are reported in Table 3. The estimation uses stopping education at the bachelor’s degree as the reference group, and so positive (negative) signs suggest an increased (decreased) probability of the educational choice relative to stopping at the B.A. level.

Family background variables are highly significant in influencing the choice of whether or not to pursue and advanced degree. As mother’s and father’s education levels rise, the probability of seeking an advanced degree increases. The effect is strongest at the PhD level.

B.A. recipients who grew up in rural areas are less likely to pursue an advanced degree. U.S. citizens are less likely to seek a Master's or doctorate but are more likely to pursue a professional degree. Asians are more likely than whites to pursue a Master's or Ph.D., while Hispanics and Blacks are less likely to pursue the doctorate.

Measures of expected cost of pursuing a graduate degree performed as expected. Individuals who received the bachelor's degree in years with higher real graduate and medical school tuition levels were less likely to pursue an advanced degree. However, the negative effect is only statistically significant for the effect of graduate school tuition on PhD or Professional degrees. The percentage of self-supporting graduate students also significantly decreased the probability of pursuing an advanced degree. We also interacted the probability of self-support with a measure of parental education with the expectation that parents with higher education levels might moderate the adverse effects of a low probability of receiving graduate support.[6] That expectation was also realized in that all signs on the interacted terms were positive, although only significant in predicting the likelihood of obtaining a Master's degree.

GRE scores have an interesting impact on the probability of pursuing a higher degree. Undergraduates in majors with higher verbal scores and lower quantitative scores are more likely to pursue the doctorate or professional degrees. The standard deviation of GRE scores in the major tend to reinforce the effects of the mean scores: higher standard deviation of GRE verbal scores raises the likelihood of pursuing the doctorate, while increasing the standard deviation of the quantitative score lowers the likelihood of pursuing the doctorate. In separate regressions, we found that the impact of the quantitative score on schooling choice has not changed over time. If returns to quantitative skills have risen over time, the impacts must have been neutral across education levels. The GRE verbal score may have gained modestly in importance over time, but the effect is much smaller than the quantitative score.

Our main results concerning the impact of changing cognitive skills on graduate school choice are illustrated in Figures 3-5, using the results from Table 3. The simulations are carried through to 1993 because all necessary information was available, although the parameter estimates are based on data just through 1986. The most dramatic changes are due to changes in the GRE quantitative score. As shown in Figure 3, the proportion of students stopping at the bachelor's degree has risen since the mid 1980s while the likelihood of seeking doctoral or professional degrees has fallen due to rising average quantitative GRE scores. The finding that the marginal impact of the GRE quantitative score does not vary across graduation cohorts suggests that this is a result of rising quantitative skills and not rising returns to those skills.

Because verbal scores raise the likelihood of seeking advanced degrees, rising GRE verbal scores in the 1960s and 1970s tended to increase the likelihood of entering graduate school. However, the erosion in verbal skills indicated by the steady decline in average GRE verbal scores since 1975 have tended to reverse that effect. By 1993, most of the increase in predicted probability of seeking advanced degrees associated with verbal skills had disappeared.

Putting the two effects together, we show in Figure 5 that changes in quantitative skills increased the probability of seeking a doctorate until 1978 and then the probability began a slow, steady decline. The probability of stopping at the bachelor's degree level began to rise in the mid 1980s at the same time as the probability of seeking a professional degree began to fall. The net impact of changing verbal and quantitative skills of bachelor's degree cohorts has been to lower the supply of doctorates since the late 70s and to lower the supply of professionals since the mid 80s.

B. Estimated Returns to Post Graduate Education

Table 4 reports the results from Ordinary Least Squares and Two-stage estimation of the log earnings equation (1). Both sets of results correct for sample weights. Least squares estimates of returns to graduate education are positive and significant. However, the implied annual returns are small. Assuming a Master's program takes two years and a PhD program takes 6, implied annual returns are only 5.8% and 4.2% respectively.[7] Annualized returns to professional degrees are more reasonable at 14.1%, assuming a four year program. There is a significant positive return to GRE mathematics scores, but no measurable return to verbal skills. There is a significant premium for postgraduate degrees in business and a significant discount for postgraduate degrees in the sciences.

Controlling for the likely endogeneity of the schooling choices raises the measured returns to advanced degrees.[8] The implied annual return to a Master's degree rises to 14.5%, and the returns to a Ph.D. rises to 12.6%, very similar to instrumental variable estimates of the returns to a year of education obtained at lower levels of education. The annualized return to a professional degree rises to 20.9%.[9]

Returning to the two alternative possibilities discussed at the beginning of the paper, our findings are consistent with the hypothesis that students who would be atypically successful in graduate school are actually more likely to halt their education at the bachelor's level. Consequently, average earnings of bachelor's degree recipients overstate the opportunity cost faced by those opting to pursue advanced degrees.

Our assessment is that the sorting is most easily observed when examining the role of the average GRE quantitative score. As indicated before, higher average GRE quantitative scores actually lower the probability of pursuing graduate education, even though strong quantitative skills are presumed to increase the likelihood of success in graduate school. Consequently, atypically strong graduate school prospects are actually less likely to pursue graduate training.

We can illustrate the impact of changing GRE scores on observed returns to schooling. We simulate how GRE scores alter log earnings directly and indirectly through their implied impact on the probability of receiving an advanced degree illustrated earlier in Figure 5. The results of the simulation are shown in Figure 6. The direct effect of increases in the GRE quantitative score is to raise earnings, although the coefficient is no longer precisely estimated. There was little direct effect of the verbal score on earnings. The rise in average GRE scores also lowers the likelihood of attending graduate school, which counteracts the positive direct returns to quantitative scores.

The GRE verbal score does have an impact on earnings through its influence on post graduate training. However, when GRE scores start to slide, the resulting earnings retreat to just 2% above their 1963 level. The summed effects of the changes in GRE scores is a modest increase in average earnings across all college graduates, suggesting that changing skill content of bachelor's degree cohorts can only explain about 2% of the 35% increase in relative earnings for graduate degree holders shown in Figure 1.

These are the average earnings effects, but they can be used to motivate the hypothesized sorting effect discussed above. Those who do not go on to graduate school are drawn atypically from the upper tail of the GRE quantitative distribution and the lower tail of the GRE verbal distribution, both of which are expected to raise their earnings. On the other hand, those who go on to graduate school are drawn disproportionately from the lower tail of the quantitative GRE distribution and from the upper tail of the GRE verbal distribution, both of which lower their opportunity costs of graduate school. Consequently, the observed premium of average earnings for post graduate degree holders over bachelor's degree recipients understates the true returns to graduate school. Correcting for the sorting raises the estimated returns, as found in Table 4.

C. Unobserved Ability

Unobserved individual abilities may also affect the likelihood of pursuing an advanced degree. To test that hypothesis, we follow Rosenweig and Schultz (1983) by collecting the residuals from the earnings equation. These residuals represent individual ability uncorrelated with education level, major level skills, parents' education level, or demographic variables included in the model. They will also include random noise in the earnings function, so they will measure the unobserved ability with error. An auxiliary multinomial logit estimation of education choices on the earnings residuals will illustrate the direction of the effect of unobserved ability to earn income on the probability of seeking graduate or professional education. Note that the measurement error inherent in this method will tend to bias the coefficients toward zero.

Table 5 reports the estimated marginal effect of the earnings residual on the probability of pursuing each degree. Those with higher unobserved ability to earn income were less likely to stop at the bachelor's degree level and were more likely to pursue advanced degrees of all types. Consequently, sorting on unobserved ability works in the opposite direction as sorting on observed quantitative skills.

V. Conclusions

Returns to advanced degrees are positive and significant. Least squares estimates for returns to Master's or doctoral education are quite low, on the order of 5% per year. Estimates increase in magnitude after controlling for likely endogeneity of the choice of pursuing an advanced degree. Our estimates of 14.5% return to a Master's degree and 12.6% return to a doctoral degree are of comparable size to those estimated for lower levels of schooling. Our finding of downward bias in least squares estimates of returns to graduate education are similar to the conclusions from estimated returns to lower levels of schooling.

Our study points out an interesting role for cognitive skills in the market for advanced degrees. Students in majors with higher average quantitative GRE scores are less likely to attend graduate school, even though such students presumably are more likely to be successful in graduate education. The opposite happens for verbal skills—students in majors with higher average verbal GRE scores are more likely to attend graduate school. This leads to a sorting effect whereby students whose cognitive skills would suggest lower earnings at the bachelor's level are more likely to attend graduate school. This sorting effect appears to be part of the cause of the downward bias in estimated returns to graduate education—the average earnings of those who do not go to graduate school overstate the opportunity costs of graduate education for those who do pursue advanced degrees. However, changes in verbal and quantitative skills over time do not explain the large increases in relative returns to graduate and professional education since 1980. Future work is needed to identify the source of those rising returns.

These conclusions are subject to the usual caveat that our instruments may not be valid, although our measures of the costs of graduate education perform as expected, and we do try to control for unmeasured ability to a greater extent than has been possible in most studies.

Nevertheless, our results may still be subject to biases that we cannot control with the data at hand.

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Table 1. Descriptive Statistics: 1963-1986 (N = 67565)

	Variable	Mean	Std. Err.
Demographics	Age	41.2	(0.027)
	Experience	17.4	(0.025)
	Male	0.723	(0.002)
	US Citizen	0.956	(0.001)
	Rural Background	0.319	(0.002)
Education	BA	0.549	(0.002)
	MA	0.287	(0.002)
	Ph. D.	0.063	(0.001)
	Prof. Degree	0.101	(0.001)
	Posdoc	0.004	(>0.001)
Race	Hispanic	0.031	(0.001)
	White	0.849	(0.001)
	Black	0.052	(0.001)
	Asian	0.066	(0.001)
	Native Am.	0.002	(>0.001)
BA Major Field	Science Majors	0.342	(0.002)
	Engineering Majors	0.205	(0.002)
	Social Sci. Majors	0.326	(0.002)
	Business Major	0.032	(0.001)
	Other Majors	0.095	(0.001)
Earnings (1993 dollar)	Overall	53,864	(113.319)
	BA	47,900	(161.490)
	MA	53,325	(208.694)
	Ph.D.	59,657	(165.362)
	Professional Degree	84,155	(727.269)

Table 1. (cont'd)

Parents Education	Mother Ed 11 -	0.154	(0.001)
	Mother Ed 12	0.398	(0.002)
	Mother Ed 12 – 15	0.211	(0.002)
	Mother Ed 16	0.151	(0.001)
	Mother Ed 17 +	0.086	(0.001)
	Father Ed 11 -	0.189	(0.002)
	Father Ed 12	0.268	(0.002)
	Father Ed 12 – 15	0.181	(0.001)
	Father Ed 16	0.176	(0.001)
	Father Ed 17 +	0.185	(0.001)
	Med. School Tuition (1993 dollar)	10,651	(10.324)
	Grad. School Tuition (1993 dollar)	3,501	(1.052)
	% Self-Supported	26.3%	(0.020)

Table 2: Average GRE Score for the major, by attributes of individuals in the major

Individual Attribute	Verbal GRE	Quantitative GRE
BA	500.8	581.9
MA	502.4	568.7
PhD	508.2	573.0
Professional Degree	515.4	555.7
Science Majors	512.0	606.0
Engineering Majors	469.2	649.5
Social Science Majors	518.6	518.5
Business Major	475.4	542.3
Other Majors	502.4	507.5
White	503.6	573.9
Black	504.9	553.2
Asian	497.1	604.0
Native American	506.9	563.2
Male	501.0	585.3
Female	509.0	547.8

Table 3. Multinomial Logit Estimation of Higher Education Choices

Variable	MA		PhD		Professional	
Mother Ed 11 -	0.113	(0.046)	0.196	(0.054)	-0.106	(0.095)
Mother Ed 12 – 15	0.045	(0.042)	0.214	(0.047)	0.178	(0.070)
Mother Ed 16	-0.228	(0.118)	0.152	(0.118)	0.123	(0.177)
Mother Ed 17 +	-0.041	(0.127)	0.641	(0.123)	0.352	(0.184)
Father Ed 11 -	-0.068	(0.047)	-0.149	(0.055)	-0.293	(0.092)
Father Ed 12 – 15	-0.012	(0.046)	0.013	(0.053)	0.092	(0.081)
Father Ed 16	-0.195	(0.117)	0.059	(0.115)	0.149	(0.179)
Father Ed 17 +	0.133	(0.119)	0.615	(0.118)	0.782	(0.178)
Experience/100	0.317	(5.316)	0.237	(5.442)	7.178	(8.429)
Experience squared/100	0.018	(0.120)	0.071	(0.125)	-0.331	(0.192)
Verbal mean/100	0.319	(0.099)	1.343	(0.104)	1.923	(0.145)
Quant. Mean/100	0.049	(0.056)	-0.494	(0.052)	-1.565	(0.092)
Verbal stdv/100	0.228	(0.038)	0.114	(0.040)	-0.307	(0.074)
Quant. Stdv/100	-0.202	(0.034)	-0.109	(0.037)	0.266	(0.065)
Foreign Student Ratio/100	-50.84	(15.86)	156.2	(12.21)	169.2	(17.76)
Science Majors	-0.890	(0.078)	-0.098	(0.085)	2.495	(0.187)
Engineering Majors	-0.620	(0.103)	-0.451	(0.117)	1.640	(0.267)
Social science Majors	-0.726	(0.065)	-0.952	(0.077)	1.160	(0.165)
Business Major	-0.628	(0.099)	-1.529	(0.179)	-1.085	(0.557)
Rural background	-0.180	(0.032)	-0.231	(0.035)	-0.396	(0.057)
Male	-0.230	(0.035)	0.343	(0.041)	0.664	(0.060)
Citizen	-0.389	(0.056)	-1.544	(0.060)	0.338	(0.117)
Hispanic	-0.042	(0.057)	-0.292	(0.084)	0.072	(0.088)
Black	-0.040	(0.050)	-0.330	(0.090)	-0.162	(0.087)
Asian	0.238	(0.043)	0.394	(0.050)	-0.069	(0.079)
Native Am.	0.111	(0.153)	0.256	(0.170)	-0.549	(0.276)
Medical School Tuition/100	-0.007	(0.005)	-0.003	(0.006)	-0.003	(0.009)
Graduate School Tuition/100	-0.010	(0.023)	-0.100	(0.025)	-0.065	(0.038)
% Self-Supported	-0.028	(0.010)	-0.035	(0.010)	-0.041	(0.016)
Parent Ed 16+*% Self-Supported	0.021	(0.001)	0.006	(0.008)	0.010	(0.012)
Constant	0.012	(0.763)	-1.902	(0.823)	-2.928	(1.190)

Pseudo $R^2 = 0.082$

Standard errors in parentheses. Tuition is in constant 1983-84 dollars.

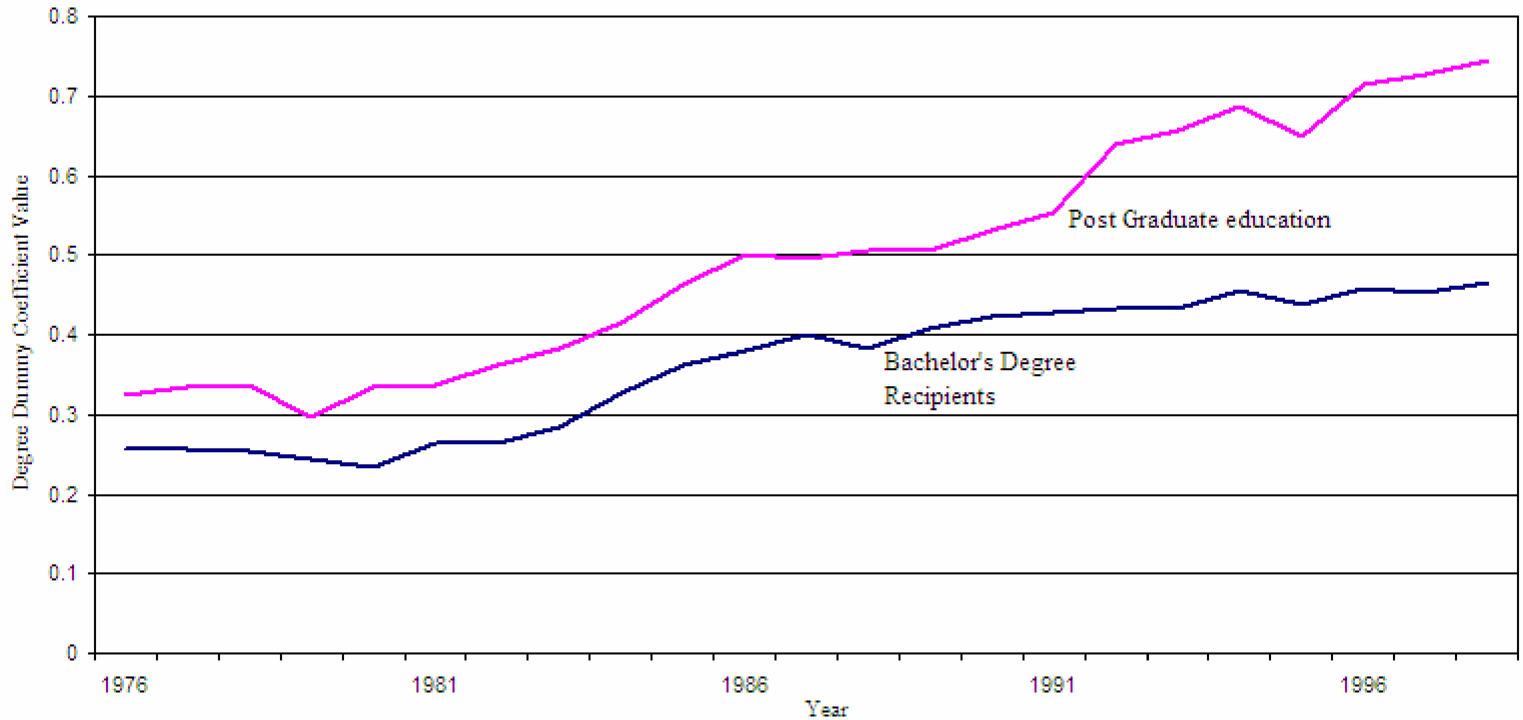
Table 4: Ordinary Least Squares and Two-Stage Estimation of the Log Earnings Function

Equation	OLS Estimates		IV Estimates	
Variables	Coefficient	Std. Err.	Coefficient	Std. Err.
MA	0.115	(0.007)	0.289	(0.158)
PhD	0.249	(0.008)	0.756	(0.109)
Professional Degree	0.565	(0.013)	0.837	(0.085)
Experience/100	3.189	(0.286)	3.058	(10.04)
Experience Squared/100	-0.039	(0.008)	-0.044	(0.027)
Male/100	16.695	(0.738)	15.592	(0.023)
Citizen/100	10.448	(1.256)	16.872	(0.011)
Posdoc/100	-36.757	(1.105)	-26.589	(0.010)
Verbal mean/100	-0.072	(0.020)	-0.154	(0.331)
Quant. mean/100	0.186	(0.012)	0.230	(1.515)
Verbal stdv/100	0.030	(0.007)	0.024	(0.009)
Quant. Stdv/100	-0.026	(0.007)	-0.020	(2.019)
Foreign Student Ratio/100	-4.692	(2.846)	-12.08	(1.095)
Science Majors	-0.066	(0.016)	-0.084	(0.011)
Engineering Majors	0.001	(0.021)	-0.012	(0.009)
Social Science Majors	0.015	(0.013)	0.042	(0.011)
Business Major	0.100	(0.019)	0.135	(0.034)
Hispanic	-0.053	(0.011)	-0.042	(0.051)
Black	-0.094	(0.009)	-0.078	(0.051)
Asian	-0.081	(0.009)	-0.098	(0.046)
Native Am.	-0.150	(0.034)	-0.141	(0.032)
Constant	9.342	(0.087)	9.394	(0.029)
R^2	0.228		0.139	

Table 5. Marginal Effect of Individual Heterogeneity on Probability to Pursue Advanced Degree

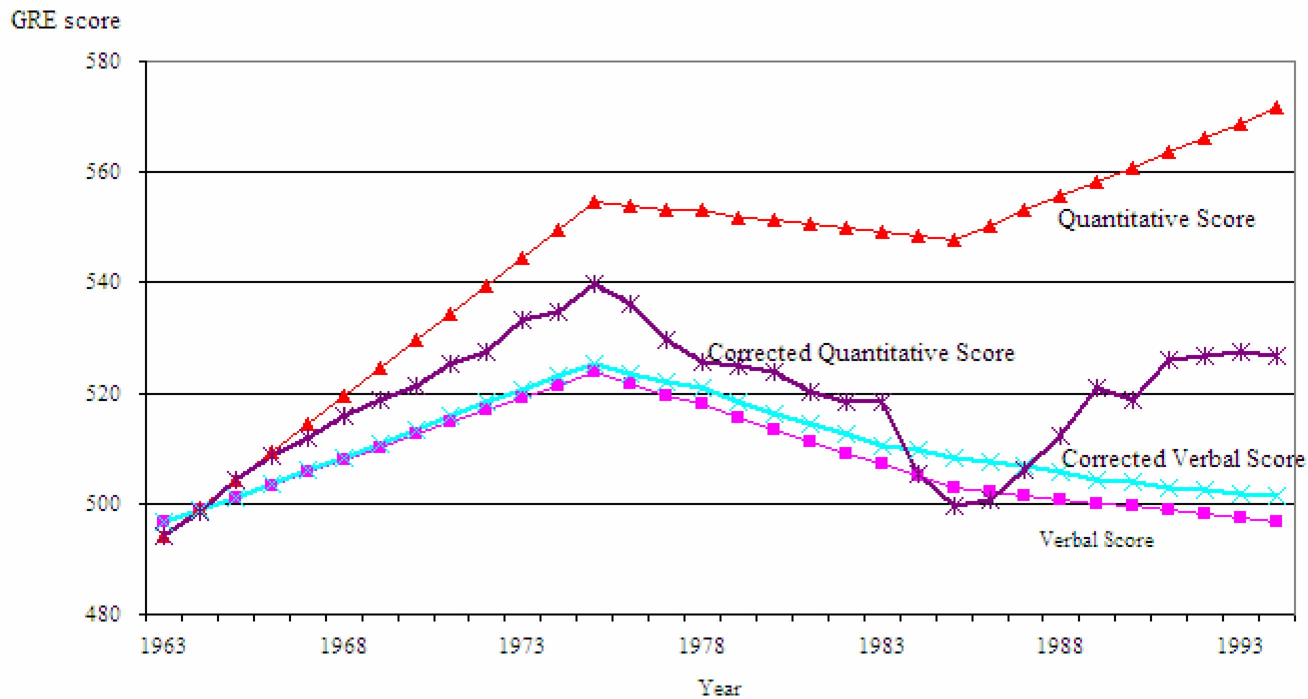
Dependent Variable	Marginal Effect	Std. Err.
BA	-0.224	(0.007)
MA	0.029	(0.007)
Ph.D.	0.038	(0.002)
Professional Degree	0.157	(0.004)

Figure 1. Estimated Returns to Schooling Relative to High School Graduates: 1976-1998



Notes: Values based on coefficients from annual regressions of log weekly wage on a vector of dummy variables indicating educational attainment, age, age squared, and a vector of demographic dummy variables. Data taken from the March Current Population Survey (1976-1998).

Figure 2: Trends of Observed and Corrected GRE Verbal and Quantitative Scores, 1963-1997



Note: Corrected Scores remove the estimated effect of foreign test takers from the mean score. Data taken from the Educational Testing Service and the Survey of Earned Doctorates, various years.

Figure 3: Simulated Probability of Schooling Choices from Changes in the Quantitative GRE Score, all else equal
(1963 normalized to 1)

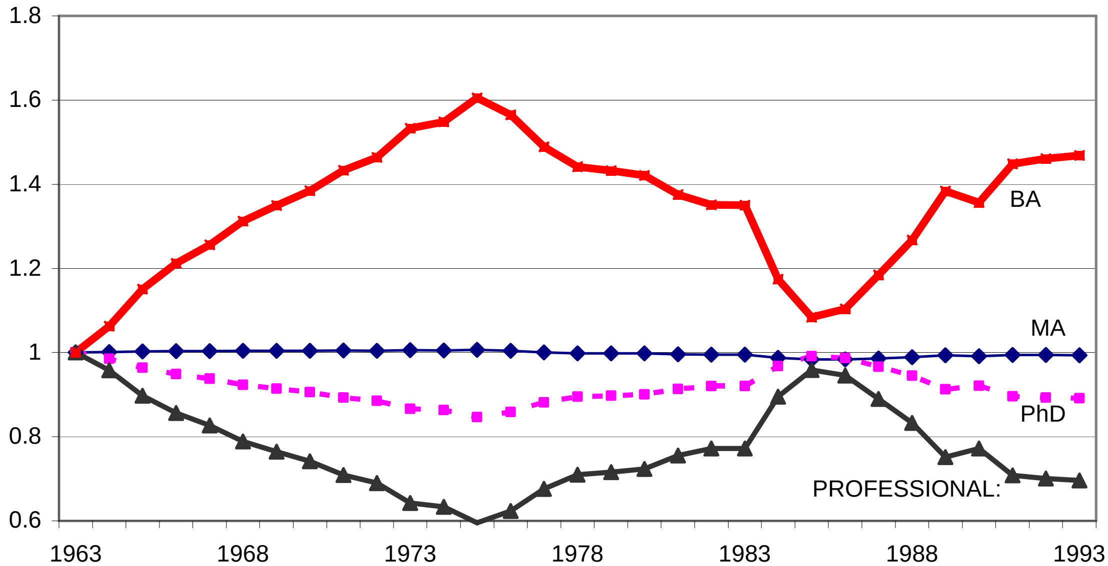


Figure 4: Simulated Probability of Schooling Choices from Changes
in the Verbal GRE Score, all else equal
(1963 normalized to 1)

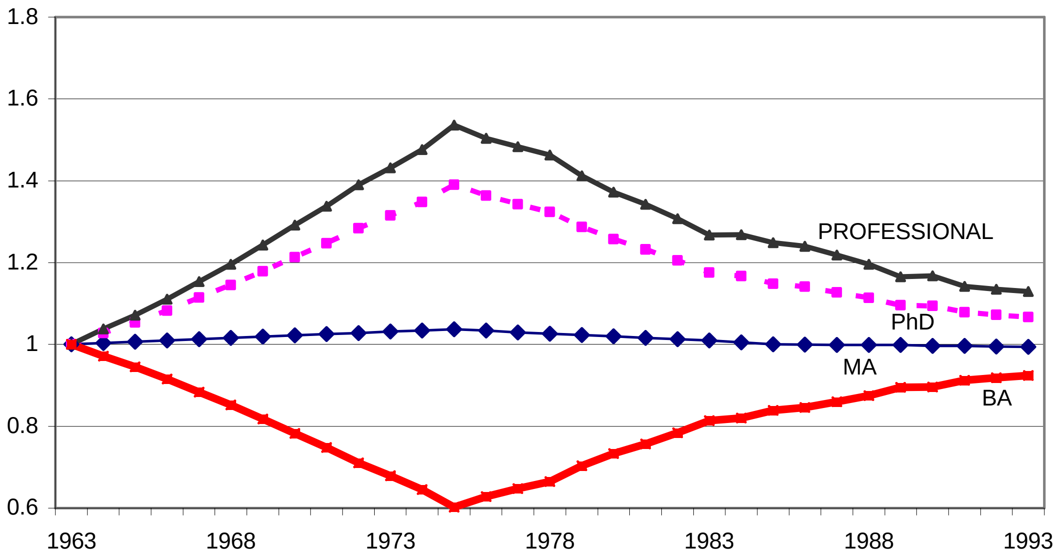


Figure 5: Simulated Probability of Schooling Choices from Changes in both the Quantitative and Verbal GRE Scores, all else equal
(1963 normalized to 1)

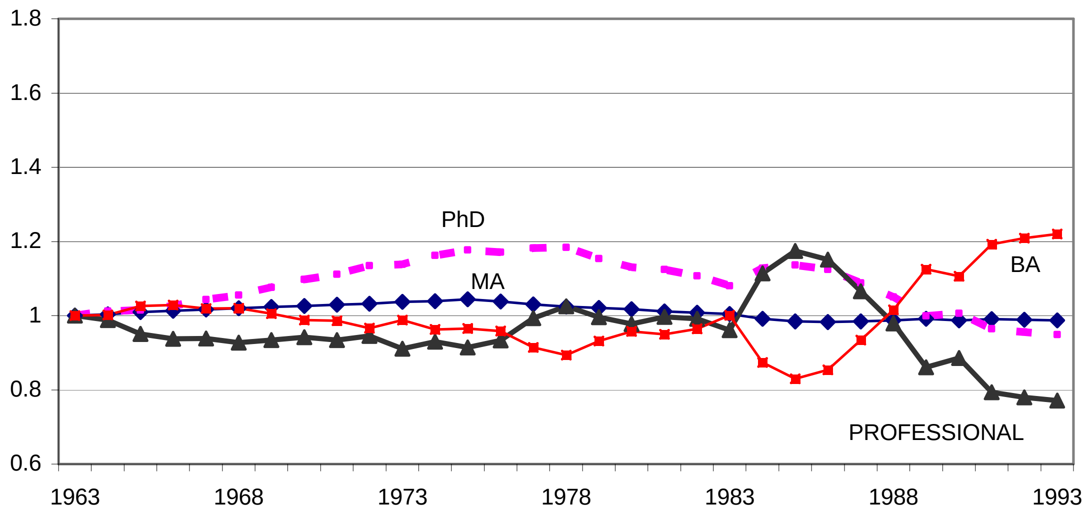
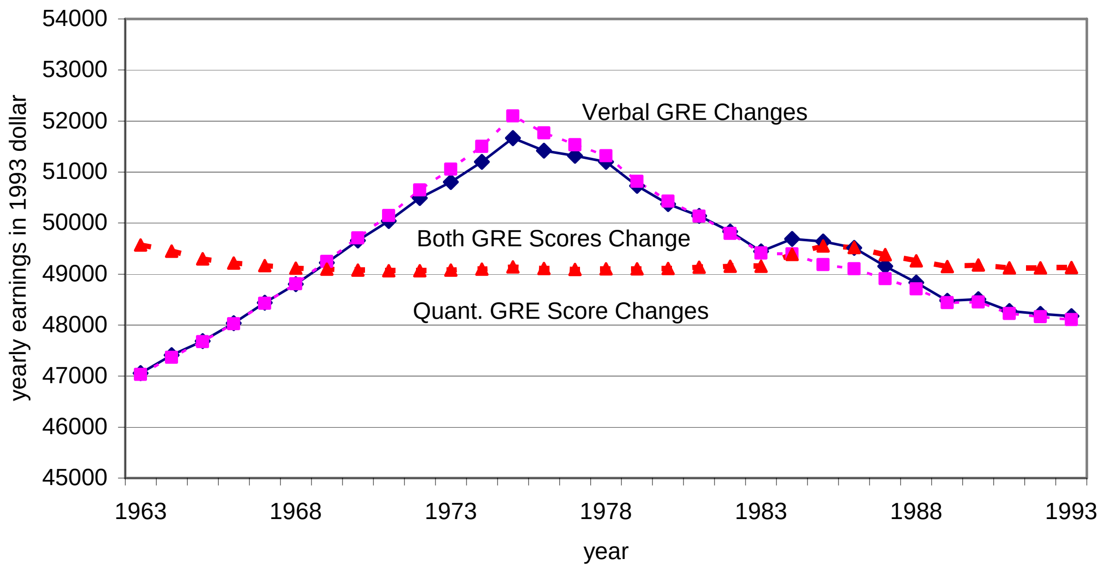


Figure 6: Simulated Direct and Indirect Impact of Changes in GRE Scores on the Average Earnings of Bachelor's Degree Recipients, 1963-1993 (in 1993 dollars)



[1] See Ehrenberg (1992) for a review. The most recent study of which we are aware is Jaeger and Page (1996). Earlier studies include Ashenfelter and Mooney (1968) and Taubman and Wales (1973). There is a vast literature on incentives to enter and returns to specific graduate degrees, pioneered by Richard Freeman (1976 a, b; 1999).

[2] In their study of twins data, Ashenfelter and Rouse (1998) found that family background variables strongly affected educational choices but did not affect earnings, exactly what one would want in an instrument. However, as Card (1999) argues, even that is not sufficient to validate family background measures as instruments if family background is correlated with unobservable ability.

[3] The Educational Testing Service provided this data for selected years:1963, 1974 to 1976, 1983 to 1986. The number of majors included in the report varied from 21 majors in 1963; 92 majors in 1974 – 76; and 98 majors in 1983 – 86. These were aggregated into 28 major groups to correspond with the majors reported in the SESTAT. The GRE did not report data on 9 of the majors 1963, and so the nearest included major was used: e.g. computer science was placed in mathematics; agricultural and food science was placed in biology; and so on. Once consistent data series were generated for the four reporting dates, the values were interpolated to generate continuous values for the intervening years. As most average scores change very slowly, this process is unlikely to generate wildly inaccurate estimates of average scores by major.

[4] We presume that the average doctoral program takes six years and that the percentage of foreign graduates completing the program is proportional to the percentage taking the GRE exam six years earlier.

[5] Bishop (1989) traced the time path of 12th grade high school cognitive skills. Our GRE scores would lag his measures by four years. The timing of the decline in verbal and quantitative scores is roughly consistent with the pattern of scores he reported for the Iowa Test of Basic Skills.

[6] Parents education level variable is 1 if both parents are more than college graduate, ½ if either one of them is more than college graduate, and 0 if both are less than college graduate.

[7] Jaeger and Page (1996) also estimate similarly small returns to Master's and PhD degrees under the assumption of exogenous education levels. Their estimation method includes both years of schooling as well as dummy variables indicating degree, so our annualized results are not directly comparable to theirs.

[8] Estimates that also included parental education in the second-stage earnings functions yielded comparable estimates of returns to graduate and professional education.

[9] These are likely to be overstated in that we do not incorporate tuition costs into the estimated return to professional degrees, and so these returns are gross of tuition costs. In contrast, tuition is often waived in doctoral programs, so those estimates are presumably closer to the true net return.