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

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Abstract

Existing studies on the returns to college selectivity have mixed results, mainly due to the difficulty of controlling for selection into more-selective colleges based on unobserved ability. Moreover, researchers have not considered graduate degree attainment in the analysis of labour market returns to college selectivity. In this paper, I estimate the effect of a U.S. four-year undergraduate program's 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 labour 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 graduate degree attainment. The results show that the former effects dominate the latter, but both are small in magnitude.

JEL: I21, C30

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

1. Introduction

In recent years, the focus on increasing inequality and decreasing economic mobility has motivated policy-makers, more than ever before, to better understand the labour market returns in higher education. Moreover, the returns to college selectivity occupy the thoughts of many high school students and their parents due to rising college costs.[1] There are reasons to believe that earning a bachelor's degree from a more-selective college relative to a less-selective one leads to higher wages.[2] In a more-selective institution, course offerings and faculty quality might be better, the alumni network might be richer, the access to information about advanced studies might be less costly, and peers' academic performance or aspirations might be higher than at less-selective institutions. However, college selectivity may not in fact increase future wages. Students and their parents may prefer selective colleges because there is a consumption value, that of enjoying college life in a selective institution, or non-pecuniary benefits including self-accomplishment, health, marriage outcomes, and parenting style, regardless of labour market outcomes.[3] These two competing motivations behind the choice of a college make it unclear whether there are large labour market returns to college selectivity. In addition, it is difficult to estimate these labour market returns since it is hard to control for selection into higher-ranking 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 labour market returns to college selectivity, has not been fully investigated in the literature. According to the Current Population Survey (CPS), 35% of the labour force with bachelor's degrees in the U.S. labour market from 1992 to 2007 have graduate degrees (i.e., a master's, professional or doctoral degree). The share of graduate degree holders in the labour force aged 25 or older increased from 9.1% to 12.5% during the same period.[4] 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

[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?" (Nov. 29, 2010), "Is Going to an Elite College Worth the Cost?" (Dec. 17, 2010), and "Do Elite Colleges Produce the Best-Paid Graduates?" (Jul. 20, 2009).

[2]Throughout this paper, I use the word "college" to mean a four-year undergraduate program in the United States, which is equivalent to a university undergraduate program in Canada.

[3]Oreopoulos and Salvanes (2011) review the non-pecuniary benefits of an additional year of schooling. A similar outcome may hold for the dimension of college selectivity. See also Haveman and Wolfe (1984) and Ge (2011) for non-market returns of education.

[4]Enrolment in graduate programs rose about 67 percent between 1985 and 2007, while undergraduate enrolment increased by about 47 percent. Total autumn enrolment 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)).

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 labour 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. If the returns to college selectivity differ by graduate degree attainment, it is 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.[5]

Estimating the returns to college selectivity is challenging because of the potential bias arising from selection on unobserved abilities.[6] 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 for going to a flagship university against a less-selective one (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. One of the major factors that contributes to this variance is the difficulty of controlling for selection. For this reason, I apply a different empirical approach to control for selection. I use the factor structure model of Carneiro, Hansen, and Heckman (2003), since this method has the following advantages over others used in the literature.[7] 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.[8] 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.

[5]See Buchinsky (1994) and Brand and Xie (2010) for a discussion of the heterogeneous returns to schooling.

[6]In this paper, I consider mainly cognitive abilities, due to data limitations. See Heckman, Humphries, Urzua, and Veramendi (2011) for the effects of non-cognitive abilities on labour market outcomes.

[7]Heckman and Navarro (2007) discuss the semi-parametric identification of dynamic discrete choice and dynamic treatment effects using the factor structure model. Empirical applications of factor structure model of Carneiro, Hansen, and Heckman (2003) can be found in Cunha and Heckman (2008), Heckman, Stixrud, and Urzua (2006), Cooley, Navarro, and Takahashi (2009), Cunha, Heckman, and Schennach (2010), and Heckman, Humphries, Urzua, and Veramendi (2011).

[8]This is essentially mapping the information from multiple test scores into fewer dimensions. 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.

For the estimation, I use sample moments calculated from two data sets.[9] This is because there is no single data set that contains sufficient information to answer this question, the returns to college selectivity and how they vary by graduate degree attainment and individual ability, on its own. The first is Baccalaureate and Beyond 93/03 (B&B 93/03), which includes nearly 9,000 individuals who completed a bachelor's degree in 1992–93. Among those, about 25% completed a post-baccalaureate degree. The final wage observation in the survey is from 2003, ten years after college graduation; by that time, most of those who contined to graduate schools obtained their graduate degrees.[10] However, B&B 93/03 does not have any other test scores prior to college enrolment besides the Scholastic Assessment Test (SAT) (or American College Testing (ACT)). College admission test scores cannot be used as a perfect 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 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 (IV) approach.[11] 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 enrolment, 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 this paper, I use the 75th percentile SAT/ACT composite score as the measure of college selectivity.[12]

The empirical results show that graduating from a college that is one standard deviation (s.d.) higher in selectivity leads to a 3.7% higher hourly wage ten years after college graduation regardless of graduate degree attainment.[13] Relative to 20% returns (flagship vs. non-flagship) in Hoekstra (2009), these results are 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 more-selective college also has an effect on wages by increasing the probability of earning a graduate degree. Graduating from a college of one standard deviation higher selectivity leads to a 4.3% higher probability of

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

[10] See Figure 5 of Choy and Cataldi. (2011) for the years until the enrollment for graduate and first-professional students (after Bachelor's degree; measured in 2007-2008), by degree program. Also, Krantz, Natale, and Krolik (2004) summarize the labour market conditions for the United States in 2003.

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

[12] In this paper, I assume that college selectivity is the summary statistics of the undergraduate institutions' education quality, that is a multidimentional object in reality. One such aspect would be professor quality. See Oreopoulos and Hoffman (2009) for more discussion about the effect of professor quality on student achievement.

[13] 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.

graduate degree attainment. College selectivity does not have statistically significant effects on returns to a graduate degree for MBAs, law school and engineering master's degrees. The correlation between college selectivity and the returns to a graduate degree is negative for medical and doctoral degrees, but this is most likely because the panel is not long enough to capture their wages after fellowship or post-doctoral periods. This negative correlation suggests that MD holders from less-selective colleges earn more than those from more-selective colleges ten years after they completed their undergraduate degree program. One possible explanation is the length of fellowship periods by 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 in the labour market. However, verbal ability is rewarded only in degree attainment and not financially rewarded in the labour market. Lastly, I find that there is a fundamental heterogeneity in the returns to 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 with math ability.

Based on these findings, I conclude that college ranking is relevant for future labour 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, college selectivity increases the probability of graduate degree attainment but not the wage return itself to the graduate degree, for the majority of graduate programs.[14] College selectivity has a significant and positive effect on future wages for both types of students, those planning and not 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 higher graduate degree attainment. There is not a simple 'yes' or 'no' response to the question: do more-selective colleges lead to higher wage returns? From a policy perspective, the findings suggest that the U.S. higher-education system is not discouraging economic mobility. Firstly, the magnitude of returns to college selectivity is small regardless of graduate degree attainment. Secondly, college selectivity does not affect the returns to the graduate degree itself as long as the student earns a graduate degree. On the other hand, students who go to lower-ranking colleges are less likely to attain a graduate degree, probably discouraging economic mobility. Policies addressing the latter could help improve economic mobility and mitigate increasing inequality.

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.

[14] The effect of college selectivity on graduate degree attainment is causal in my interpretation as long as my model perfectly controls for selection into a graduate degree. However, it is beyond the scope of this model to analyze 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 colleges are successful in advanced studies. In contrast, high school students might choose for themselves a higher-ranking college so that they can attain a graduate degree at a higher rate.

2. Previous Literature

There are many studies that estimate returns to undergraduate degrees while controlling for selection on observed ability.[15] However, few studies estimate the return to college selectivity while controlling for selection on unobserved abilities. Unfortunately, Baccalaureate and Beyond 93/03 (B&B 93/03), which I will use in this paper, does not contain home state information (prior to college entry). Therefore, Card's IV approach is not applicable.[16] Using the two-step Heckman selection model (Heckman (1976), Heckman (1979)), Brewer, Eide, and Ehrenberg (1999) find a 9–15% higher return to attending a top private university instead of a bottom public university. Using a regression discontinuity design, Hoekstra (2009) finds 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) examine students who were accepted to specific (selective) colleges and compare the wages of students who chose to attend college and those who did not.[17] This assumes that students who were accepted to the same set of colleges have similar levels of unobservable ability. The authors use the National Longitudinal Study of the High School Class of 1972 (NLS72) and find 1.3% returns for attending college with a 100-point-higher SAT composite score, but the point estimate is statistically insignificant. Their approach is not robust to measurement error in college selectivity measured by admission test scores. The fourth approach is structural estimation. Arcidiacono (2005) uses NLS72 and finds 0.0–2.9% returns for attending college with a 100-point-higher average SAT math score. The returns vary by college majors but the estimates are all statistically insignificant. None of the studies described above considers graduate degree attainment as an additional path to earn higher wages.

Even fewer studies estimate the returns to graduate degrees controlling for selection on unobserved abilities. Arcidiacono, Cooley, and Hussey (2008) find 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.[18] My findings should be comparable to their estimates, on average, across MBA

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

[16] Using propensity score matching, Black and Smith (2004) find a 15% higher return for attending a top-quartile school instead of a bottom-quartile school using the National Survey of Youth 1979 (NLSY79). Propensity score matching controls for selection on observable characteristics, but cannot address selection on unobservable traits. Black and Smith (2004) avoid this issue by using the Armed Services Vocational Aptitude Battery (ASVAB)'s cognitive test scores in the NLSY; however, the NLSY does not contain a sufficient sample of those who go to graduate school. Therefore, I cannot use the same method for this paper.

[17] Dale and Krueger (2011) find the same pattern using a longer panel of post-college earnings.

[18] Oyer and Schaefer (2009) examine the returns for attending a prestigious law school. The authors find 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%

rankings. This 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, this paper is the first to examine the extent to which undergraduate college selectivity affects returns to graduate education while controlling for selection.

Lastly, Eide, Brewer, and Ehrenberg (1998) document a positive correlation between college selectivity and the likelihood of graduate degree attendance. They treat the likelihood of graduate degree attendance as one of the outcomes of attending a selective college. My empirical model treats graduate degree attainment as an optional step in higher education, and labour market return as the ultimate outcome measure. Hence, this 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:

$$log(W_i) = X_i'\beta + \gamma_1 \cdot Q_i + \gamma_2 \cdot G_i + \gamma_3 \cdot G_i Q_i + \theta_i'\alpha + e_i, \tag{1}$$

where W_i stands for the wage of individual i, and X_i is a vector of observable exogenous characteristics of 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 selectivity of individual i's college. To measure this, I use the 75th percentile of the school's freshman SAT scores. 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 graduate degree.[19] 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 joint 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.

return relative to attending a school ranked between 21 and 100. Their models do not control for unobserved ability.

[19] Since an MA in education has different wage patterns from other types of graduate degree holders, for now 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. In the sensitivity analysis, I examine returns to graduate degree by graduate degree types.

Returns to College Selectivity 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. The wage will be $\gamma_1 * \Delta\%$ higher if a student obtains a bachelor's degree from a college selectivity of $q + \Delta$ instead of q without a graduate degree. Similarly, γ_2 represents the average return of earning a graduate degree at the mean college selectivity. The wage will be $\gamma_2\%$ higher if a student, who graduated from an average undergraduate program, obtains a graduate degree. If the cross-term, γ_3, is close to zero, returns to college selectivity do not vary by graduate degree attainment nor do returns to graduate degree vary by college selectivity. If γ_3 is positive, returns to college selectivity are bigger in magnitude for those who obtain a graduate degree. This would happen if graduates of more-selective colleges accumulate more human capital during college and therefore gain more from graduate programs than graduates of less-selective colleges. Alternatively, college selectivity may function as a signal. Even if there is no difference in accumulated human capital between students from more- and less-selective 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 more-selective college works as a signal of students' ability. In contrast, if γ_3 is negative, then attending a more-selective college leads to lower returns to graduate education. This may occur if high-ability students happen to enroll in less-selective colleges due to an adverse shock (e.g., health problem or financial issues), yet obtain a graduate degree and then obtain the same wage as graduate school peers from more-selective colleges. Alternatively, it could be caused by a timing of wage observations.

In the sensitivity analysis, I differentiate between types of graduate programs (i.e., MBA, engineering MS, law school, medical school, MA in education, other MAs, and a doctoral degree). In the other specification, a college selectivity measure interacts with a dummy variable which indicates whether a student majored in science, technology, engineering or mathematics (STEM fields).[20]

3.1 Decomposition of returns to college selectivity

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

[20] Arcidiacono (2004) documents that college students select certain majors and fields by assessing their ability via their grade point average (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 a student's own academic ability over time. See Arcidiacono, Hotz, and Kang (2010) for more discussion.

college selectivity ($\overline{q}$ or $\underline{q}$) conditioning on ability (θ):

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

Rearranging equation (2) generates three components:

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

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

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

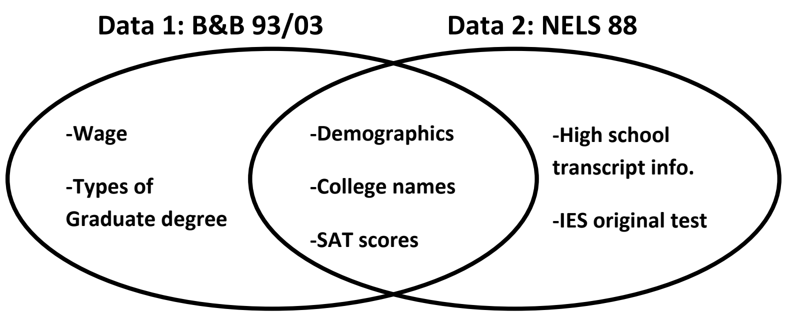
where the selection bias arises in the returns to college selectivity estimates from $\left\{E\left[\theta_i|X_i, Q_i = \overline{q}\right] - E\left[\theta_i|X_i, Q_i = \underline{q}\right]\right\}' \alpha$.[21] This is primarily because person-specific math and

[21] 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.

verbal abilities are confounded with college selectivity.[22] 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., $E[\theta_i \cdot Q_i] = 0$ and $E[\theta_i \cdot G_i] = 0$). 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 this selection bias, this paper extends the factor structure model of Carneiro, Hansen, and Heckman (2003).

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 93/03). B&B 93/03 contains wage and schooling information, but does not have any information on test scores taken prior to college enrolment 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 contains SAT scores and other test scores (IRTs) prior to college, subject-specific high school grades, and demographics. The following Venn diagram summarizes the data of the two surveys. To jointly use sample moments from these two data sets, I assume that the underlying distribution of ability, attainment and wage is the same across these two nationally representative surveys.[23] The use of sampling weights is also critical.



Overlap of Variables between Two Data Sets

B&B 93/03 is a longitudinal study of students who earned a bachelor's degree in 1992–93. The sample contains a sizable number of college graduates who completed a graduate program by the final wave of the survey.[24] B&B 93/03 drew its 1993 cohort (about 11,000 students) from the 1993

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

[23] I restrict the NELS 88 sample to college graduates as of 2000.

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

National Postsecondary Student Aid Study, and 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, Chen, and Carroll (2007)).[25] 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-years, two-to-three years, four-years non-doctorate-granting, and four-years 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 75th 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.[26]

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 were in their senior year of high school by 1992. 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. Post-secondary education transcripts collected in the autumn of 2000 contain data on the enrolment and completion of all post-secondary institutions for the sample. In addition, 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 most variables in NELS 88 are close to those in B&B 93/03. 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 93/03 sample, but there is no earnings-based sample deletion from the NELS 88 sample. As a robustness check, I run estimation only using the male sample and do not find differences in the main conclusions. SAT verbal scores are low relative to those of B&B 93/03, but this could be due to a different reporting method. In the B&B 93/03 sample, SAT scores are

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 93/03, in contrast, also covers lower-ranked schools.

[25]For more details, see Appendix B: Technical Notes and Methodology in Nevill, Chen, and Carroll (2007).

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

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 93/03 does not contain those variables.

Tables 3 shows the mean hourly wages for students by college quartile. 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. The comparisons among students with different types of graduate programs show a similar pattern. These findings suggest that returns may vary by college qualities for different graduate degree programs, which are potentially correlated with occupational choices.[27] Tables 4 shows differences in years of work experience and graduate program enrolment years.[28] In the estimation, I control for work experience using the data displayed here.

The distribution of occupations by graduate degree attainment status does not clearly show how occupation and graduate degree attainment status correlate.[29] However, the occupational distributions for each graduate degree program indicate that there is a strong concentration in specific occupations for different graduate degrees.[30] For example, 93% of medical school graduates are actually working as medical professionals. Similarly, 79% of law school graduates are working as legal professionals and 86% of education MA holders work as educators. MBA holders are more disperse, but 73% work in business and management, and 57% of engineering MS holders work in a related occupation.

5. Identification

I use the factor structure model of Carneiro, Hansen, and Heckman (2003) to control for selection into a more-selective college on unobserved abilities. I extend their identification approach to two samples, since neither data set has sufficient information on its own. Identification of the model parameters works 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.[31]

[27] See 13 in Appendix F.

[28] See 14 in Appendix F shows comparisons by different graduate degree types.

[29] See Tables 15 in Appendix F

[30] See Tables 16 and 17 in Appendix F

[31] 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 $\frac{I\tilde{R}T_m}{\alpha_{Im}} = \theta_m + \frac{u_{Im}}{\alpha_{Im}}$.

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. Nonetheless, this data set does not have a sufficient number of ability measures to identify the distribution of unobserved ability. The only measures of ability that the main data set contains are SAT scores; however, if there is a measurement error in these test scores, they cannot be used as a proxy or instrument for unobserved ability.[32] 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 the same population distribution. In other words, the identification does not rely on matching on observable characteristics.

I use the following specifications. The wage equation is the same as equation (1). I specify a functional form 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:

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

A key assumption is that the unobserved random components (e_j, u_{Ij}, u_{Hj} and θ_j) are uncorrelated. In other words, I assume that these measures (SAT_j, IRT_j and HSG_j) are only correlated through unobserved ability (θ_j) conditional on observable characteristics (X^S, X^I, X^H). Note that unobserved abilities θ_{mi} and θ_{vi} are allowed to be correlated. Policy-makers and econometricians 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:

$$
\frac{Cov(\tilde{IRT}_m, \tilde{HSG}_m)}{Cov(\tilde{IRT}_m, \tilde{SAT}_m)} = \frac{\alpha_{Im}\alpha_{Hm}\sigma^2_{\theta_m}}{\alpha_{Im}\sigma^2_{\theta_m}} = \alpha_{Hm},
$$

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

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 functions of (e_1) and (e_2) do not vanish.[33]

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 the 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.[34] 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:[35]

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

[33] The characteristic function of ($S\tilde{A}T_1$,$S\tilde{A}T_2$) can be written as follows: $E[exp(it_1(\theta_1 + e_1) + it_2(\theta_2 + e_2))] = E[exp(it_1\theta_1 + it_2\theta_2)] \cdot E[exp(it_1 e_1)] \cdot E[exp(it_2 e_2)]$. Since I estimate the joint distribution of ($S\tilde{A}T_1$, $S\tilde{A}T_2$) and identify the distribution of e_m and e_v at this point, I can identify the joint distribution of (θ_1, θ_2).

[34] 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: $[Q - X\beta_Q - \delta_m SAT_m - \delta_v SAT_v] = [\alpha_{Qm}\theta_m + \alpha_{Qv}\theta_v] + e_Q$.

[35] I can calculate covariances from the following joint distributions:

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

$$= \rho\sigma_Q^2 + \alpha_{Gv} Cov(\frac{I\tilde{R}T_v}{\alpha_{Iv}}, SAT_v).$$

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:[36]

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

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.[37]

6. Results

6.1 Main analysis

Table 5 shows the main regression results (excluding medical and doctoral degree holders). The two columns of results demonstrate how adding the 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 a one standard deviation (s.d.) more-selective college are 3% higher than those earned by graduates of less-selective colleges. Here, one s.d. of the college selectivity measure is a 118-point difference in a 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,

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

[37] Alternatively, I can estimate this model using generalized method of moments (GMM) if the model is simplified. Appendix C discusses a simplified version of GMM. A discussion including a discrete graduate degree attainment choice remains for future work.

the annual net cost of college is 2,300 dollars more expensive, on average, for a one s.d. more-selective college.[38] The mean hourly wage is 26 dollars per hour, so the 3% increase in wage is equivalent to 78 cents extra per hour 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 are about 18.6% for graduating from a one s.d. more-selective college. It is equivalent to 96 cents and $4.84 extra per hour for the mean wage earners, respectively. Wages increase with 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 12), and discuss potential scenarios. 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 earning a graduate degree capture only the average returns in the main specification, so the variation in returns to the graduate degree is captured by the work experience term.

By comparing the results from two specifications, I find that the returns to college selectivity are biased downward in 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 as well as large in magnitude. Without a graduate degree dummy in the specification, variation in math ability captures these returns to a graduate degree. As a result, returns to college selectivity are biased downward because the variation in wage returns by college selectivity for graduate degree holders is absorbed by the variation in math ability.

Table 6 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 earning a graduate degree is 4.3% higher for graduating from a one s.d. more-selective college.

The results reported in Table 7 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, which implies that the returns to college selectivity are constant across individual abilities. This finding is consistent with two possibilities. First, college selectivity may function as a signal to employers when an individual student's ability is not fully observed. 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 percentages, so the returns in levels are still higher for higher wage earners. The cross-term between unobserved math ability and

[38]See Appendix E for a scatter plot of the net college 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 the net college cost ($1,000)= tuition + other direct costs - all grants. If we assume that a person spends four years to obtain a bachelor's degree, works 2,000 hours annually, has a $0.97/hour higher wage for 44 years, as well as a discount factor of 0.95 and a marginal tax rate of 30%, then the life-cycle benefit is $19,806 and the cost is $8,533. This rough cost-benefit calculation tells us that graduating from a more-selective college will pay off, but not by a big margin.

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 attainment are complements. Since graduate degree holders tend to work in specialized fields, employers might be able to accurately evaluate an individual's math ability. In this case, a graduate degree does not function as a signal but rather as a minimum qualification to work in a specific industry. The results discussed so far exclude medical and doctoral degree holders. The results including all graduate program types are discussed next.

6.2 Analysis by graduate program types

Table 8 shows the wage regression by all graduate program types. In this model, I allow different graduate degrees (e.g., MBA, JD, MD) to have different returns and cross-terms.[39] Respondents with an MD, JD, MBA or master's in engineering earn 27–35% more than respondents without a graduate degree. In contrast, respondents with other MAs 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-doctoral salaries for doctoral degree holders. Wages for the MA 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 52 weeks per year of work regardless of occupation. In reality, teachers work fewer months than other workers, so this negative coefficient on the MA in education could be smaller in magnitude if I adjust for weeks they actually work.[40] A negative cross-term between MD and college selectivity suggests that returns to an MD vary by college selectivity. This is because highly demanding specialties like surgery, neurosurgery or cardiology require fellowship periods after residency.[41] This creates a difference in training periods across medical degree holders. It is possible that MD holders from more-selective colleges select themselves into more-competitive specialties, as opposed to MD holders from less-selective colleges who might choose less-competitive specialties like family practice. A cross-term between MD and college selectivity could be negative if graduates from more-selective colleges work in post-doctoral or fellowship positions after residency while those from less-selective colleges move directly into careers.[42]

[39] As an extension of the specification, I include three dummies to distinguish the selectivity of MBA programs (i.e., Top50 MBA, Below50 MBA and Uncategorized MBA) instead of estimating average returns to an MBA. I use *US News & World Report*'s graduate program ranking for convenience. Although returns are higher for the Top50 MBA relative to Below50 MBA (43% and 24%, respectively), the coefficient on the Top50 MBA is insignificant due to the sample size issue (i.e., fewer people obtain MBAs from selective programs). I could not get a precise estimate for other graduate programs due to the sample size issue.

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

[41] See the Association of American Medical Colleges 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/.

[42] I also estimate a heterogeneous returns model for this specification (i.e., interact unobserved math and verbal abilities to college selectivity and each graduate dummy). However, the standard errors are large and I cannot further

6.3 Comparison with OLS results

Table 9 shows ordinary least squares (OLS) estimates corresponding to estimates of the factor structure model in Table 5. OLS estimates use SAT math and verbal scores as a proxy for ability. Returns to college selectivity stay almost the same or slightly higher after controlling for selection using the factor structure model for parsimonious specifications. However, returns to college selectivity go down from the OLS specification to the factor structure model with finer categorization of graduate programs (i.e., Tables 10 and 8). The decrease of returns to college selectivity is a consistent pattern in other specifications with additional variables.[43] These findings suggest that returns to college selectivity in the parsimonious specification with one graduate are suitable for presenting the main story, but not necessarily for detailed interpretation. Rather, college selectivity wage returns reported in Table 8 with finer categories of graduate program types would be more suitable for interpreting the coefficients' magnitudes.

6.4 Sensitivity analysis

As a robustness check, I run the estimation with only a male subsample (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 labour force. The results with a male subsample are shown in Table 11. The returns to college selectivity are 2.4% but statistically insignificant.[44] Returns to a graduate degree are statistically significant for law school and an MBA, but the cross-terms between college selectivity and graduate degree attainment are not statistically significant. The coefficient on math ability is positive and significant, but that on verbal ability is negative and significant.

I also estimate a model with occupation dummies. The results are summarized in Table 12 (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 workers with high verbal ability. Rather it suggests that people with low math and high verbal abilities are penalized most in the labour market (holding college selectivity and graduate degree attainment constant). However, the estimated correlation between math and verbal abilities is high (0.87), so such a type is not a majority. Potential scenarios supporting the negative coefficient on unobserved verbal

investigate which program drives heterogeneous returns for graduate dummy by math ability (see Table 7). Results are available upon request. Another variant examined is 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 (both groups without a graduate degree), since the cross-term between college selectivity and the STEM dummy is not significant. However, for STEM majors, graduate degree returns (at the mean college selectivity) are twice as high. The cross-term between college selectivity and graduate degree is negative only for the STEM majors, because medical degree programs require college students to major in STEM fields (i.e., pre-med requirements).

[43] OLS estimation results corresponding to Tables 7 and other variants are not reported for reasons of space, but are available upon request.

[44] I consider that the insignificance of the coefficient is due to the imprecision coming from the small sample size. One solution is to explicitly include a selection into the labour market and further examine the more-precise estimates.

ability are as follows. First, workers with high verbal ability might choose occupations based on preferences rather than financial returns. Compensating differentials could explain such a choice. However, it is beyond this study's 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 labour market, holding other things constant. This is likely because the cognitive test scores I use to recover verbal ability may not be useful in the labour market. For the younger cohort, scores from written tests are available via SAT. Such scores might better reflect a verbal ability relevant to the labour market than would scores from verbal tests.[45] Third, a high verbal score might be correlated with other attributes of a worker. If high verbal ability is irrelevant for labour market outcomes and yet is correlated with other negative attributes of a worker, the coefficient could be negative. Nevertheless, the negative coefficient on verbal ability in the wage regression is found in a model using SAT scores as an ability control, which is summarized in Table 9. This shows that the negative correlation between verbal ability and wages exists in the raw data and is not unique to the estimation results of the factor structure model.

6.5 Signal-to-noise ratio of the measurements

Lastly, the signal-to-noise ratio of the measurements can 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, demonstrating 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 a student's ability relative to scores from SAT or IRT cognitive tests. 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.

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

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 earning a graduate degree while controlling for selection on unobserved abilities. I use the factor structure model of Carneiro, Hansen, and Heckman (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 use an explicit source of identification for unobserved ability that is 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 labour 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, but not the wage return itself to the graduate degree. I also find that math ability is rewarded, both in degree attainment and the labour market. However, verbal ability is rewarded only in degree attainment; it is negatively correlated in the labour market. Lastly, I find that there is a fundamental heterogeneity in the returns to graduate degree attainment but not to college selectivity. Specifically, returns to college selectivity are the same across individuals but returns to graduate degree attainment increase with math ability.

College selectivity has a significant and positive effect on future wages for both types of students, those planning and not planning to attain a graduate degree. In addition, if a student is willing to earn a graduate degree, going to a more-selective college increases the expected future wage through higher rates of graduate degree attainment. From a policy perspective, the findings suggest that, on the one hand, the U.S. higher-education system is not discouraging economic mobility, since graduate degree attainment likely leads to high wages regardless of college ranking. On the other hand, students who go to lower-ranking colleges are less likely to attain a graduate degree, likely discouraging economic mobility. Policies addressing the latter could help improve economic mobility and mitigate increasing inequality. It would be worth studying these issues with Canadian data, especially utilizing administrative data.

References

ANGRIST, J. D., AND A. B. KRUEGER (1992): "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*, 87(418), pp. 328–336.

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

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

ARCIDIACONO, P., J. COOLEY, AND A. HUSSEY (2008): "The Economic Returns To An MBA," *International Economic Review*, 49(3), 873–899.

ARCIDIACONO, P., V. J. HOTZ, AND S. KANG (2010): "Modeling College Major Choices using Elicited Measures of Expectations and Counterfactuals," Working Paper 15729, National Bureau of Economic Research.

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

BLACK, D. A., AND J. A. SMITH (2004): "How robust is the evidence on the effects of college quality? Evidence from matching," *Journal of Econometrics*, 121(1-2), 99–124.

BRAND, J. E., AND Y. XIE (2010): "Who Benefits Most From College? Evidence for Negative Selection in Heterogeneous Economic returns to Higher Education," *American Sociological Review*, 75(2), 273–302.

BREWER, D. J., E. R. EIDE, AND R. G. EHRENBERG (1999): "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*, 34(1), 104–123.

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

CARD, D. (1993): "Using Geographic Variation in College Proximity to Estimate the Return to Schooling," Working Paper 4483, National Bureau of Economic Research.

CARNEIRO, P., K. HANSEN, AND J. HECKMAN (2003): "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*, 44(2), 361–422.

CHOY, S. P., AND E. F. CATALDI. (2011): "Graduate and First-Professional Students: Who They Are and How They Pay for Their Education: 2007-08.," *Statistics in Brief*, (NCES 2011174).

COOLEY, J., S. NAVARRO, AND Y. TAKAHASHI (2009): "A Framework for the Analysis of Time-varying Treatment Effects: How The Timing of Grade Retention Affects outcomes," .

CUNHA, F., AND J. J. HECKMAN (2008): "Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Journal of Human Resources*, 43(4).

CUNHA, F., J. J. HECKMAN, AND S. M. SCHENNACH (2010): "Estimating the Technology of Cognitive and Noncognitive Skill Formation," *Econometrica*, 78(3), 883–931.

DALE, S., AND A. B. KRUEGER (2011): "Estimating the Return to College Selectivity over the Career Using Administrative Earnings Data," Working Paper 17159, National Bureau of Economic Research.

DALE, S. B., AND A. B. KRUEGER (2002): "Estimating The Payoff To Attending A More Selective College: An Application Of Selection On Observables And Unobservables," *The Quarterly Journal of Economics*, 117(4), 1491–1527.

EIDE, E. R., D. J. BREWER, AND R. G. EHRENBERG (1998): "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*, 17(4), 371–376.

GE, S. (2011): "Womenï¿œs College Decisions: How Much Does Marriage Matter?," *Journal of Labor Economics*, 29, 773–818.

HAVEMAN, R. H., AND B. L. WOLFE (1984): "Schooling and Economic Well-Being: The Role of Nonmarket Effects," *The Journal of Human Resources*, 19(3), 377–407.

HECKMAN, J. J. (1976): "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, pp. 120–137. National Bureau of Economic Research, Inc.

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

HECKMAN, J. J., J. HUMPHRIES, S. URZUA, AND G. VERAMENDI (2011): "The Effects of Educational Choices on Labor Market, Health, and Social Outcomes," *Unpublished manuscript*.

HECKMAN, J. J., AND S. NAVARRO (2007): "Dynamic discrete choice and dynamic treatment effects," *Journal of Econometrics*, 136(2), 341–396.

HECKMAN, J. J., J. STIXRUD, AND S. URZUA (2006): "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, 24(3), 411–482.

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

ICHIMURA, H., AND E. MARTINEZ-SANCHIS (2005): "Identification and Estimation of GMM Models by Combining Two Data Sets," *Manuscript*.

INOUE, A., AND G. SOLON (2010): "Two-Sample Instrumental Variables Estimators," *The Review of Economics and Statistics*, 92(3), 557–561.

KOTLARSKI, I. (1967): "On characterizing the gamma and the normal distribution," *Pacific Journal of Mathmatics*, 20(1), 69–76.

KRANTZ, R., M. D. NATALE, AND T. J. KROLIK (2004): "The U.S. Labor Market in 2003: Signs of Improvement by Yearâs End," *BLS Monthly Labor Review*, pp. 3 – 29.

MINCER, J. A. (1974): *Schooling, Experience, and Earnings*. National Bureau of Economic Research, Inc.

NCES (2009): "The Digest Education of Statistics 2009," Discussion paper, U.S. Department of Education.

NEVILL, S., X. CHEN, AND D. CARROLL (2007): "The Path Through Graduate School: A Longitudinal Examination 10 Years After Bachelor's Degree Post secondary Education Descriptive Analysis Report," Discussion paper, U.S. Department of Education.

OREOPOULOS, P., AND F. HOFFMAN (2009): "Professor Qualities and Student Achievement," *Review of Economics and Statistics*, 91(1), 83–92.

OREOPOULOS, P., AND K. G. SALVANES (2011): "Priceless: The Nonpecuniary Benefits of Schooling," 25(1), 159 – 184.

OYER, P., AND S. SCHAEFER (2009): "The Returns to Attending a Prestigious Law School," .

RIDDER, G., AND R. MOFFITT (2007): "The Econometrics of Data Combination," *Handbook of Econometrics*, 6B.

TABER, C. R. (2001): "The Rising College Premium in the Eighties: Return to College or Return to Unobserved Ability?," *Review of Economic Studies*, 68(3), 665–91.

WILLIS, R. J., AND S. ROSEN (1979): "Education and Self-Selection," *Journal of Political Economy*, 87(5), S7–36.

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, non-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 labour 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	MA in business school	0.060	0.238
Eng.	MS in engineering field	0.023	0.150
Edu.	MA 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 selectivity	College selectivity measured by freshmen 75th SAT/ACT composite score	1227	118
SAT math		546	95
SAT verbal		546	96

Notes: Sample weight (BNBPANL3) is used to calculate mean and standard deviation. The number of observations is 3,140, which is rounded to the nearest ten due to confidentiality concerns. FP=First professionals.

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, non-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 selectivity	College selectivity measured by freshmen 75th SAT/ACT composite score	1233	118
SAT math		529	109
SAT verbal		469	99
Other measures	IRT math, IRT reading High school math, English.		

Notes: Sample weight (F4F2PNWT) is used to calculate mean and standard deviation. The number of observations is 1,710, which is rounded to the nearest ten due to confidentiality concerns.

Table 3: College Selectivity and Hourly Wage by Graduate Degree Dummy

	Graduate Dummy = 0			Graduate Dummy = 1		
College selectivity	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
25-50th%	25.04	44.45	55,696	28.66	47.75	70,390
50-75th%	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 4: College Selectivity and Work Experience by Graduate Degree Dummy

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

Notes: Sample weight (BNBPANL3) is used to calculate mean and standard deviation. The number of observations is 3,140, which is rounded to the nearest ten due to confidentiality concerns.

Table 5: Wage Regression without and with Graduate Degree Dummy
(excluding medical and doctoral degree holders)

Dependent variable: log (wage)	1	2
College selectivity (γ_1)	0.030**	0.037**
	(0.014)	(0.015)
Graduate dummy(γ_2)	-	0.170***
		(0.037)
College selectivity · 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)

Notes: Other covariates controlled in the estimation include demographics as follows: first regress demographic variables onto the dependent variable, subtract the predicted value, and then use the remaining as the dependent variable. The number of observations is 2,910 for B&B 93/03 and 1,710 for NELS 88, which are both rounded to the nearest ten due to confidentiality concerns. 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 6: Graduate Degree Attainment and College Selectivity
(excluding medical and doctoral degree holders)

Dependent variable:	Graduate degree attainment
College selectivity (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)

Notes: Other covariates controlled in the estimation include demographics as follows: first regress demographic variables onto the dependent variable, subtract the predicted value, and then use the remaining as the dependent variable. The number of observations is 2,910 for B&B 93/03 and 1,710 for NELS 88, which are both rounded to the nearest ten due to confidentiality concerns. 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 7: Wage Regression and Heterogeneous Returns
(excluding medical and doctoral degree holders)

Dependent variable:log (wage)	
College selectivity (γ_1)	0.028*
	(0.016)
Grad. dummy (γ_2)	0.218***
	(0.039)
College selectivity · 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 selectivity · Math ability	0.009
	(0.067)
College selectivity · Verbal ability	-0.008
	(0.081)
Grad.dummy · Math ability	0.075**
	(0.031)
Grad. dummy · 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)

Notes: Other covariates controlled in the estimation include demographics as follows: first regress demographic variables onto the dependent variable, subtract the predicted value, and then use the remaining as the dependent variable. The number of observations is 2,910 for B&B 93/03 and 1,710 for NELS 88, which are both rounded to the nearest ten due to confidentiality concerns. Sample weight-adjusted asymptotic standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: Wage Regression and Graduate Program Types
(including medical and doctoral degree holders)

Dependent variable: log (wage)

College selectivity (γ_1)	0.027*		
	(0.015)		
Medical school degree	0.301***	College selectivity · Med.	-0.260***
	(0.082)		(0.062)
Law school degree	0.241***	College selectivity · Law	0.029
	(0.084)		(0.088)
MBA	0.270***	College selectivity · MBA	0.002
	(0.068)		(0.067)
MS in engineering	0.262**	College selectivity · Eng.	-0.062
	(0.131)		(0.101)
MA in education	-0.127***	College selectivity · Edu.	0.035
	(0.055)		(0.079)
Other MA	-0.025	College selectivity · Other	-0.026
	(0.045)		(0.035)
Doctoral degree	-0.012	College selectivity · 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)		

Notes: Other covariates controlled in the estimation include constant term and demographics as follows: first regress demographic variables onto the dependent variable, subtract the predicted value, and then use the remaining as the dependent variable. The number of observations is 3,120 for B&B 93/03 and 1,710 for NELS 88, which are both rounded to the nearest ten due to confidentiality concerns. Sample weight-adjusted asymptotic standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9: 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 selectivity (γ_1)	0.031*	0.029
	(0.017)	(0.020)
Graduate dummy(γ_2)	-	0.199***
		(0.041)
College selectivity · 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 work dummy	-0.080*	-0.075
	(0.047)	(0.047)

Notes: Other covariates controlled in the estimation include demographics: first regress demographic variables onto the dependent variable, subtract the predicted value, and then use the remaining as the dependent variable. The number of observations is 2,910 for B&B 93/03, which is rounded to the nearest ten due to confidentiality concerns. 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 10: OLS Results for Comparison
Wage Regression and Graduate Program Types
(The sample includes medical and doctoral degree holders)

Dependent variable: log (wage)

College selectivity (γ_1)	0.036*		
	(0.022)		
Medical school degree	0.299***	College selectivity · Med.	-0.266***
	(0.101)		(0.080)
Law school degree	0.261***	College selectivity · Law	-0.044
	(0.068)		(0.053)
MBA	0.258***	College selectivity · MBA	0.012
	(0.057)		(0.042)
MS in engineering	0.247**	College selectivity · Eng.	-0.032
	(0.061)		(0.045)
MA in education	-0.145***	College selectivity · Edu.	-0.049
	(0.054)		(0.037)
Other MA	0.011	College selectivity · Other	-0.039
	(0.055)		(0.052)
Doctoral degree	0.001	College selectivity · Dr.	-0.150**
	(0.071)		(0.062)
SAT math θ_m (α_m)	0.052***		
	(0.018)		
SAT verbal θ_v (α_v)	-0.038***		
	(0.018)		
Experience	-0.013		
	(0.016)		
Experience squared / 100	0.127		
	(0.158)		
Part-time work dummy	-0.061		
	(0.045)		

Notes: Other covariates controlled in the estimation include constant term and demographics: first regress demographic variables onto the dependent variable, subtract the predicted value, and then use the remaining as the dependent variable. The number of observations is 3,120 for B&B 93/03, which is rounded to the nearest ten due to confidentiality concerns. Sample weight-adjusted asymptotic standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 11: Sensitivity Analysis with Male-only Sample
Wage Regression by Graduate Program Types
(excluding medical and doctoral degree holders)

Dependent variable: log (wage)

College selectivity (γ_1)	0.024		
	(0.024)		
Law school degree	0.263**	College selectivity · Law	-0.033
	(0.121)		(0.147)
MBA	0.228**	College selectivity · MBA	-0.011
	(0.107)		(0.089)
MS in engineering	0.204	College selectivity · Eng.	-0.016
	(0.164)		(0.132)
MA in education	-0.163	College selectivity · Edu.	0.040
	(0.174)		(0.218)
Other MA/FP	-0.039	College selectivity · 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)		

Notes: Other covariates controlled in the estimation include demographics: first regress demographic variables onto the dependent variable, subtract the predicted value, and then use the remaining as the dependent variable. The number of observations is 1,410 for B&B 93/03 and 740 for NELS 88, which are both rounded to the nearest ten due to confidentiality concerns. Sample weight-adjusted asymptotic standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 12: Sensitivity Analysis with Occupational Sorting
Wage Regression with Occupation Dummies
(excluding medical and doctoral degree holders)

Dependent variable:log (wage)	
College selectivity (γ_1)	0.017
	(0.015)
Grad. dummy (γ_2)	0.107***
	(0.037)
College selectivity · 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)

Notes: Other covariates controlled in the estimation include demographics: first regress demographic variables onto the dependent variable, subtract the predicted value, and then use the remaining as the dependent variable. The number of observations is 2,910 for B&B 93/03 and 1,710 for NELS 88, which are both rounded to the nearest ten due to confidentiality concerns. Sample weight-adjusted asymptotic standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

A. Likelihood Function

The original likelihood is specified as follows:

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

This will be reduced to the following log likelihood by integrating 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 each survey.

B. Sample Selection

I select a sample from Baccalaureate and Beyond 93/03 (B&B 93/03) as follows. Starting with a sample of 9,000 respondents, I drop 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 select students with data for both SAT math and verbal scores.[46] I also eliminate observations if 2003 wage data were missing. I use 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 drop students who graduated from an institution that is either not recognized in the IPEDS or did not report SAT and ACT test scores to IPEDS. Further, I select students with data on SAT math and verbal scores, IRT test scores, and high school grades. I use listwise deletion in this analysis. These deletions result in a total of 1,770 observations. I use the sample weights provided in the data.

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

C. GMM approach

In this appendix, I discuss how I estimate a 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 interest (γ and α) as follows:

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

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

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

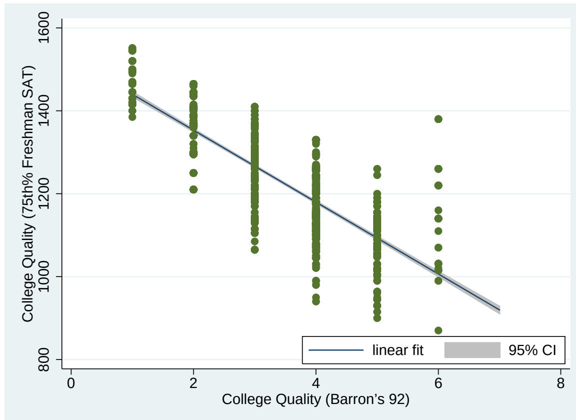
Find parameters that minimize the moments below:

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

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

D. College Selectivity Measures

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

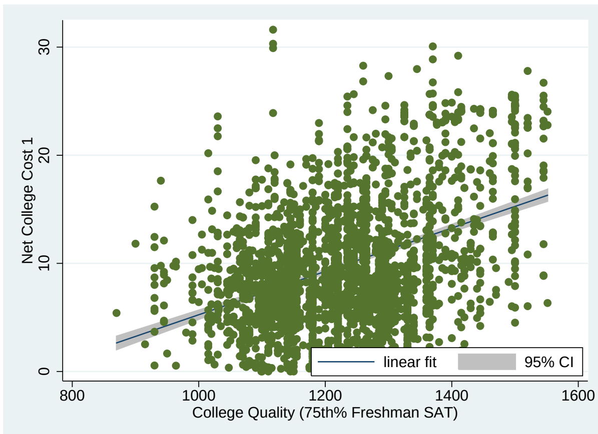


Note: Slope is -0.07 and R-squared is 0.60.

Notes: Barron's index is based on the SAT/ACT scores of those students who were accepted during 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 Selectivity

Figure E: Net Cost of College ($1,000) and College Selectivity (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).

F. Additional Descriptive Statistics of B&B 93/03

Table 13: College Selectivity and Hourly Wage by Graduate Program Types

	No Graduate Degree			MA in education		
College selectivity	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
25-50th%	25.40	44.32	56,368	18.77	46.25	42,873
50-75th%	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 selectivity	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
25-50th%	39.31	59.72	111,508	33.84	48.53	84,706
50-75th%	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 selectivity	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
25-50th%	31.28	47.71	74,256	29.85	45.48	70,191
50-75th%	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 selectivity	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
25-50th%	22.44	44.28	52,189	24.59	46.77	60,032
50-75th%	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

Notes: Sample weight (BNBPANL3) is used to calculate mean and standard deviation. The number of observations is 3,140, which is rounded to the nearest ten due to confidentiality concerns.

Table 14: College Selectivity and Work Experience by Graduate Program Types

	No Graduate Degree		MA in education	
College selectivity	Experience	Graduate Program Enrolment Years	Experience	Graduate Program Enrolment Years
Bottom 25%	9.86	0.00	6.71	3.09
25-50th%	9.84	0.00	7.21	2.50
50-75th%	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 selectivity	Experience	Graduate Program Enrolment Years	Experience	Graduate Program Enrolment Years
Bottom 25%	3.07	4.33	5.32	2.61
25-50th%	2.52	4.19	5.35	3.13
50-75th%	3.70	3.94	5.26	3.25
Top 25%	3.07	3.91	4.85	3.27
	MBA		MS in engineering	
College selectivity	Experience	Graduate Program Enrolment Years	Experience	Graduate Program Enrolment Years
Bottom 25%	6.70	3.22	7.38	2.15
25-50th%	7.35	2.54	7.15	2.34
50-75th%	6.55	2.95	7.33	2.26
Top 25%	6.94	2.33	7.21	2.19
	Other MA/FP		Doctoral degree	
College selectivity	Experience	Graduate Program Enrolment Years	Experience	Graduate Program Enrolment Years
Bottom 25%	6.49	2.61	6.49	2.61
25-50th%	6.93	2.45	6.93	2.45
50-75th%	6.41	2.60	6.41	2.60
Top 25%	6.43	2.33	6.43	2.33

Notes: Sample weight (BNBPANL3) is used to calculate mean and standard deviation. The number of observations is 3,140, which is rounded to the nearest ten due to confidentiality concerns. FP=First professionals.

Table 15: 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, labourers	2.08%	-
Service industries	10.55%	3.94%
Other, military	1.50%	2.12%
Total	100%	100%
n	2280	860

Notes: Sample weight (BNBPANL3) is used to calculate mean and standard deviation. The number of observations is rounded to the nearest ten due to confidentiality concerns. Cells with small observations ("-") are merged to the "Other, military" category.

Table 16: Occupation and Graduate Program Types

Occupation	No Grad. Degree	MA in education	Medical school	Law school
Educators	13.98%	86.18%	-	-
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%	-	0.00%	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%	-	-	0.00%
Administrative/clerical/legal support	3.61%	-	0.00%	10.69%
Mechanics, labourers	2.20%	0.00%	0.00%	0.00%
Service industries	11.01%	4.42%	-	-
Other, military	1.61%	2.05	7.30%	2.98%
Total	100%	100%	100%	100%
n	2050	210	90	110

Notes: Sample weight (BNBPANL3) is used to calculate mean and standard deviation. The number of observations is rounded to the nearest ten due to confidentiality concerns. Cells with small observations ("-") are merged to the "Other, military" category.

Table 17: Occupation and Graduate Program Types

Occupation	MBA	MS in engineering	Other MA	Doctoral degree
Educators	2.83%	-	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%	-
Medical professionals	-	0.00%	15.63%	31.55%
Editors/writers/performers	-	-	8.79%	-
Human/protective service/legal profess	-	0.00%	10.26%	14.23%
Research, scientists, technical	2.65%	8.12%	8.67%	23.93%
Administrative/clerical/legal support	-	0.00%	-	0.00%
Mechanics, labourers	0.00%	0.00%	-	0.00%
Service industries	6.97%	3.37%	5.50%	0.00%
Other, military	5.46%	13.62%	2.79%	2.85%
Total	100%	100%	100%	100%
n	170	90	280	120

Notes: Sample weight (BNBPANL3) is used to calculate mean and standard deviation. The number of observations is rounded to the nearest ten due to confidentiality concerns. Cells with small observations ("-") are merged to the "Other, military" category.