Heterogeneous Returns to College Selectivity and the Value of Graduate Degree Attainment

Mai Seki *
Department of Economics
University of Wisconsin-Madison †

November 18, 2011

Abstract

Existing studies on the returns to college selectivity have mixed results, mainly due to the difficulty of controlling for selection into higher quality colleges based on unobserved ability. Moreover, researchers have not considered graduate degree attainment in the analysis of labor market returns to college selectivity. I estimate the causal effect of college selectivity on wages including graduate degree attainment. I control for both observed and unobserved selection by extending the model of Carneiro, Hansen, and Heckman (2003). There are two channels through which college selectivity affects future labor market outcomes. The first is the wage returns to college selectivity conditional on graduate degree attainment. The second is the effect of college selectivity on the probability of graduate degree attainment and the wage returns to a graduate degree attainment. The results show that graduating from a college of one standard deviation higher selectivity leads to a 3.7% higher hourly wage ten years after college graduation regardless of graduate degree attainment. In addition, a one standard deviation increase in college quality increases the expected returns to graduate degree attainment by 0.8% (4.3% increase in the probability of graduate degree attainment multiplied by 18.6% returns to a graduate degree).

JEL: I21, C30

Keywords: returns to education, heterogeneous treatment effect, selection, data combination

---

*Email: seki@wisc.edu

†I would like to thank Christopher Taber, John Karl Scholz, Jane Cooley Fruehwirth, Salvador Navarro, and Yuya Takahashi for helpful guidance and invaluable advice. All errors are my own.

1. Introduction

The labor market returns to college selectivity are a concern of many high school students and their parents due to rising college costs.[1] There are reasons to believe that attaining a bachelor's degree from a more selective college leads to higher wages. In a more selective institution, course offerings and faculty quality could be better, the alumni network could be richer, the access to information about advanced studies could be less costly, and peers' academic performance or aspirations could be higher than at less selective institutions. However, college selectivity may not increase future wages. Students and their parents might prefer selective colleges because there is a consumption value: the value of enjoying college life in a selective institution regardless of labor market outcomes. These two competing motivations behind the college selectivity choice make it unclear whether there are large labor market returns to college selectivity. In addition, it is difficult to estimate labor market returns to college selectivity since it is hard to control for selection into higher quality colleges based on students' unobserved abilities. In other words, it is hard to construct comparable control and treatment groups of students with the same set of characteristics. This is mainly because we cannot fully observe students' abilities in the data.

Moreover, graduate degree attainment, one channel of the labor market returns to college selectivity, has not been fully investigated in the literature. According to the Current Population Survey (CPS), 35% of the labor force with bachelor's degrees in the U.S. labor market from 1992 to 2007 has graduate degrees (i.e., master's, professional, or a doctoral degree). The share of graduate degree holders in the labor force aged 25 or older increased from 9.1% to 12.5% during the same period.[2] This suggests that for a significant proportion of college graduates, the returns to college selectivity may depend on the probability of success in advanced studies and the returns to graduate degrees. In addition, there is a different pattern in the correlation between college selectivity and wages for those who obtain a graduate degree and those who do not. Unconditional average wages increase with college selectivity for non-graduate degree holders. On the other hand, the unconditional average wages are similar regardless of college selectivity for graduate degree holders. Instead, the percentage of graduate degree holders increases with college selectivity.

In this paper, I examine the returns to college selectivity and how they vary by graduate degree attainment and individual ability. Answering these questions will help us understand two channels through which college selectivity affects future labor market outcomes. The first is the wage returns to college selectivity conditional on graduate degree attainment. The second is the effect of college selectivity on the probability of graduate degree attainment and the wage returns to a graduate degree.[3] If the returns to college selectivity differ by graduate degree attainment, it is

[1] *The New York Times*, for example, has published articles targeted at parents and students with titles such as "Does it Matter Where you Go to College," "Is Going to an Elite College Worth the Cost," and "Do Elite Colleges Produce the Best-Paid Graduates."

[2] Enrollment in graduate programs rose about 67 percent between 1985 and 2007, while undergraduate enrollment increased by about 47 percent. Total fall enrollment in undergraduate programs increased from 10.6 million to 15.6 million from 1985 and 2007, while that in graduate programs increased from 1.4 million to 2.3 million (NCES (2009)).

[3] My paper focuses on a financial return. See Haveman and Wolfe (1984) and Ge (2011) for non-market returns of education.

an indication of the complementarity or substitutability between college selectivity and graduate degree measured by wages. If there is a significant effect of college selectivity on graduate degree attainment, it is an indication that there is some additional value added in the college years that increases the chance of success in advanced studies. In addition, I calculate heterogeneous returns to college selectivity, depending on both students' observable characteristics and unobservable math and verbal abilities.[4]

Estimating the returns to college selectivity is challenging because of the potential bias arising from selection on unobserved abilities.[5] Previous estimates of the return to college selectivity vary widely, with some authors finding no effect (Dale and Krueger (2002), Arcidiacono (2005)), while others estimate a 20% return (Hoekstra (2009)). It is hard to attribute this wide variance to the differences in measurement of college selectivity, cohort of the sample, or the college selectivity margin that the authors used. Because one factor is the difficulty of controlling for selection, I apply a different empirical approach. I use the factor structure model of Carneiro et al. (2003) since the method has following advantages over the methods used in the literature.[6] This approach controls for selection on unobserved abilities, the results apply to all levels of college selectivity, and identification of the source of unobserved ability is explicit and robust to measurement error in admission test scores. Identification of the model parameters works in two steps. With scores from multiple tests and assumptions on the covariance structure of unobserved ability and other error terms, I can identify the distribution of unobserved abilities.[7] With knowledge of the distribution of unobserved ability, I can control for the correlation between the endogenous variables and the unobserved abilities in the wage equation.

For the estimation, I use sample moments calculated from two data sets.[8] This is because there is no single dataset that contains sufficient information to answer this question on its own. The first is Baccalaureate and Beyond 93/03 (B&B:93/03), which includes about 9,000 individuals who completed a bachelor's degree in 1992-93. About 25% of those individuals complete a post-baccalaureate degree. The final wage observation in the survey is from 2003, ten years after college graduation; at this time, most students had already obtained their graduate degrees. However, B&B does not have any other test scores prior to college enrollment besides the SAT (or ACT). College admission test scores cannot be used as a proxy for unobserved abilities for the following reason. Colleges can observe students' admission test scores, so the measurement errors of the admission test scores are correlated with the college selectivity. This correlation between the

[4] See Buchinsky (1994) and Brand and Xie (2010) for discussion on the heterogeneous returns to schooling.

[5] In my paper, I mainly consider cognitive abilities due to data limitations. See Heckman et al. (2011) for the effects of non-cognitive abilities on labor market outcomes.

[6] Heckman and Navarro (2007) discuss the semiparametric identification of dynamic discrete choice and dynamic treatment effects using the factor structure model. Empirical applications of Carneiro et al. (2003)'s factor structure model can be found in Cunha and Heckman (2008), Carneiro et al. (2003), Heckman et al. (2006), Cooley et al. (2009), Cunha et al. (2010), and Heckman et al. (2011).

[7] This is essentially mapping the information from multiple test scores into fewer dimensional. I call these unobserved abilities. The specification allows measurement errors to enter into the test score equation, so the estimates are robust to measurement errors by construction.

[8] See Ridder and Moffitt (2007) and Ichimura and Martinez-Sanchis (2005) for details about data combination.

measurement errors of the admission test scores and college selectivity will potentially generate a bias in the coefficient of college selectivity in the wage regression. This is also the reason why I cannot apply a split-sample instrumental variable approach.[9] In order to identify the distribution of unobserved ability, I use a second sample, the National Education Longitudinal Study of 1988 (NELS:88). NELS:88 includes 8th graders in 1988 and follows them through 2000. NELS:88 contains SAT scores and the survey original test scores (IRTs) prior to college enrollment, and high school grades as well as demographic variables. The key assumption which justifies the joint use of these two data sets is that the underlying joint distributions between individual ability, degree attainments, and wage realization are the same across these two nationally representative surveys. Throughout my paper, I use the 75th percentile SAT/ACT composite score as the measure of college selectivity.[10]

The empirical results show that graduating from a college of one standard deviation higher selectivity leads to a 3.7% higher hourly wage ten years after college graduation regardless of graduate degree attainment.[11] Relative to the Hoekstra (2009)'s 20% returns (a flagship vs. non-flagship), it is quite low and rather closer to the findings of Dale and Krueger (2002) and Arcidiacono (2005) (1.3% for 100 point increase in average SAT composite score and 0-2.9% for 100 point increase in average SAT math score). Going to a marginally higher quality college also have an effect on wages by increasing the probability of attaining a graduate degree. Graduating from a college of a one s.d. higher selectivity leads to 4.3% higher probability of a graduate degree attainment. College selectivity does not have statistically significant effects on returns to graduate degree for MBAs, law school, and engineering master's degrees. The correlation between college selectivity and the returns to graduate degree is negative for medical and doctoral degrees, but this is because the panel is not long enough to capture their wages after fellowship or post-doctoral periods. This negative correlation means that the M.D. holders from less selective colleges earn more than those from more selective college. One possible explanation is the length of fellowship periods by a specialty. For example, family practice and neurosurgery require different fellowship periods. In addition, I find that math ability is rewarded both in degree attainment and the labor market. However, verbal ability is only rewarded in degree attainment and penalized in the labor market. Lastly, I find that there is a fundamental heterogeneity in the returns to a graduate degree attainment but not to college selectivity. Specifically, returns to college selectivity are the same across individuals but returns to graduate degree attainment are increasing in math ability.

Based on these findings, I conclude that college ranking is relevant for future labor market outcomes through two channels. First, college selectivity increases the wage return conditional on graduate degree attainment, which is the same regardless of graduate degree attainment. Second,

[9]Split-sample IV or two-sample IV was developed by Angrist and Krueger (1992) and Inoue and Solon (2010).

[10]In my paper, I assume college selectivity summarizes various aspects of education quality of the undergraduate institutions. One such aspect would be professor quality. See Oreopoulos and Hoffman (2009) for more discussion about the effect of professor quality on the student achievement.

[11]A one s.d. in the college selectivity measure is 118 points in the 75th% SAT math and verbal composite score. One example of this score gap is UCLA (1400) and UC-Santa Barbara (1300). The average wage is $26 per hour, so the 3% return at the mean wage is about 80 cents per hour.

college selectivity increases the probability of graduate degree attainment and the returns to graduate degree increase wages, which is the same regardless of college selectivity for the majority of graduate programs.[12] College selectivity has significant and positive effect on future wages for both types of students, not planning and planning to attain a graduate degree. In addition, if a student is planning to attain a graduate degree, going to a more selective college increases the expected future wage through the higher graduate degree attainment. It turns out that there is not a simple 'yes' or 'no' response to the question: do higher quality colleges lead to higher wage returns?

The rest of the paper proceeds as follows. In Section 2, I summarize the previous literature on the returns to both college selectivity and graduate school. In section 3, I discuss empirical models and selection bias. In Section 4, I summarize the two data sets used in the estimation. In Section 5, I discuss the identification of the model parameters. In Section 6, I outline the regression results. Finally, in Section 7, I conclude by exploring possible directions for future work.

2. Previous Literature

There are many studies that estimate returns to undergraduate degrees while controlling for selection on observed ability.[13] However, few papers estimate the return to college selectivity while controlling for selection on unobserved abilities.[14] Using the two-step Heckman selection model (Heckman (1976), Heckman (1979)), Brewer et al. (1999) found a 9-15 % higher return to attending a top-private university instead of a bottom public university. Using a regression discontinuity design, Hoekstra (2009) found a 20% return for going to a flagship university for students on the margin of admission and those who stay in the state after college graduation. Regression discontinuity controls for selection on unobservables but the results are not generalizable beyond those on the margin. A third approach uses quasi-experimental designs. Dale and Krueger (2002) and Dale and Krueger (2011) examined students who were accepted to specific (selective) colleges and compared the wages of students who chose to attend the college and those who did not. This assumes that students who were accepted to the same set of colleges have similar levels of unobservable

[12] The effect of college selectivity on graduate degree attainment is causal in my interpretation as long as my model perfectly controls for the selection into graduate degree. However, it is beyond the scope of this model to analyze the mechanisms why I find the positive coefficient of college selectivity on the probability of graduate degree attainment. This could be because selective colleges provide better education and the college graduates from selective college are successful in advanced studies. In contrast, high school students might select themselves into a more selective college so that they can attain a graduate degree at higher rate.

[13] Becker (1962) discussed the theoretical meaning of schooling in relation to human capital accumulation and labor market outcomes. His work acknowledged that control for selection is a difficult empirical challenge in this field. Willis and Rosen (1979) was one of the earliest structural papers that carefully examined the returns to undergraduate degree while controlling for selection on unobserved ability. There are papers that used instrumental variable approaches. For example, Card (1993) estimated returns to undergraduate attendance using a geographical variation as an instrument to control for selection bias.

[14] Using propensity score matching, Black and Smith (2004) found a 15% higher return to attending a top-quartile school instead of a bottom quartile school using NLSY79. Propensity score matching controls for selection on observable characteristics, but cannot address selection on unobservable traits.

ability. The authors used NLS72 and found 1.3% returns for attending college with 100 point higher SAT composite score but the point estimate was statistically insignificant. Their approach is not robust to measurement error in college selectivity measured by the admission test scores. The fourth approach is structural estimation. Arcidiacono (2005) used NLS72 and found 0.0-2.9% returns for attending college with 100 point higher average SAT math score. The returns vary by college majors but the estimates are all statistically insignificant. None of the papers described above consider graduate degree attainment as an additional path to earn higher wages.

Even fewer papers estimate the returns to graduate degrees controlling for selection on unobserved abilities. Arcidiacono et al. (2008) found about a 10% return for obtaining an MBA degree from one of the top 25 programs instead of a lower-ranked program, using individual fixed effects.[15] My findings should be comparable to their estimates on average across MBA rankings. My paper further examines the average returns for obtaining a degree from medical school, law school, engineering master's programs, education master's programs, other master's programs, and doctoral degrees, controlling for selection. Moreover, my paper is the first to examine to what extent undergraduate college selectivity affects returns to graduate education while controlling for selection.

Lastly, Eide et al. (1998) documented a positive correlation between college selectivity and the likelihood of graduate degree attendance. They treated the likelihood of graduate degree attendance as one of the outcomes of attending a selective college. My model treats graduate degree attainment as an optional step in higher education and labor market return as the ultimate outcome measure. Therefore, my paper is the first to examine how college selectivity affects wages and advanced degree attainment while controlling for selection on unobserved abilities.

3. Empirical Model

Following the returns to college selectivity literature, I estimate a modified Mincer (1974) model that includes a college selectivity measure, a graduate degree dummy variable, and an interaction term between the two variables.

$$log(W_i) = X_i'\beta + \gamma_1 \cdot Q_i + \gamma_2 \cdot G_i + \gamma_3 \cdot G_i Q_i + \theta_i'\alpha + e_i. \quad (1)$$

In equation (1), W_i stands for the wage of individual i, and X_i is a vector of observable exogenous characteristics of an individual i. The vector X_i includes demographic information such as race and gender, work experience, experience squared, and part-time work status. Q_i is a measurement of the quality of individual i's college. To measure this, I use the 75^{th} percentile of the school's freshman SAT scores of the school. The dummy variable G_i takes a value of one for students with a graduate degree (i.e., master's, professional, or a doctoral degree) and zero for those without a

[15] Oyer and Schaefer (2009) examined the returns for attending a prestigious law school. The authors found a 25% return for attending one of the top 10 law schools, relative to attending one of the top 11-20 schools, and a greater than 50% return relative to attending a school ranked between 21 and 100. Their models do not control for unobserved ability.

graduate degree.[16] θ_i stands for a vector of unobservable abilities or skills and e_i is the remaining residual term. The random variable e_i is uncorrelated with all the covariates, X_i, Q_i, and G_i. The random variable e_i and a vector of unobserved ability θ_i are also uncorrelated by assumption.

The parameters of interest are γ_1, γ_2, and γ_3 in the wage regression. These three parameters capture the join distribution of returns to college selectivity and graduate degree attainment. The following table summarizes the wage returns of college selectivity and graduate degree attainment for the same person.

Returns to College Quality and Graduate Degree Attainment

	G=0	G=1
$Q = q$	$\gamma_1 \cdot Q$	$[(\gamma_1 + \gamma_3) \cdot Q] + \gamma_2$
$Q = q + \Delta$	$\gamma_1 \cdot (Q + \Delta)$	$[(\gamma_1 + \gamma_3) \cdot (Q + \Delta)] + \gamma_2$

The magnitude and significance of γ_1 capture the returns to college selectivity without a graduate degree. Similarly, γ_2 represents the average return of attaining a graduate degree at the mean college selectivity. If the cross-term, γ_3, is close to zero, college selectivity affects wages primarily through the returns to holding a bachelor's degree. If γ_3 is positive, college selectivity also affects wages by increasing the returns to graduate education. This would happen if graduates of high-quality colleges accumulate more human capital during college and therefore gain more from graduate programs than graduates of low-quality colleges. Alternatively, college selectivity may function as a signal. Even if there is no difference in accumulated human capital between students from high- and low-quality colleges, γ_3 will still be positive if firms place a greater value on a graduate degree for students from more selective colleges than they place on the same graduate degree held by students from less selective colleges. This could happen if a bachelor's degree from a high quality college works as a signal of students' ability. In contrast, if γ_3 is negative, then attending a high-quality college leads to lower returns to graduate education. This may occur if high-ability students happen to enroll in lower-quality colleges due to an adverse shock (e.g., health problem or financial issues), yet graduate from graduate school and then obtain the same wage as graduate school peers from high-quality colleges. Alternatively, γ_3 could be negative if graduates from high quality colleges work in post-doc or fellowship status after residency while those from low quality colleges move directly into careers.[17]

In the sensitivity analysis, I differentiate between types of graduate programs (i.e., MBA, engineering M.S., law school, medical school, M.A. in Education, other M.A., and a doctoral degree). In the other specification, I interact a college selectivity measure with a dummy variable which

[16] Since a M.A. in Education has different wage patterns from other types of graduate degree holders, I categorize them as no graduate degree in the main analysis. In particular, their average academic achievement and wages are lower than those of bachelor's degree holders, while those of other types of graduate degree holders are generally higher than average bachelor's degree holders. Later, I examine returns to graduate degree by graduate degree types.

[17] See the Association of American Medical Colleges (AAMC)'s website which summarizes the length of training/residency for each specialty. They also have salary information for most of the specialties. https://www.aamc.org/students/medstudents/cim/specialties/

indicates whether a student majored in science, technology, engineering, or mathematics (STEM fields).[18]

3.1 Decomposition of Returns to College Quality

Returns to college selectivity can be expressed as a difference in expected wages between marginally higher ($\bar{q}$) and low ($\underline{q}$) college selectivity types as shown below. $P_{G,Q,\theta}$ and $W_{G,Q,\theta}$ stand for the probability and wages of a graduate degree attainment status ($G = 0$ or $G = 1$) and college selectivity ($\bar{q}$ or $\underline{q}$) conditioning on ability (θ).

$$\begin{aligned} & E\left[W_{Q=\bar{q}} - W_{Q=\underline{q}} | X, \theta\right] \\ & = (P_{G=1,\bar{q},\theta} \cdot W_{G=1,Q=\bar{q},\theta} + P_{G=0,\bar{q},\theta} \cdot W_{G=0,Q=\bar{q},\theta}) \\ & -(P_{G=1,\underline{q},\theta} \cdot W_{G=1,Q=\underline{q},\theta} + P_{G_i=0,\underline{q},\theta} \cdot W_{G=0,Q=\underline{q},\theta}). \end{aligned} \tag{2}$$

Rearranging equation (2) generates three components.

$$\begin{aligned} & = (W_{G=0,Q=\bar{q},\theta} - W_{G=0,Q=\underline{q},\theta}) \\ & +(P_{G=1,\bar{q},\theta} - P_{G=1,\underline{q},\theta}) \cdot (W_{G=1,Q=\underline{q},\theta} - W_{G=0,Q=\underline{q},\theta}) \\ & + \left\{ (W_{G=1,Q=\bar{q},\theta} - W_{G=0,Q=\bar{q},\theta}) - (W_{G=1,Q=\underline{q},\theta} - W_{G=0,Q=\underline{q},\theta}) \right\} \cdot P_{G=1,\bar{q},\theta}. \end{aligned}$$

The effect of going to a marginally higher quality college on wages is represented by the direct return, the differences in probability of attaining graduate degree multiplied by the returns to graduate degree, and the differences in the returns to graduate degree multiplied by the probability of graduate degree attainment. The first component is the direct return for a holder of a bachelors degree from a more selective college without an advanced degree ($= \gamma_1 \cdot (\bar{q} - \underline{q})$). The remaining component represents the differences in the expected returns to graduate degree due to college selectivity. Specifically, the second line is the differences in the probability of graduate degree attainment due to college selectivity ($P_{G=1,\bar{q}} - P_{G=1,\underline{q}}$) multiplied by the returns to graduate degree for a less selective college. The third line is the differences in returns to graduate degree due to college selectivity ($exp(\gamma_3 \cdot (\bar{q} - \underline{q})) - 1$) multiplied by the probability of graduate degree attainment for a more selective college.

3.2 Unobserved Heterogeneity and Selection Bias

The key challenge in estimating the returns to college selectivity is to account for the endogeneity of schooling choices, which results from the correlation between schooling choices and unobserved ability in the wage regression. This correlation potentially leads to selection bias in the

[18] Arcidiacono (2004) documented that college students select into certain majors and fields by assessing their ability via their GPA each semester. In this paper I move away from this type of process and instead assume that students can predict their college majors and GPAs at the time they make a choice about college selectivity. In other words, I assume that students have perfect foresight and I do not model information updating about a student's own academic ability over time. See Arcidiacono et al. (2010) for more discussion.

returns to college selectivity, as well as the returns to a graduate degree. If θ is unobserved, the returns to college selectivity, including the possibility of attaining a graduate degree, are expressed as follows:

$$\begin{aligned} & E\left[W_i|X_i, Q_i=\bar{q}\right]-E\left[W_i|X_i, Q_i=\underline{q}\right] \\ = & \gamma_1 \cdot (\bar{q}-\underline{q})+P_{G_i=1,Q_i=\bar{q}} \cdot (\gamma_2+\gamma_3 \cdot \bar{q})-P_{G_i=1,Q_i=\underline{q}} \cdot (\gamma_2+\gamma_3 \cdot \underline{q}) \\ & +\left\{E\left[\theta_i|X_i, Q_i=\bar{q}\right]-E\left[\theta_i|X_i, Q_i=\underline{q}\right]^{\prime} \alpha\right\}. \end{aligned} \tag{3}$$

In equation (3), the selection bias arises in the returns to college selectivity estimates from $\left\{E\left[\theta_i|X_i, Q_i=\bar{q}\right]-E\left[\theta_i|X_i, Q_i=\underline{q}\right]^{\prime} \alpha\right.$.[19] This is primarily because person-specific math and verbal abilities are confounded with college selectivity.[20] The only case where the estimates of schooling returns are unbiased is when there is no correlation between unobserved ability and observable covariates, (i.e., $E\left[\theta_i \cdot Q_i\right]=0$ and $E\left[\theta_i \cdot G_i\right]=0$). However, this assumption typically does not hold since we do not observe all the individual heterogeneity correlated with schooling outcomes in the data. In order to deal with these selection bias, this paper extends Carneiro et al. (2003)'s factor structure model.

4. Data

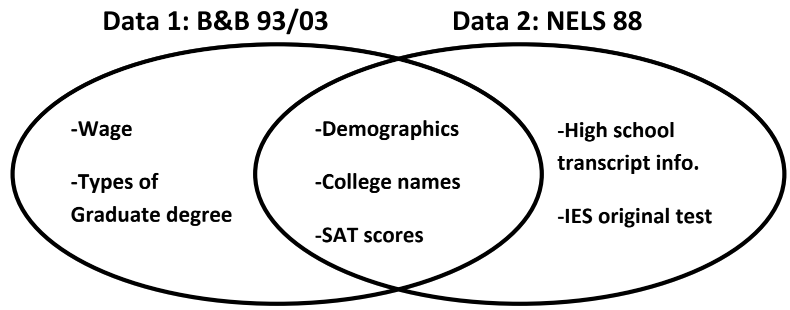
I use sample moments from two data sets since no single sample contains a sufficient amount of information to identify parameters of the empirical model. The first is Baccalaureate and Beyond 93/03 (B&B). B&B contains wage and schooling information, but does not have any information on test scores taken prior to college enrollment other than SAT (or ACT). In order to identify the distribution of unobserved ability, I use the National Education Longitudinal Study of 1988 (NELS:88). NELS:88 contain SAT scores and other test scores (IRTs) prior to college, subject-specific high school grades, and demographics. The following Venn diagram in the next page summarizes the data of the two surveys. To jointly use sample moments from these two data sets, I assume that the underlying distribution is the same across these two nationally representative surveys. The use of sampling weights is also critical.

The Baccalaureate and Beyond 93/03 (B&B) is a longitudinal study of students who earned a bachelor's degree in 1992-1993. The sample contains a sizable number of college graduates who completed a graduate program by the final wave of the survey.[21] The B&B drew its 1993 cohort (about 11,000 students) from the 1993 National Postsecondary Student Aid Study (NPSAS), and

[19]With similar logic, I cannot obtain consistent estimates of $Pr(G_i=1|X_i, Q_i, \theta)$. This does not affect the estimation of γ_1 or γ_3; however, it will be an additional source of bias when I calculate the expected returns to college selectivity.

[20] Similarly, returns to a graduate degree are expressed as follows:
$E\left[W_i|X_i, G_i=1, Q_i\right]-E\left[W_i|X_i, G_i=0, Q_i\right]=\gamma_2+\gamma_3 \cdot Q_i$
$+\left\{E\left[\theta_i|X_i, G_i=1, Q_i\right]-E\left[\theta_i|X_i, G_i=0, Q_i\right]\right\}^{\prime} \alpha$.
The selection bias arises in the returns to graduate degree from $\left\{E\left[\theta_i|X_i, G_i=1, Q_i\right]-E\left[\theta_i|X_i, G_i=0, Q_i\right]\right\}^{\prime} \alpha$. Again, person-specific math and verbal abilities are confounded with graduate degree completion.

[21]College and Beyond (C&B) was also a good potential data set for this study. C&B provides information on students



Overlap of Variables between Two Datasets

followed up with surveys in 1994, 1997, and 2003. About 9,000 respondents remained through 2003. I use the wage observation from the final year of the survey (2003), which was 10 years after college graduation. At this time, most students had already obtained their graduate degrees. The selected students are not a simple random sample. Instead, the survey sample was selected using a three-step procedure (Nevill et al. (2007)).[22] The first sampling level is geographic areas, the second level is institution type (public, private not-for-profit, or private-for-profit), and the last level is degree offering (less than two-year, two-to-three year, four-year non-doctorate-granting, and four-year doctorate-granting). Approximately 40 percent of the students in the sample enrolled in a graduate degree program and 25 percent completed a graduate degree.

Table 1 includes descriptions of each variable and weighted summary statistics of the samples. Researchers have used different variables as proxies for college selectivity. Common measures are freshman SAT/ACT scores and Barron's index of competitiveness. I employ the 75^{th} percentile freshmen SAT/ACT scores in 2001 as a measure in the main analysis and assume that the ranking of schools did not change significantly over several years.[23]

The National Education Longitudinal Study of 1988 (NELS:88) is a longitudinal study of students who were 8th graders in 1988, and the majority of the sample was in their senior year of high school by 1992. The NELS:88 drew its sample from a middle school/junior high school cohort (about 11,000 students), and followed up with surveys in 1990, 1992, 1994, and 2000. The sample contains information on K-16 schooling experiences and outcomes. High school transcripts collected in 1992 contain schooling outcomes such as subject specific grades, GPA, and SAT (or ACT) scores. Postsecondary education transcripts collected in the fall of 2000 contain data on the enrollment and completion of all postsecondary institutions for the sample. In addition,

who entered 32 academically selective colleges and universities in 1951, 1976, and 1989. The initial sample size was 45,000 and the response rate in the following survey waves (conducted through 1996) was about 70%. C&B, however, is drawing its sample from students of highly selective colleges. B&B, in contrast, also covers lower ranked schools.

[22] for more details, see Appendix B: Technical Notes and Methodology in Nevill et al. (2007).

[23] The correlation coefficient between colleges' 25^{th} and 75^{th} percentile SAT scores is 0.97 and regression results are not affected by replacing one measure with the other. When I regress colleges' 75^{th} percentile SAT scores on the Barron's College Selectivity Index, the R-squared is 0.60. See Appendix D for more details.

the survey administered independent cognitive tests on four subject areas (reading, mathematics, science, and social studies). These test scores, along with high school grades and SAT scores, are used to identify the distribution of unobserved ability.

Table 2 includes descriptions of each variable and weighted summary statistics. For the identification strategy to work, the population distribution of the two samples must be the same. The mean values of the most variable in the NELS:88 are close to those in the B&B. The percentage of women is higher for NELS:88, which is probably because I drop samples with no earnings reported in 2003 in the B&B sample but there is no earnings based sample deletion from NELS:88 sample. As a robustness check, I run estimation only using the male sample and do not find differences in main conclusion. SAT verbal scores are low relative to that of B&B, but this could be due to a different reporting method. In the B&B, SAT scores are self-reported. On the other hand, the SAT scores in NELS:88 are reported by schools, not students. Summary statistics of the IRT test scores and high school average grades from high school transcripts are omitted since B&B does not contain those variables.

Table 3 (A) and Table 4 (A) illustrate the mean hourly wages for students by college quartile. Panel (A) of Table 3 compares the wages of students who obtained graduate degrees and those who did not. The mean wage difference between students with and without a graduate degree is \$5/hour for graduates of the lowest-quartile schools. In contrast, the mean wage difference is less than \$1/hour for graduates of the top-quartile schools. These findings suggest that graduate degree returns may vary for colleges of differing qualities. Panel (A) of Table 4 shows a similar pattern, but compares students with different types of graduate programs. These findings suggest that returns may vary by college qualities for different graduate degree programs, which are potentially correlated with occupational choices. Table 3 (B) and Table 4 (B) show differences in years of work experience and graduate program enrollment years. In the estimation, I control for work experience using the data displayed here.

Table 5 summarizes the distribution of occupations by graduate degree attainment status. Similarly, Table 6 shows the occupational distribution for each graduate degree program. It is not clear how occupation and graduate degree attainment status correlate in the Table 5. However, Table 6 indicates that there is a strong concentration in specific occupations for different graduate degrees. For example, 93% of medical school graduates are actually working as medical professionals. Similarly, 79% of the law school graduates are working as legal professionals and 86% of education M.A. holders work as educators. MBA holders are more disperse, but 73% work in business and management and 57% of engineering M.S. holders work in a related occupation.

5. Identification

I use the factor structure model of Carneiro et al. (2003) in order to control for selection into a higher quality college on unobserved abilities. I extend the model to two samples since neither dataset I use has sufficient information on its own. Identification of the model parameters works roughly in two steps. First, I identify the distribution of unobserved ability using the variation in scores from multiple tests. I assume that all test scores are a linear function of unobserved ability (i.e., the factors) and a random error term. I can obtain consistent estimates of the coefficient on unobserved ability in the test score equation (i.e., factor loading) by regressing the first test score on the second test score, using the third test score as an instrument. Then, I can identify the distributions of unobserved ability and the error terms non-parametrically.[24] Once I know the distribution of unobserved ability, I can control for the correlation between this unobservable dimension and the endogenous variables in the wage equation.

Again, I use moments from two samples to identify the model parameters. The main data set is B&B:93/03, which contains wage observations and a sufficiently large number of graduate degree earners. This is essential for estimating the returns to college selectivity and graduate degrees jointly. However, this data set does not have a sufficient number of ability measures to identify the distribution of unobserved ability. The only measure of ability that the main data set contains are SAT scores; however, if there is measurement error in these test scores, they cannot be used as a proxy or instrument for unobserved ability.[25] I also use NELS:88 since it contains a sufficient number of ability measures and college selectivity. An additional assumption required is that the two samples are drawn from same population distribution. In other words, the identification does not rely on matching on observable characteristics.

To be more specific, I use the following specifications. The wage equation is the same as equation (1). I specify a functional from for the two endogenous variables in the wage equation, college selectivity (Q) and graduate degree dummy (G). The last three equations are measures of ability. They are SAT scores, IRT, and HSG. IRT stands for NELS:88 original cognitive test scores. HSG stands for high school subject-specific average grades. In principle, I can use more than three measurements to uncover the distribution of unobserved ability, but I discuss identification with the minimum requirement.

$$
\begin{aligned}
& W = X^W \beta_W + \gamma_1 Q + \gamma_2 G + \gamma_3 QG + \alpha_m \theta_m + \alpha_v \theta_v + e_W, \\
& G = 1\{G^* \geq 0\} \text{ where } G^* = X^G \beta_G + \rho Q + \alpha_{Gm} \theta_m + \alpha_{Gv} \theta_v + e_G, \\
& Q = X^Q \beta_Q + \delta_m SAT_m + \delta_v SAT_v + \alpha_{Qm} \theta_m + \alpha_{Qv} \theta_v + e_Q, \\
& SAT_j = X^S \beta_j^S + \theta_j + e_j, \\
& IRT_j = X^I \beta_j^I + \alpha_{Ij} \theta_j + u_{Ij}, \\
& HSG_j = X^H \beta_j^H + \alpha_{Hj} \theta_j + u_{Hj} \text{ where j} \in \{m, v\}.
\end{aligned}
$$

A key assumption is that the unobserved random components, e_j u_j, and θ_j, are uncorrelated. Note that unobserved abilities θ_{mi} and θ_{vi} are allowed to be correlated. Policy maker and econometri-

[24]Kotlarski's Theorem: Let X_1, X_2, and θ be three independent real-valued random variables and define $Y_1 = X_1 + \theta$ and $Y_2 = X_2 + \theta$. If the characteristic function of (Y_1,Y_2) does not vanish, then the joint distribution of (Y_1,Y_2) determines the distributions of X_1, X_2, and θ up to a change of the location (Kotlarski (1967)). We can apply this theorem to our model for example: $S\tilde{A}T_m = \theta_m + e_m$ and $\frac{IR\tilde{T}_m}{\alpha_{Im}} = \theta_m + \frac{u_{Im}}{\alpha_{Im}}$.

[25]SAT is the only common ability measure between the two sample. However, if I use SAT as a proxy or instrument of unobserved ability, measurement error of SAT will be correlated with college selectivity in the wage regression because SAT is one of the determinants of college selectivity.

cians cannot observe θ_{mi} and θ_{vi}, but these unobserved abilities affect college selectivity, graduate degree attainment, and wages.

First, I identify coefficients on unobserved abilities in the test scores (α_{Ij} and α_{Hj} for j$\in \{m, v\}$) and the distribution of factors (θ_j). Using demeaned measurement equations and given $\theta_m \perp e_m$, $\theta_m \perp u_{lm}$, and $e_m \perp u_{km}$ for $l \in \{I, H\}$, I identify α_{Hm} from the following second moments:

$$\frac{Cov(I\tilde{R}T_m, H\tilde{S}G_m)}{Cov(I\tilde{R}T_m, S\tilde{A}T_m)} = \frac{\alpha_{Im}\alpha_{Hm}\sigma^2_{\theta_m}}{\alpha_{Im}\sigma^2_{\theta_m}} = \alpha_{Hm},$$

where $S\tilde{A}T_j = \theta_j + e_j$, $I\tilde{R}T_j = \alpha_{Ij}\theta_j + u_{Ij}$, $H\tilde{S}G_j = \alpha_{Hj}\theta_j + u_{Hj}$ for j$\in \{m, v\}$. Similarly, α_{Im}, α_{Iv}, and α_{Hv} can be identified. Intuitively, the consistent estimates of the coefficients on unobserved abilities in the test scores (α_{Hj}) are obtained by regressing one ability measure (SAT_j) on the other ability measure (HSG_j), using IRT_j as an instrument for $j \in \{m, v\}$, $l \in \{I, H\}$. Given the identified coefficient α_{Im}, I identify the distributions of θ_m, e_m, and u_{Im} non-parametrically using Kotlarski's Theorem (Kotlarski (1967)). Similarly, the distributions of u_{Hm}, u_{Hv}, θ_v, e_v, and u_{Iv} are identified. The joint distribution of two unobserved abilities are non-parametrically identified if the characteristic function of (e_1) and (e_2) do not vanish.[26]

Using a similar approach, I identify the parameters in the college selectivity equation. First, I substitute one of the ability measures (IRT_j) for unobserved ability (θ_j). I use one of the ability measures (HSG_j) as an instrument for the other ability measure (IRT_j), and then identify the coefficient on SAT score (δ_j) and the coefficient on unobserved abilities (α_{Qj} for $j \in \{m, v\}$) in the college selectivity equation.

$$Q = X\beta_Q + \delta_m SAT_m + \delta_v SAT_v + \frac{\alpha_{Qm}}{\alpha_{Im}} I\hat{R}T_m + \frac{\alpha_{Qv}}{\alpha_{Iv}} I\hat{R}T_v + \tilde{e_Q}.$$
$$IRT_j = \phi_j HSG_j + \xi_j,$$

where $\phi_j = \frac{Cov(IRT_j, HSG_j)}{Var(HSG_j)}$ and $\tilde{e_Q} = e_Q - \frac{\alpha_{Qm}}{\alpha_{Im}} u_{Im} - \frac{\alpha_{Qv}}{\alpha_{Iv}} u_{Iv}$ for $j \in \{m, v\}$. Given $F(e_{\theta_m})$, $F(e_{\theta_v})$, δ_j, and α_{Qj} for $j \in \{m, v\}$, the distribution of e_Q can be identified using the Convolution Theorem.[27] Next, I identify the parameters in the graduate degree attainment equation in the following way: I can identify three unknowns, a coefficient on college selectivity (ρ), and coefficients on unobserved abilities (α_{Gm} and α_{Gv}) in the graduate degree attainment equation from the following three equations:[28]

$$Cov(\rho Q + \quad \alpha_{Gm}\theta_m + \alpha_{Gv}\theta_v + e_G, Q) = \rho\sigma^2_Q + \alpha_{Gm}Cov(\theta_m, Q) + \alpha_{Gv}Cov(\theta_v, Q)$$

[26] The characteristic function of ($S\tilde{A}T_1$,$S\tilde{A}T_2$) can be written in the following way. $E\left[exp(it_1(\theta_1 + e_1) + it_2(\theta_2 + e_2))\right] = E\left[exp(it_1\theta_1 + it_2\theta_2)\right] \cdot E\left[exp(it_1 e_1)\right] \cdot E\left[exp(it_2 e_2)\right]$. Since I estimate the joint distribution of ($S\tilde{A}T_1$, $S\tilde{A}T_2$) and identified the distribution of e_1 and e_2 at this point, I can identify the joint distribution of (θ_1, θ_2).

[27] The Convolution Theorem: Under specified conditions, the integral transform of the convolution of two functions is equal to the product of their integral transforms. The theorem will be applicable to the model as follows: $\left[Q - X\beta_Q - \delta_m SAT_m - \delta_v SAT_v\right] = \left[\alpha_{Qm}\theta_m + \alpha_{Qv}\theta_v\right] + e_Q$.

[28] I can calculate covariances from the following joint distributions.

$$Pr(G = 0, Q|X) = Pr(\rho Q + \alpha_{Gm}\theta_m + \alpha_{Gv}\theta_v + e_G \leq -x, Q \leq q) = F_{\rho Q + \alpha_{Gm}\theta_m + \alpha_{Gv}\theta_v + e_G, Q}(x, q),$$
$$Pr(G = 0, SAT_m|X) = Pr(\rho Q + \alpha_{Gm}\theta_m + \alpha_{Gv}\theta_v + e_G \leq -x, SAT_m \leq s) = F_{\rho Q + \alpha_{Gm}\theta_m + \alpha_{Gv}\theta_v + e_G, SAT_m}(-x, s),$$

$$
\begin{aligned}
&= \rho\sigma_Q^2 + \alpha_{Gm} Cov(\frac{I\tilde{R}T_m}{\alpha_{Im}}, Q) + \alpha_{Gv} Cov(\frac{I\tilde{R}T_v}{\alpha_{Iv}}, Q), \\
Cov(\rho Q + &\alpha_{Gm}\theta_m + \alpha_{Gv}\theta_v + e_G, SAT_m) = \rho\sigma_Q^2 + \alpha_{Gm} Cov(\theta_m, SAT_m) \\
&= \rho\sigma_Q^2 + \alpha_{Gm} Cov(\frac{I\tilde{R}T_m}{\alpha_{Im}}, SAT_m), \\
Cov(\rho Q + &\alpha_{Gm}\theta_m + \alpha_{Gv}\theta_v + e_G, SAT_v) = \rho\sigma_Q^2 + \alpha_{Gv} Cov(\theta_v, SAT_v) \\
&= \rho\sigma_Q^2 + \alpha_{Gv} Cov(\frac{I\tilde{R}T_v}{\alpha_{Iv}}, SAT_v).
\end{aligned}
$$

Finally, I identify the parameters in the wage equation. I identify γ_1 using the moments constructed from the data on people who do not attain a graduate degree ($G = 0$),

$$W(G=0) = \gamma_1 Q + \alpha_1^W \theta_m + \alpha_2^W \theta_v + e_W.$$

Given $F(\theta_k)$, $F(e_k)$, $\theta_k \perp e_k$, $\theta_k \perp e_Q$, $\theta_k \perp e_W$, $e_k \perp e_Q$, $e_k \perp e_W$, for $k \in \{m, v\}$, I identify γ_1, $\alpha_m^{G=0}$, and $\alpha_v^{G=0}$ using the following three moments,[29]

$$
\begin{aligned}
Cov(\tilde{W}, \tilde{Q}) \quad &= \gamma_1 \left[(\delta_m + \alpha_{Qm}) + \alpha_m\right](\delta_m + \alpha_{Qm})\sigma_{\theta_m}^2 + \gamma_1 \delta_m^2 \sigma_{e_m}^2 \\
&+ \gamma_1 \left[(\delta_v + \alpha_{Qv}) + \alpha_m\right](\delta_v + \alpha_{Qv})\sigma_{\theta_v}^2 + \gamma_1 \delta_v^2 \sigma_{e_v}^2 + \gamma_1 \sigma_{e_W}^2 \\
Cov(\tilde{W}, S\tilde{A}T_m) \quad &= \gamma_1 \left[(\delta_m + \alpha_{Qm}) + \alpha_m\right]\sigma_{\theta_m}^2 + \gamma_1 \delta_m \sigma_{e_m}^2 \\
Cov(\tilde{W}, S\tilde{A}T_v) \quad &= \gamma_1 \left[(\delta_v + \alpha_{Qv}) + \alpha_m\right]\sigma_{\theta_v}^2 + \gamma_1 \delta_v \sigma_{e_v}^2.
\end{aligned}
$$

Similarly, I identify γ_3, $\alpha_m^{G=1}$, and $\alpha_v^{G=1}$ using three moments constructed from the data on people who do attain a graduate degree ($G = 1$) (i.e. $Cov(\tilde{W}, \tilde{Q})$, $Cov(\tilde{W}, S\tilde{A}T_m)$, $Cov(\tilde{W}, S\tilde{A}T_v)$).

Lastly, γ_2 is identified by calculating $E[\theta|G=1]$ and $E[\theta|G=0]$:

$$
\begin{aligned}
&E[W|G=1] - E[W|G=0] \\
&= \{\gamma_1 + \gamma_3\} E[Q|G=1] + \gamma_2 + \alpha_m^{G=1} E[\theta_m|G=1] + \alpha_v^{G=1} E[\theta_v|G=1] + E[e_W|G=1] \\
&- \gamma_1 E[Q|G=0] - \alpha_m^{G=0} E[\theta_m|G=0] - \alpha_v^{G=0} E[\theta_v|G=0] - E[e_W|G=0].
\end{aligned}
$$

I estimate this model using maximum likelihood. In order to integrate the likelihood function over unobserved ability (θ_m and θ_v), I use numerical integration.[30]

6. Results

6.1 Main Analysis

The main regression results using the factor structure model are reported in Table 7 (excluding medical and doctoral degree holders). The two columns of results demonstrate how adding the

$$Pr(G=0, SAT_v|X) = Pr(\rho Q + \alpha_{Gv}\theta_m + \alpha_{Gv}\theta_v + e_G \le -x, SAT_v \le s) = F_{\rho Q + \alpha_{Gm}\theta_m + \alpha_{Gv}\theta_v + e_G, SAT_v}(-x, s).$$

[29] $\tilde{W}(G=0) = \gamma_1 \left[(\delta_m + \alpha_{Qm}) + \alpha_m\right]\theta_m + \gamma_1 \left[(\delta_v + \alpha_{Qv}) + \alpha_v\right]\theta_v + \gamma_1 \delta_m e_m + \gamma_1 \delta_v e_v + \gamma_1 e_Q + e_W.$

[30] Alternatively, I can estimate this model using GMM. Appendix C discusses a simplified version of GMM.

graduate degree dummy variable and the cross-term to the model affects the returns to college selectivity. As shown in column (1), wages earned by graduates of one standard deviation (s.d.) higher quality college is 3% higher than the wages earned by graduates of less selective colleges. Here, one s.d. of the college selectivity measure is 118 point difference in freshman 75th% SAT math and verbal composite score. One example of this score gap is UC-Los Angeles (1400) and UC-Santa Barbara (1300). As a reference, college costs 2,300 dollars on annual basis more for one s.d. higher quality college on average.[31] The mean hourly wage is 26 dollars per hour, so the 3% increase in wage is equivalent to 78 cents for a mean wage earner.

In column (2), I add a term for the interaction between college selectivity and the graduate degree dummy variable. In this specification, the return to college selectivity is 3.7% and the returns to holding a graduate degree is about 18.6% for graduating from one s.d. higher quality college. It is equivalent to 96 cents and $4.84 for the mean wage earners, respectively. Wages are increasing in math ability; however, the coefficient on verbal ability is negative and significant. I show that this finding is not due to occupational sorting in the robustness check (Table 14) and discuss potential stories. Finally, the coefficients on work experience and experience squared are counterintuitive, but this is mainly due to the differences in graduate school program length. The returns to a graduate degree attainment only capture the average returns in the main specification, so the variation in returns to graduate degree is captured by the work experience term.

By comparing the results from two specifications, I find that the returns to college quality are downwardly biased in the column (1) due to the omission of graduate degree attainment. Math ability is highly correlated with graduate degree attainment and returns to graduate degree attainment are positive and the magnitude is large. Without a graduate degree dummy in the specification, variation in math ability captures these returns to graduate degree. Returns to college quality is biased downward since the variation in wage returns by college quality for graduate degree holders are absorbed by the variation in math ability.

Table 8 shows the graduate degree attainment estimation results (again, excluding medical and doctoral degree holders). The coefficients of math and verbal abilities are both positive and significant. The probability of attaining a graduate degree is 4.3% higher for graduating from 1 s.d. higher quality college.

The results in Table 9 examine heterogeneous returns to college selectivity (excluding medical and doctoral degree holders). The cross terms between the unobserved heterogeneity and college selectivity are not statistically significant. This implies that the returns to college selectivity are constant across individual abilities. This finding implies two stories. First, college selectivity may function as a signal when an individual student's ability is not fully observed by employers. In this case, the returns to college selectivity are the same across students from the same college. Second, the returns to college selectivity may be homogeneous across students' abilities. Note that the returns are measured as a percentages, so the returns in levels are still higher for higher wage

[31] See Appendix E for a scatter plot between the college net cost and college selectivity. Net college cost = 9.75+0.36*Female-0.62*non-White/Asian+2.30*Q (R-squared=0.15) where net college cost ($1,000)= tuition + other direct costs - all grants.

earners. The cross term between unobserved math ability and the graduate degree dummy is statistically significant and positive. This suggests that there is fundamental heterogeneity in the returns to graduate degrees. More precisely, the results indicate that math ability and graduate degree are complements. Since graduate degree holders tend to work in specialized fields, employers might be able to evaluate an individual's math ability accurately. In this case, a graduate degree does not function as a signal but rather functions as a minimum qualification to work in a specific industry. The results discussed so far excluded medical and doctoral degree holders. I show results including all graduate program types next.

6.2 Analysis include Medical and Doctoral Degree Holders

Table 10 shows the wage regression by graduate program types including all graduate program types. In this model, I allow different graduate degrees (e.g., MBA, J.D., M.D.) to have different returns and cross-terms. Respondents with a M.D., a J.D., an MBA, or a master's in engineering earn 27-35% more than respondents without a graduate degree. In contrast, respondents with other M.A.s or doctoral degrees earn the same wage as individuals without graduate degrees at the time they are observed in the data. It is likely that the wage ten years after college graduation captures post-doc salaries for doctoral degree holders. Wages for the M.A. in education are significantly lower than wages for individuals without graduate degrees. However the interpretation is not straightforward since I have not adjusted for months that teachers actually get paid. In the current specification, I assume every worker works 52 weeks per year regardless of occupation. In reality, teachers work fewer months than other workers, so this negative coefficient on the M.A. in education could be smaller in magnitude if I could adjust for weeks they actually work.[32] A negative cross-term between M.D. and college selectivity suggests that returns to an M.D. varies by college selectivity. This is because highly demanding specialties like surgery, neurosurgerugery, or cardiology require fellowship periods after residency. This creates a difference in training periods across medical degree holders. It is possible that M.D. holders from high quality colleges select themselves into more competitive specialties as opposed to M.D. holders from less selective colleges who might choose less competitive specialties like family practice.

Table 11 shows the wage regression with college major interactions. Science, technology, engineering, or math (STEM) majors have about the same returns to college selectivity as non-STEM majors (without a graduate degree) since the cross-term between college selectivity and STEM dummy is not significant. However, STEM majors have twice as high graduate degree returns (at the mean college selectivity). The cross term between college selectivity and graduate degree is negative only for the STEM majors. This is because medical degree programs require college students to major in STEM fields (i.e., pre-med requirements).

Table 12 shows the same specification as Table 7 but the sample includes medical and doctoral degree holders. A negative cross-term is there due to the medical and doctoral degree holders.

[32] I will assume teachers work 42 weeks per year and run a sensitivity analysis in the future.

6.3 Sensitivity Analysis

As a robustness check, I run estimation only with a male sub-sample (excluding medical and doctoral degree holders). Estimates from a female sample might be biased since I cannot observe wages for females who are out of the labor force. The results with a male sub-sample are shown in Table 13. The returns to college selectivity are 2.4% but statistically insignificant. Returns to graduate degree are statistically significant for law school and MBA, but the cross-terms between the college selectivity and graduate degree attainment are not statistically significant. The coefficient of math ability is positive and significant, but that of verbal ability is negative and significant.

I also estimate a model with occupation dummies. The results are summarized in Table 14 (excluding medical and doctoral degree holders). I run this specification to control for occupational sorting. The negative coefficient on unobserved verbal ability is still significant. This suggests that occupational sorting is not the reason for having a wage penalty on high verbal ability type workers. It rather suggests that people with low-math and high-verbal ability type are penalized most in the labor market (holding college selectivity and graduate degree attainment constant). However, the estimated correlation between math and verbal abilities are high (0.87), so such type (low-math and high-verbal ability combination) is not a majority. Potential stories supporting the negative coefficient on unobserved verbal ability are as follows. First, high verbal ability types might choose occupations based on his preferences rather than on financial returns. Compensating differentials could explain such a story. However, it is beyond my scope to address why differences in ability types lead to heterogeneity in preference. Second, verbal ability is rewarded highly in degree attainment, but not in the labor market holding other things constant. This is likely because I use cognitive test scores to recover verbal ability and these test scores may not be useful in the labor market. For the younger cohort, writing test scores are available in SAT. Writing test scores might reflect labor market relevant verbal ability than verbal test scores. [33] Third, high verbal score might be correlated with other attributes of a worker. If high verbal ability is irrelevant for labor market outcomes and yet is correlated with other negative attributes of a worker, the coefficient could be negative. It is hard to come up with an example, but such omitted variable bias could be a reason. Nevertheless, the negative coefficient on the verbal ability in the wage regression is found in a model using SAT scores as ability control, which is summarized in Table 15. This indicates that the negative correlation between the verbal ability and the wage exist in the raw data.

[33] See Taber (2001)'s Table 2. In the third specification, he finds a negative coefficient on the cross-term between the word knowledge score and a college dummy. The data is from NLSY79, so the negative correlation between the word knowledge and the wage for college graduates is documented for old cohort.

6.4 Signal to Noise Ratio of the Measurements

Lastly, the signal to noise ratio of the measurements could be calculated from the estimated variances of factor and error terms combined with the factor loadings as follows.

$$Signal = \frac{\alpha_A^2 \cdot Var(\theta)}{\alpha_A^2 \cdot Var(\theta) + Var(\eta)}$$

$$Noise = \frac{Var(\eta)}{\alpha_A^2 \cdot Var(\theta) + Var(\eta)}$$

	SAT	IRT	HS-Grade
	Math	Math	Math
θ_m	82.2%	83.8%	53.1%
	Verbal	Reading	English
θ_v	65.2%	53.2%	41.7%

SAT scores have less noise relative to other measures of ability. In the case of math ability, the IRT test score has a relatively high signal ratio. None of the measurements of verbal ability have high signal ratios, and this shows that it is hard to construct a unique verbal ability term from multiple test scores. Overall, high school grades do not have high signal ratios with the current set of measurements. This indicates that high school grades contain different types of information about student's ability relative to SAT or IRT cognitive test scores. One possibility is that high school grades capture not only the cognitive ability of a student but also non-cognitive abilities such as aspirations, motivation, tastes for schooling, or social skills.

7. Conclusion

The existing studies on the returns to college selectivity find mixed results because of the difficulty of controlling for selection. Moreover, researchers have not investigated whether college selectivity affects the probability of attaining a graduate degree while controlling for selection on unobserved abilities. I use the factor structure model of Carneiro et al. (2003) in order to address this issue. I extend the model to two samples since no data set has sufficient information in isolation. By using this approach, I control for selection on unobserved abilities, estimate the returns across all levels of college selectivity margins, and the identification of the source of unobserved ability is explicit and robust to measurement error in admission test scores. In addition, the model allows me to calculate heterogeneous returns to college selectivity, depending on both observable characteristics and unobservable math and verbal abilities.

The results show that college selectivity is relevant for future labor market outcomes through two channels. First, college selectivity increases the wage returns conditional on graduate degree attainment. Second, college selectivity increases the probability of graduate degree attainment and the returns to graduate degree increase the wage, which is the same regardless of college selectivity for the majority of graduate programs. I also find that math ability is rewarded both in degree attainment and the labor market. However, verbal ability is only rewarded in degree attainment and penalized in the labor market. Lastly, I find that there is a fundamental heterogeneity in the returns to graduate degree but not to college selectivity. Specifically, returns to college selectivity are the same across individuals but returns to graduate degree attainment increases with math ability.

College selectivity has significant and positive effect on future wages for both types of students, not planning and planning to attain a graduate degree. In addition, if a student is willing to attain a graduate degree, going to a more selective college increases the expected future wage through higher rates of graduate degree attainment. It turns out the question of do more selective colleges lead to higher wage returns has a more complicated answer than 'yes' or 'no'.

In the next version of my paper, I will include medical and doctoral degree holders into the main analysis. In the new specification, I will break down a graduate degree attainment dummy into two separate dummies: one is a dummy for medical and doctoral degrees; the other is a dummy for graduate degrees from the rest of the graduate programs. In the graduate degree attainment equation, I use a nested multinomial logit model to control for selection into graduate degree attainment in two steps. The first layer is the selection into graduate degree attainment. The second layer is the selection in to medical or doctoral degree attainment conditional on attaining a graduate degree. As a future work, I will use graduate school admission test scores (e.g., GRE, MCAT, GMAT) and further control for selection at the graduate program enrollment stage as a robustness check. I am also interested in allowing a third unobserved ability using school achievement measures (i.e., college GPA, honor, high school grades of all fields, high school rank) since these measures might capture aspirations and inter-personal skills that are something different from cognitive abilities measured by test scores.

A. Likelihood Function

The likelihood function is: The original likelihood is specified as follows:

$$L = \prod_{i=1}^{I+J} \int_{-\infty}^{\infty} \quad f_W(W|X,\theta_m,\theta_v) \cdot$$
$$f_G(G|X,\theta_m,\theta_v) \cdot f_Q(Q|X,\theta_m,\theta_v) \cdot f_{SAT}(SAT_m|X,\theta_m) \cdot f_{SAT}(SAT_v|X,\theta_v) \cdots$$
$$f_{IRT}(IRT_m|X,\theta_m) \cdot f_{IRT}(IRT_v|X,\theta_m) \cdot$$
$$f_{HSG}(HSG_v|X,\theta_v) \cdot f_{HSG}(HSG_v|X,\theta_v) \cdot f_\theta(\theta_m,\theta_v) d\theta.$$

This will be reduced to the following log likelihood by integrating out missing variables for each sample.

$$logL = \sum_{i=1}^{I} \omega_{Data1} \cdot log(l_i^{Data1}) + \sum_{j=1}^{J} \omega_{Data2} \cdot log(l_j^{Data2}),$$

where ω_{Data1} and ω_{Data2} are sample weights in the each survey.

B. Sample Selection

I selected a sample from the Baccalaureate and Beyond 93/03 (B&B) as follows. Starting with a sample of 9,000 respondents, I dropped students who graduated from an institution that is either not recognized in the Integrated Postsecondary Education Data System (IPEDS) or did not report SAT and ACT test scores to IPEDS. Among students who graduated from colleges that reported freshman SAT/ACT test quartiles, I selected students with data for both SAT math and verbal scores.[34] I also eliminated observations if 2003 wage data were missing. I use a listwise deletion in this analysis, although this is not the only way to handle missing variables. These deletions result in a total of 3,150 observations. I use the sample weights provided in the data.

For the National Education Longitudinal Study of 1988 (NELS:88), I keep students who completed a bachelor's degree or above as of 2000 starting with a sample of 11,000 respondents. Among those who graduated from four year colleges, I dropped students who graduated from an institution that is either not recognized in the Integrated Postsecondary Education Data System (IPEDS) or did not report SAT and ACT test scores to IPEDS. Further, I selected students with data on SAT math and verbal scores, IRT test scores, and high school grades. I use a listwise deletion in this analysis. These deletions result in a total of 1,770 observations. I use the sample weights provided in the data.

[34] Dropping students without SAT scores may result in a geographically imbalanced sample.

C. GMM approach

Here, I discuss how I estimate simplified model (no graduate degree attainment and one measure of unobserved ability) using GMM. Suppose the empirical model is given as follows:

$$
\begin{aligned}
W_i &= \gamma \cdot Q_i + \alpha \cdot \theta_i + e_i \\
Q_i &= \delta \cdot SAT_i + \alpha^Q \cdot \theta_i + e_i^Q \\
SAT_i &= \theta_i + \epsilon_i \\
IRT_i &= \alpha^I \cdot \theta_i + \eta_i \\
HSG_i &= \alpha^H \cdot \theta_i + v_i.
\end{aligned}
$$

We can identify the parameters of interests (γ and α) as follows:

$$
\begin{aligned}
\alpha^I &= \frac{Cov(HSG, IRT)}{Cov(HSG, SAT)} \\
\sigma_\theta^2 &= \frac{Cov(IRT, SAT)}{\alpha^I} \\
\sigma_\epsilon^2 &= Var(SAT) - \frac{Cov(IRT, SAT)}{\alpha^I}
\end{aligned}
$$

$$
\begin{aligned}
\delta &= \frac{Cov(Q, SAT) - (\delta + \alpha^Q) \cdot \sigma_\theta^2}{\sigma_\epsilon^2} \\
\alpha^Q &= \frac{Cov(Q, SAT)}{Cov(IRT, SAT)} - \delta \\
\sigma_{e^Q}^2 &= Var(Q) - (\delta + \alpha^Q)^2 \cdot \sigma_\theta^2 - \delta^2 \cdot \sigma_\epsilon^2
\end{aligned}
$$

$$
\begin{aligned}
\gamma &= \frac{(\delta + \alpha^Q) \cdot Cov(W, SAT) - Cov(W, Q)}{(\delta + \alpha^Q) \cdot \sigma_\epsilon^2 - \sigma_{e^Q}^2} \\
\alpha &= \frac{Cov(W, SAT) - \gamma \cdot (\delta + \alpha^Q) \cdot \sigma_\theta^2 - \delta \cdot \gamma \cdot \sigma_\epsilon^2}{\sigma_\theta^2} \\
\sigma_e^2 &= Var(W) - (\gamma \cdot (\delta + \alpha^Q) + \alpha)^2 \cdot \sigma_\theta^2 - (\gamma \cdot \delta)^2 \cdot \sigma_\epsilon^2 + \gamma^2 \cdot \sigma_{e^Q}^2
\end{aligned}
$$

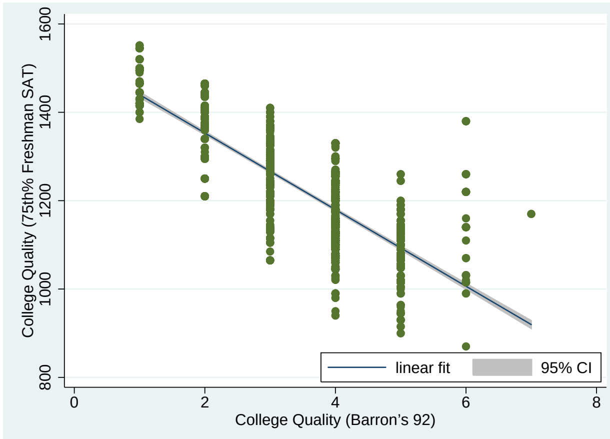
Find parameters that minimize the moments below:

$$
\begin{aligned}
&E[IRT_i \cdot HSG_i - \alpha^I \cdot SAT_i \cdot HSG_i] = 0 \\
&E[HSG_i \cdot IRT_i - \alpha^H \cdot SAT_i \cdot IRT_i] = 0 \\
&E[IRT_i \cdot SAT_i - \alpha^I \cdot \sigma_\theta^2] = 0 \\
&E[\alpha^I \cdot SAT_i \cdot SAT_i - IRT_i \cdot SAT_i - \alpha^I \cdot \sigma_\epsilon^2] = 0 \\
&E[\sigma_\epsilon^2 \cdot Q_i \cdot SAT_i - (\delta + \alpha^Q) \cdot \sigma_\theta^2 - \sigma_\epsilon^2 \cdot \delta] = 0 \\
&E[Q_i \cdot SAT_i - \delta IRT_i \cdot SAT_i - \alpha^Q \cdot IRT_i \cdot SAT_i] = 0
\end{aligned}
$$

$$
\begin{aligned}
&E[Q_i \cdot Q_i - (\delta + \alpha^Q)^2 \cdot \sigma_\theta^2 - \delta^2 \cdot \sigma_\epsilon^2 - \sigma_{e^Q}^2] = 0 \\
&E[(\delta + \alpha^Q) \cdot W_i \cdot SAT_i - W_i \cdot Q_i - \gamma \cdot ((\delta + \alpha^Q) \cdot \sigma_\epsilon^2 - \sigma_{e^Q}^2)] = 0 \\
&E[W_i \cdot SAT_i - \gamma \cdot (\delta + \alpha^Q) \cdot \sigma_\theta^2 - \delta \cdot \gamma \cdot \sigma_\epsilon^2 - \alpha \cdot \sigma_\theta^2] = 0 \\
&E[W_i \cdot W_i - (\gamma \cdot (\delta + \alpha^Q) + \alpha)^2 \cdot \sigma_\theta^2 - (\gamma \cdot \delta)^2 \cdot \sigma_\epsilon^2 + \gamma^2 \cdot \sigma_{e^Q}^2 - \sigma_e^2] = 0
\end{aligned}
$$

D. College Quality Measures

Figure 1: Barron's College Selectivity Index (1992) and Freshman 75th% SAT/ACT score (2001)

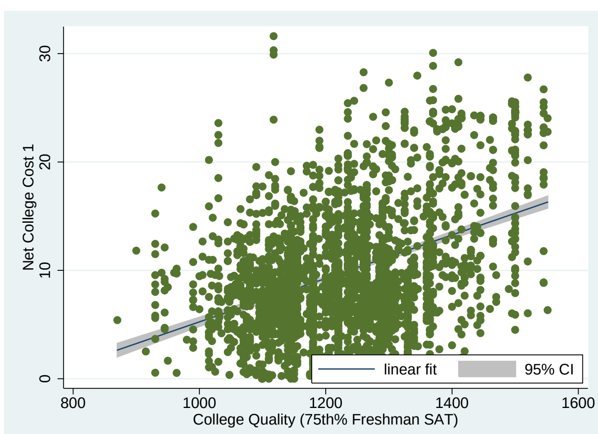


Note: Slope is -0.07 and R-squared is 0.60.

Note: Barron's Index is based off the SAT/ACT scores of those students who were accepted the previous year at a given institution, the grade point average (GPA) required for admission, the class rank required for admission, and the percentage of applicants accepted at a given institution the previous year. 1: Most Competitive; 2: Highly Competitive; 3:Very Competitive; 4:Competitive; 5:Less Competitive; 6:Noncompetitive; 7:Special.

E. Net Cost of College by College Quality

Figure 2: Net Cost of College ($1,000) and College Quality (Freshman 75th percentile SAT/ACT composite score)



Note: Net college cost = 9.75+0.36*Female-0.62*non-White/non-Asian+2.30*Q (R-squared=0.15).

Table 1: B&B:93/03 Descriptive Statistics

Variable Name	Description	Mean	s.d.
Female	A dummy variable takes 1 if female	0.482	0.500
Non-White/Asian	A dummy variable takes 0 if White or Asian	0.102	0.303
White		0.833	0.373
Asian		0.065	0.247
Black		0.057	0.231
Hispanic		0.042	0.201
Work experience	Work experience in years. 10 years minus unemployment, out of labor force, and graduate program participation years.	8.559	2.405
Graduate Degree Dummy	A dummy variable takes 1 for MA, professional degrees, and doctoral degrees. MA in Education takes 0 for estimation purpose.	0.258	0.438
Med.	Professional degree in medical school	0.031	0.173
Law	Professional degree in Law school	0.031	0.174
MBA	M.A. in Business school	0.060	0.238
Eng.	M.S. in Engineering field	0.023	0.150
Edu.	M.A. in Education	0.058	0.235
Other	Other MA and other FP	0.082	0.274
Dr.	Any doctoral degrees	0.031	0.172
STEM College Major	Science, Technology, Engineering, or Math major	0.250	0.433
College Quality	College quality measured by freshmen 75th SAT/ACT composite score	1227	118
SAT math		546	95
SAT verbal		546	96

Note: Sample weight (BNBPANL3) is used to calculate mean and standard deviation.

Table 2: NELS:88 Descriptive Statistics

Variable Name	Description	Mean	s.d.
Female	A dummy variable takes 1 if female	0.557	0.497
Non-White/Asian	A dummy variable takes 0 if White or Asian	0.095	0.293
White		0.847	0.360
Asian		0.058	0.234
Black		0.047	0.212
Hispanic		0.047	0.211
College Quality	College quality measured by freshmen 75th SAT/ACT composite score	1233	118
SAT math		529	109
SAT verbal		469	99
Other measures	IRT math, IRT reading, IRT science, IRT social studies,		
	High school math, English, science, social studies average grades		

Note: Sample weight (F4F2PNWT) is used to calculate mean and standard deviation.

Table 3 (A): College Quality and Hourly Wage by Graduate Degree Dummy

	Graduate Dummy = 0			Graduate Dummy = 1		
College Quality	Wage ($)	Weekly Work hrs	Annual Earnings	Wage ($)	Weekly Work hrs	Annual Earnings
Bottom 25 %	24.49	45.98	55,827	29.71	44.47	63,024
25-50 th %	25.04	44.45	55,696	28.66	47.75	70,390
50-75 the %	26.69	45.84	60,368	29.63	46.21	68,279
Top 25 %	27.75	45.90	63,146	28.92	50.72	70,875

Table 3 (B): College Quality and Work Experience by Graduate Degree Dummy

	Graduate Dummy = 0		Graduate Dummy = 1	
College Quality	Experience	Graduate Program Enrollment Years	Experience	Graduate Program Enrollment Years
Bottom 25 %	9.54	0.32	6.22	2.84
25-50 th %	9.69	0.15	5.97	2.97
50-75 the %	9.45	0.21	5.64	3.12
Top 25 %	9.46	0.17	5.47	3.00

Note: Sample weight (BNBPANL3) is used to calculate mean and standard deviation.

Table 4 (A): College Quality and Hourly Wage by Graduate Program Types

	No Graduate Degree			MA in Education		
College Quality	Wage ($)	Weekly Work hrs	Annual Earnings	Wage ($)	Weekly Work hrs	Annual Earnings
Bottom 25 %	25.00	46.02	57,034	20.12	45.75	45,658
25-50 th %	25.40	44.32	56,368	18.77	46.25	42,873
50-75 th %	26.44	45.87	60,989	23.51	45.86	46,959
Top 25 %	28.32	46.05	64,314	19.45	42.32	42,312
	Medical School Degree			Law School Degree		
College Quality	Wage ($)	Weekly Work hrs	Annual Earnings	Wage ($)	Weekly Work hrs	Annual Earnings
Bottom 25 %	68.18	32.67	89,024	29.88	45.89	70,388
25-50 th %	39.31	59.72	111,508	33.84	48.53	84,706
50-75 th %	32.31	52.68	79,182	31.92	48.37	80,516
Top 25 %	26.55	65.20	78,374	30.45	52.74	84,324
	MBA			MS in Engineering		
College Quality	Wage ($)	Weekly Work hrs	Annual Earnings	Wage ($)	Weekly Work hrs	Annual Earnings
Bottom 25 %	30.46	45.67	71,962	29.46	48.46	71,191
25-50 th %	31.28	47.71	74,256	29.85	45.48	70,191
50-75 th %	30.22	47.36	74,461	33.89	46.07	80,196
Top 25 %	36.67	47.13	85,550	32.14	45.75	76,947
	Other MA			Doctoral degree		
College Quality	Wage ($)	Weekly Work hrs	Annual Earnings	Wage ($)	Weekly Work hrs	Annual Earnings
Bottom 25 %	26.54	42.06	50,162	32.52	55.90	90,694
25-50 th %	22.44	44.28	52,189	24.59	46.77	60,032
50-75 th %	27.55	41.83	52,197	24.92	44.61	58,558
Top 25 %	25.62	43.93	53,120	23.40	56.25	62,629

Note: Sample weight (BNBPANL3) is used to calculate mean and standard deviation.

Table 4 (B): College Quality and Work Experience by Graduate Program Types

	No Graduate Degree		MA in Education	
College Quality	Experience	Graduate Program Enrollment Years	Experience	Graduate Program Enrollment Years
Bottom 25 %	9.86	0.00	6.71	3.09
25-50 th %	9.84	0.00	7.21	2.50
50-75 th %	9.68	0.00	6.92	2.62
Top 25 %	9.64	0.01	7.56	1.96
	Medical School Degree		Law School Degree	
College Quality	Experience	Graduate Program Enrollment Years	Experience	Graduate Program Enrollment Years
Bottom 25 %	3.07	4.33	5.32	2.61
25-50 th %	2.52	4.19	5.35	3.13
50-75 th %	3.70	3.94	5.26	3.25
Top 25 %	3.07	3.91	4.85	3.27
	MBA		MS in Engineering	
College Quality	Experience	Graduate Program Enrollment Years	Experience	Graduate Program Enrollment Years
Bottom 25 %	6.70	3.22	7.38	2.15
25-50 th %	7.35	2.54	7.15	2.34
50-75 th %	6.55	2.95	7.33	2.26
Top 25 %	6.94	2.33	7.21	2.19
	Other MA/FP		Doctoral degree	
College Quality	Experience	Graduate Program Enrollment Years	Experience	Graduate Program Enrollment Years
Bottom 25 %	6.49	2.61	6.49	2.61
25-50 th %	6.93	2.45	6.93	2.45
50-75 th %	6.41	2.60	6.41	2.60
Top 25 %	6.43	2.33	6.43	2.33

Note: Sample weight (BNBPANL3) is used to calculate mean and standard deviation.

Table 5 (A): Occupation and Graduate Degree Dummy

Occupation	Graduate Dummy=0	Graduate Dummy=1
Educators	19.61%	11.10%
Business and management	30.54%	25.87%
Engineering/architecture	5.17%	6.09%
Computer science	5.44%	4.21%
Medical professionals	6.55%	20.01%
Editors/writers/performers	4.66%	3.25%
Human/protective service/legal profess	5.21%	14.68%
Research, scientists, technical	5.33%	7.16%
Administrative/clerical/legal support	3.36%	1.57%
Mechanics, laborers	2.08%	0.16%
Service industries	10.55%	3.94%
Other, military	1.50%	1.96%
Total	100%	100%
n	2280	860

Note: Sample weight (BNBPANL3) is used to calculate mean and standard deviation. The number of observations are rounded to the nearest ten due to confidentiality concern.

Table 6: Occupation and Graduate Program Types

Occupation	No Graduate Degree	MA in Education	Medical school	Law school
Educators	13.98%	86.18%	4.63%	0.84%
Business and management	33.03%	3.30%	0.00%	7.67%
Engineering/architecture	5.67%	0.00%	0.00%	0.00%
Computer science	5.90%	0.27%	0.00%	0.00%
Medical professionals	7.01%	0.00%	92.71%	0.00%
Editors/writers/performers	5.11%	0.00%	0.00%	0.00%
Human/protective service/legal profess	5.16%	4.05%	0.00%	78.65%
Research, scientists, technical	5.71%	0.45%	1.87%	0.00%
Administrative/clerical/legal support	3.61%	0.89%	0.00%	10.69%
Mechanics, laborers	2.20%	0.00%	0.00%	0.00%
Service industries	11.01%	4.42%	0.80%	1.37%
Other, military	1.61%	0.44%	0.00%	0.77%
Total	100%	100%	100%	100%
n	2050	210	90	110

Note: Sample weight (BNBPANL3) is used to calculate mean and standard deviation. The number of observations are rounded to the nearest ten due to confidentiality concern.

Table 6 (cont'): Occupation and Graduate Program Types

Occupation	MBA	MS in Engineering	Other MA	Doctoral degree
Educators	2.83%	2.97%	22.95%	18.68%
Business and management	72.96%	17.78%	18.26%	3.93%
Engineering/architecture	3.13%	35.07%	5.24%	4.84%
Computer science	5.99%	22.04%	1.91%	2.03%
Medical professionals	0.94%	0.00%	15.63%	31.55%
Editors/writers/performers	1.03%	1.35%	8.79%	0.82%
Human/protective service/legal profess	0.97%	0.00%	10.26%	14.23%
Research, scientists, technical	2.65%	8.12%	8.67%	23.93%
Administrative/clerical/legal support	0.84%	0.00%	0.24%	0.00%
Mechanics, laborers	0.00%	0.00%	0.51%	0.00%
Service industries	6.97%	3.37%	5.50%	0.00%
Other, military	1.68%	9.30%	2.04%	0.00%
Total	100%	100%	100%	100%
n	170	90	280	120

Note: Sample weight (BNBPANL3) is used to calculate mean and standard deviation. The number of observations are rounded to the nearest ten due to confidentiality concern.

Table 7: Wage Regression without and with Graduate Degree Dummy
(excluding medical and doctoral degree holders)

Dependent variable: log (wage)	(1)	(2)
College Quality (γ_1)	0.030**	0.037**
	(0.014)	(0.015)
Graduate dummy(γ_2)	-	0.170***
		(0.037)
College Quality $\cdot$ Grad. dummy (γ_3)	-	0.002
		(0.029)
Math ability θ_m (α_m)	0.178***	0.081***
	(0.032)	(0.031)
Verbal ability θ_v (α_v)	-0.144***	-0.060*
	(0.035)	(0.034)
Experience	0.007	-0.03**
	(0.010)	(0.012)
Experience squared / 100	-0.053	0.249**
	(0.104)	(0.123)
Part-Time Work dummy	-0.084***	-0.100***
	(0.024)	(0.024)

Note: Other covariates controlled in the estimation include demographics. Test scores are normalized to $N(\mu = 0, \sigma = 1)$. Sample weight adjusted asymptotic standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Graduate Degree Attainment and College Quality
(excluding medical and doctoral degree holders)

Dependent variable:	Graduate degree attainment
College Quality (ρ)	0.186***
	(0.031)
Math ability θ_m (α_m)	0.111*
	(0.040)
Verbal ability θ_v (α_v)	0.311***
	(0.073)
Female dummy	0.055
	(0.056)
Non-White/Non-Asian dummy	-0.044
	(0.090)
Constant	-0.872***
	(0.040)

Table 9: Wage Regression and Heterogeneous Returns
(excluding medical and doctoral degree holders)

Dependent variable:log (wage)	
College Quality (γ_1)	0.028*
	(0.016)
Grad. dummy (γ_2)	0.218***
	(0.039)
College Quality $\cdot$ Grad. dummy(γ_3)	-0.021
	(0.035)
Math ability θ_m (α_m)	0.039
	(0.028)
Verbal ability θ_v (α_v)	-0.063
	(0.032)
College Quality $\cdot$ Math ability	0.009
	(0.067)
College Quality $\cdot$ Verbal ability	-0.008
	(0.081)
Grad.dummy $\cdot$ Math ability	0.075**
	(0.031)
Grad. dummy $\cdot$ Verbal ability	-0.045
	(0.036)
Experience	-0.041***
	(0.012)
Experience squared / 100	0.408***
	(0.123)
Part-Time Work dummy	-0.084***
	(0.024)

Note: Other covariates controlled in the estimation include demographics. Sample weight adjusted asymptotic standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 10: Analysis include Medical and Doctoral Degree Holders (1)
Wage Regression and Graduate Program Types

Dependent variable: log (wage)

College Quality (γ_1)	0.027*		
	(0.015)		
Medical School Degree	0.301***	College Quality · Med.	-0.260***
	(0.082)		(0.062)
Law School Degree	0.241***	College Quality · Law	0.029
	(0.084)		(0.088)
MBA	0.270***	College Quality · MBA	0.002
	(0.068)		(0.067)
MS in Engineering	0.262**	College Quality · Eng.	-0.062
	(0.131)		(0.101)
MA in Education	-0.127***	College Quality · Edu.	0.035
	(0.055)		(0.079)
Other MA	-0.025	College Quality · Other	-0.026
	(0.045)		(0.035)
Doctoral degree	-0.012	College Quality · Dr.	-0.143**
	(0.086)		(0.072)
Math ability θ_m (α_m)	0.189***		
	(0.052)		
Verbal ability θ_v (α_v)	-0.185***		
	(0.059)		
Experience	-0.012		
	(0.012)		
Experience squared / 100	0.113		
	(0.116)		
Part-Time Work dummy	-0.070***		
	(0.024)		

Note: Other covariates controlled in the estimation include constant term and demographics. Sample weight adjusted asymptotic standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Analysis include Medical and Doctoral Degree Holders (2)
Wage Regression and College Major

Dependent variable: log (wage)	
College Quality (γ_1)	0.030*
	(0.016)
Grad. dummy (γ_2)	0.111***
	(0.036)
College Quality · Grad. dummy (γ_3)	-0.018
	(0.030)
College Quality · STEM	0.019
	(0.040)
Grad. dummy · STEM	0.095*
	(0.056)
College Quality · Grad. dummy · STEM	-0.116*
	(0.063)
Math ability θ_m (α_m)	0.182***
	(0.030)
Verbal ability θ_v (α_v)	-0.177***
	(0.032)
Experience	-0.012
	(0.011)
Experience squared / 100	0.121
	(0.106)
Part-Time Work dummy	-0.080***
	(0.023)

Note: Other covariates controlled in the estimation include demographics. Sample weight adjusted asymptotic standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 12: Analysis include Medical and Doctoral Degree Holders (3)
Wage Regression without and with Graduate Degree Dummy

Dependent variable: ln(wage)	(1)	(2)
College Quality (γ_1)	0.011	0.034**
	(0.014)	(0.015)
Graduate dummy(γ_2)	-	0.134***
		(0.032)
College Quality · Grad. dummy (γ_3)	-	-0.06**
		(0.025)
Math ability θ_m (α_m)	0.151***	0.147***
	(0.030)	(0.030)
Verbal ability θ_v (α_v)	-0.114***	-0.129**
	(0.032)	(0.032)
Experience	0.013	-0.013
	(0.009)	(0.011)
Experience squared / 100	-0.127	0.129
	(0.094)	(0.106)
Part-Time dummy	-0.077***	-0.074***
	(0.023)	(0.023)

Note: Other covariates controlled in the estimation include constant term and demographics. Test scores are normalized to $N(\mu = 0, \sigma = 1)$. Sample weight adjusted asymptotic standard errors are in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Sensitivity Analysis with Male-only Sample
Wage Regression by Graduate Program Types
(Sample excludes medical and doctoral degree holders)

Dependent variable: log (wage)

College Quality (γ_1)	0.024		
	(0.024)		
Law School Degree	0.263**	College Quality · Law	-0.033
	(0.121)		(0.147)
MBA	0.228**	College Quality · MBA	-0.011
	(0.107)		(0.089)
MS in Engineering	0.204	College Quality · Eng.	-0.016
	(0.164)		(0.132)
MA in Education	-0.163	College Quality · Edu.	0.040
	(0.174)		(0.218)
Other MA/FP	-0.039	College Quality · Other	-0.091
	(0.084)		(0.069)
Math ability θ_m (α_m)	0.264***		
	(0.094)		
Verbal ability θ_v (α_v)	-0.276***		
	(0.102)		
Experience	-0.020		
	(0.020)		
Experience squared / 100	0.229		
	(0.204)		
Part-Time Work dummy	-0.314***		
	(0.045)		

Note: Other covariates controlled in the estimation include demographics. Sample weight adjusted asymptotic standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Sensitivity Analysis with Occupational Sorting
Wage Regression with Occupation Dummies
(Sample excludes medical and doctoral degree holders)

Dependent variable:log (wage)	
College Quality (γ_1)	0.017
	(0.015)
Grad. dummy (γ_2)	0.107***
	(0.037)
College Quality $\cdot$ Grad. dummy(γ_3)	-0.018
	(0.029)
Math ability θ_m (α_m)	0.129***
	(0.031)
Verbal ability θ_v (α_v)	-0.134***
	(0.034)
Educators	-0.197***
	(0.037)
Business and management	0.218***
	(0.030)
Human/protective service/legal profess/	-0.036
administrative/clerical/legal support	(0.048)
Medical professionals/	0.198***
research, scientists, technical	(0.039)
Engineering/architecture/computer science	0.292***
	(0.062)
Experience	-0.011
	(0.013)
Experience squared / 100	0.007
	(0.120)
Part-Time Work dummy	-0.059
	(0.025)

Note: Other covariates controlled in the estimation include demographics. Sample weight adjusted asymptotic standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 15: OLS Results for Comparison
Wage Regression without and with Graduate Degree Dummy
(The sample excludes medical and doctoral degree holders)

Dependent variable: log (wage)	(1)	(2)
College Quality (γ_1)	0.031*	0.029
	(0.017)	(0.020)
Graduate dummy(γ_2)	-	0.199***
		(0.041)
College Quality · Grad. dummy (γ_3)	-	-0.01
		(0.03)
SAT math θ_m (α_m)	0.068***	0.061***
	(0.018)	(0.018)
SAT verbal θ_v (α_v)	-0.032*	-0.037**
	(0.019)	(0.019)
Experience	0.008	-0.036**
	(0.010)	(0.015)
Experience squared / 100	-0.070	0.356**
	(0.100)	(0.144)
Part-Time dummy	-0.080*	-0.075
	(0.047)	(0.047)

Note: Other covariates controlled in the estimation include demographics. Test scores are normalized to $N(\mu = 0, \sigma = 1)$. Sample weight adjusted asymptotic standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

References

Angrist, Joshua D. and Alan B. Krueger, "The Effect of Age at School Entry on Educational Attainment: An Application of Instrumental Variables with Moments from Two Samples," *Journal of the American Statistical Association*, 1992, *87* (418), pp. 328–336.

Arcidiacono, Peter, "Ability sorting and the returns to college major," *Journal of Econometrics*, 2004, *121* (1-2), 343–375.

_ , "Affirmative Action in Higher Education: How Do Admission and Financial Aid Rules Affect Future Earnings?," *Econometrica*, 09 2005, *73* (5), 1477–1524.

_ , Jane Cooley, and Andrew Hussey, "The Economic Returns To An MBA," *International Economic Review*, 08 2008, *49* (3), 873–899.

_ , V. Joseph Hotz, and Songman Kang, "Modeling College Major Choices using Elicited Measures of Expectations and Counterfactuals," Working Paper 15729, National Bureau of Economic Research February 2010.

Becker, Gary S., "Investment in Human Capital: A Theoretical Analysis," *Journal of Political Economy*, Oct. 1962, *70* (5), 9–49.

Black, Dan A. and J.A.Jeffrey A. Smith, "How robust is the evidence on the effects of college quality? Evidence from matching," *Journal of Econometrics*, 2004, *121* (1-2), 99–124.

Brand, Jennie E. and Yu Xie, "Who Benefits Most From College? Evidence for Negative Selection in Heterogeneous Economic returns to Higher Education," *American Sociological Review*, 2010, *75* (2), 273–302.

Brewer, Dominic J., Eric R. Eide, and Ronald G. Ehrenberg, "Does It Pay to Attend an Elite Private College? Cross-Cohort Evidence on the Effects of College Type on Earnings," *The Journal of Human Resources*, 1999, *34* (1), 104–123.

Buchinsky, Moshe, "Changes in the U.S. Wage Structure 1963-1987: Application of Quantile Regression," *Econometrica*, Mar. 1994, *62* (2), 405–458.

Card, David, "Using Geographic Variation in College Proximity to Estimate the Return to Schooling," Working Paper 4483, National Bureau of Economic Research October 1993.

Carneiro, Pedro, Karsten Hansen, and James Heckman, "Estimating distributions of treatment effects with an application to the returns to schooling and measurement of the effects of uncertainty on college choice," *International Economic Review*, 2003, *44* (2), 361–422.

Cooley, Jane, Salvador Navarro, and Yuya Takahashi, "A Framework for the Analysis of Time-varying Treatment Effects: How The Timing of Grade Retention Affects outcomes," 2009.

Cunha, Flavio and James J. Heckman, "Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Journal of Human Resources*, 2008, *43* (4).

_ , _ , and Susanne M. Schennach, "Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Econometrica*, 2010, *78* (3), 883–931.

Dale, Stacy and Alan B. Krueger, "Estimating the Return to College Selectivity over the Career Using Administrative Earnings Data," Working Paper 17159, National Bureau of Economic Research June 2011.

Dale, Stacy Berg and Alan B. Krueger, "Estimating The Payoff To Attending A More Selective College: An Application Of Selection On Observables And Unobservables," *The Quarterly Journal of Economics*, November 2002, *117* (4), 1491–1527.

Eide, Eric R., Dominic J. Brewer, and Ronald G. Ehrenberg, "Does It Pay to Attend an Elite Private College? Evidence on the Effects of Undergraduate Colege Quality on Graduate School Attendance," *Economics of Education Review*, 1998, *17* (4), 371–376.

Ge, Suqin, "Womens College Decisions: How Much Does Marriage Matter?," *Journal of Labor Economics*, December 2011, *29*, 773–818.

Haveman, Robert H. and Barbara L. Wolfe, "Schooling and Economic Well-Being: The Role of Nonmarket Effects," *The Journal of Human Resources*, 1984, *19* (3), 377–407.

Heckman, James J., "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models," in "Annals of Economic and Social Measurement, Volume 5, number 4" NBER Chapters, National Bureau of Economic Research, Inc, June 1976, pp. 120–137.

Heckman, James J, "Sample Selection Bias as a Specification Error," *Econometrica*, January 1979, *47* (1), 153–61.

Heckman, James J. and Salvador Navarro, "Dynamic discrete choice and dynamic treatment effects," *Journal of Econometrics*, February 2007, *136* (2), 341–396.

_ , J.E. Humphries, S. Urzua, and G. Veramendi, "The Effects of Educational Choices on Labor Market, Health, and Social Outcomes," *Unpublished manuscript*, 2011.

_ , Jora Stixrud, and Sergio Urzua, "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, July 2006, *24* (3), 411–482.

Hoekstra, Mark, "The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach," *Review of Economics and Statistics*, 2009, *91* (4), 717–724.

Ichimura, Hidehiko and Elena Martinez-Sanchis, "Identification and Estimation of GMM Models by Combining Two Data Sets," *Manuscript*, 2005.

Inoue, Atsushi and Gary Solon, “Two-Sample Instrumental Variables Estimators,” *The Review of Economics and Statistics*, 09 2010, *92* (3), 557–561.

Kotlarski, Ignacy, “On characterizing the gamma and the normal distribution,” *Pacific Journal of Mathmatics*, July 1967, *20* (1), 69–76.

Mincer, Jacob A., *Schooling, Experience, and Earnings*, National Bureau of Economic Research, Inc, July 1974.

NCES, “The Digest Education of Statistics 2009,” Technical Report, U.S. Department of Education 2009.

Nevill, S., X. Chen, and D. Carroll, “The Path Through Graduate School: A Longitudinal Examination 10 Years After Bachelor's Degree Post secondary Education Descriptive Analysis Report,” Technical Report, U.S. Department of Education 2007.

Oreopoulos, Philip and Florian Hoffman, “Professor Qualities and Student Achievement,” *Review of Economics and Statistics*, 2009, *91* (1), 83–92.

Oyer, Paul and Scott Schaefer, “The Returns to Attending a Prestigious Law School,” 2009.

Ridder, Geert and Robert Moffitt, “The Econometrics of Data Combination,” *Handbook of Econometrics*, 2007, *6B.*

Taber, Christopher R, “The Rising College Premium in the Eighties: Return to College or Return to Unobserved Ability?,” *Review of Economic Studies*, July 2001, *68* (3), 665–91.

Willis, Robert J and Sherwin Rosen, “Education and Self-Selection,” *Journal of Political Economy*, October 1979, *87* (5), S7–36.