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EDITORS

DOMINIC J. BREWER
Associate Dean for Research and Faculty Affairs
Clifford H. and Betty C. Allen Professor in Urban Leadership
Professor of Education Economics and Policy
University of Southern California
Los Angeles, CA
USA

PATRICK J. McEWAN
Whitehead Associate Professor of Critical Thought
Associate Professor of Economics
Wellesley College, MA
USA

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Returns to Education in Developed Countries

M Gunderson and P Oreopoulos, University of Toronto, Toronto, ON, Canada

Glossary

Ability bias – The bias to the returns to schooling that can result from the fact that people who acquire more education may have greater innate skills that would allow them to earn more even without additional schooling.

Causal returns – The returns to education that are induced or caused by additional education rather than simply correlated or associated with additional education.

Endogeneity of education – The fact that education is a decision variable in that the amount of education acquired may be a function of factors such as ability, motivation, family background, income, proximity to school, and compulsory school laws.

Instrumental variables – In the context of education decision making, instrumental variables are variables that affect the amount of education acquired but do not affect the education outcomes or the returns to education (e.g., compulsory school laws or proximity to schools).

Measurement error – The possibility that collected data, like education, may be measured with error since people may not accurately report their education.

Returns to education – The financial rate of return to investing in an additional year of schooling, obtained by comparing the additional earnings from an additional year of education with the cost of acquiring the additional education; it shows how average earnings increase with added education.

Selection bias – In the context of returns to education, it is the bias that can be created by the fact that education may be a function of conventionally unobserved factors such as ability or motivation.

Sheepskin effect – The credential effect or additional returns associated with the credential of completing key phases of education like graduating from high school or university (sheepskin was used historically to make the parchment for diplomas).

importance. What are the private returns that individuals can expect from investing in education? How do those returns vary by factors such as level of education, field of study, and individual background characteristics? How have those returns varied over time and across different countries? Is there an extra effect from a year of education if that year provides the credential of completing a phase of study such as graduating from high school or university? If potential dropouts are compelled to stay in school longer by compulsory school laws do they receive returns that are higher or lower than the average returns? Are the returns the result of education enhancing the productivity and skills of individuals or are they the result of signaling of such conventionally unobserved factors such as ability, motivation, and time-management skills? What are the appropriate methodologies for estimating the returns to education, especially for dealing with factors such as measurement error, ability bias, credential effects, and financial constraints?

The purpose of the article is to address these practical and methodological questions. The emphasis here is on the causal returns to education after controlling for other observable and unobservable factors like innate ability or motivation that may affect the outcomes associated with higher education. Understanding the underlying causal relationship process is important for policy purposes so as to ascertain the effect of policy interventions, for example, to reallocate resources from fields of low returns to fields of high returns or raise the age of compulsory schooling or institute policies to deter dropping out. It can also be important for predicting future changes as the underlying causal factors change.

The article moves from the simple to the more complex. It starts with estimates of the return to education based on basic schooling equations where education is not exogenous but can be correlated with other factors that can affect outcomes. It then moves to a discussion of refinements to the basic model: the appropriate measure of earnings and the inclusion of nonwage benefits; measurement error in the schooling variable; and corrections for ability bias, omitted variables, and selection bias; and the possibility of heterogeneous returns, and credential or sheepskin effects.

Introduction

Understanding the causal relationship between education and the financial returns to such education is important for addressing a range of questions of practical and policy

Estimating Returns to Education via Schooling Equations

A wide range of methodological issues are associated with estimating the economic returns to education. (Reviews of

many of these issues include Card (1999, 2001); Chamberlain (1977); Chamberlain and Griliches (1975); Griliches (1979); and Lemieux (2002). Heckman *et al.* (2006) provide a critical review of much of the literature, emphasizing the heterogeneous returns to education and the importance of psychic costs in explaining such heterogeneous returns. Here, we have cited articles that illustrate the issues and that contain references to related articles.) In this section, the main methodological issues are outlined in a nontechnical fashion, generally referencing more technical treatments of the issues.

Basic Schooling Equation

Estimates of the private returns to education essentially build on the human capital earnings function of Mincer (1974) where the (natural) log of earnings is regressed on years of education and other control variables including years of labor-market experience. The latter is often entered in a quadratic form to capture the nonlinear relationship whereby earnings tend to advance rapidly for early years in the labor market, flatten in later years, and decline slightly thereafter. Higher-order polynomial functions for experience have also been recommended so as to better capture the more rapid earnings growth early in an individual's career and the slower decline in wages later in an individual's career, although Heckman *et al.* (2006: 333) indicate that such higher-order polynomials did not improve their estimates.

The estimated coefficient on the education variable has a convenient interpretation as the average percent increase in earnings from an additional year of schooling (e.g., a number like 0.10 or 10% which can be compared to the returns to other investments). For interpretation, Mincer and other social scientists often assume that tuition and psychological costs from schooling are negligible, that individuals do not work much while in school, and that schooling and years of experience have separate effects on earnings. Under these assumptions, the coefficient from the Mincer equation can be interpreted as the return to investing in the cost of an additional year of education and compared to alternative investments. In this case, the monetary benefits of an additional year of schooling are the additional earnings from such schooling, while the costs are the forgone income. Since both the benefits and the (opportunity) costs are in this way factored into the estimates of the earnings equation, the coefficient on the education variable yields an internal rate of return to investments in education. (Heckman *et al.* (2006) provide more detailed discussion on estimating internal rates of return from schooling and alternative approaches to assessing returns from education when the mentioned assumptions do not hold.) Since data sets often have different categories of highest level of education achieved, these are often entered in place of years of

schooling so that the returns can vary by different categories of completed education.

Estimates from a basic Mincer schooling equation tend to yield estimates around 0.07–0.10, being slightly higher for females and lower for males. The returns are slightly higher for general academic streams compared to technical vocational streams, and they are higher in the more professional fields like engineering, medicine, business, and sciences and lower in social sciences and humanities and especially in fields like fine arts. These can be thought of as the simple benchmark returns to education against which to gauge the effect of the myriad of procedures (discussed subsequently) to improve on those estimates and to consider how returns differ across particular groups of individuals.

Hourly Wages versus Measures That Include Hours of Work

The appropriate measure of earnings is one that approximates the hourly wage so as to reflect the productivity effects of education and to control for differences in hours worked given that persons with higher education tend to work longer hours. To the extent, however, that higher education leads individuals to work more hours, the additional time is an endogenous part of the returns to education. Measuring increased earnings per hour may therefore underestimate the true returns to education over a fixed period of work. Card (1999, p 1809), for example, estimates that slightly more than two-thirds of the returns to education based on annual earnings in the US in the mid-1990s reflects higher wages while one-third reflects longer hours. More specifically, he estimated returns to education of about 10% for males and 11% for females based on hourly wages, and 14.2% for males and 16.5% for females based on annual earnings. The fact that the change was higher for females than for males highlights the fact that higher education is also associated with longer hours of work (both hours per week and weeks per year in his data) and that the effect on longer hours was greater for females than for males.

Measurement Error in Schooling

Returns to schooling are typically estimated from survey data where individuals report their highest level of schooling. This reported schooling can be subject to measurement error or misreporting of education. Estimates indicate that about 10% of individuals misreport their level of education, and this is true in administrative data as well as survey data. (Misreporting is discussed, for example, in Ashenfelter and Rouse (1998) and Card (1999)). If the misreporting is random or unrelated to the level of education, then such classical measurement error leads to a downward bias in the estimated returns to

education. However, if the measurement error is systematically related to the level of education, then the bias can go in either direction. Persons with low levels of education may be prone to overstate their actual education and persons with higher education may be more accurate in their reporting, yielding an upward bias to the returns to education. However, there is also the possibility of higher-educated people having more opportunities to inflate their education given the multiplicity of different types of degree-granting institutions. In essence, the biases from measurement error in schooling can go in either direction. Overall, based on his assessment of the literature, Card (1999: 1834) concludes that measurement error in education leads to a downward bias in returns to education, with the estimated returns understating the true returns by about 10%. That is, if the estimated returns were 0.10, the true returns would be 0.11.

Ability Bias, Omitted Variables, and Selection Bias

The potentially most severe bias that can occur in estimating the causal returns to education occurs because educated people can have other characteristics that are associated with higher earnings and those other characteristics are not controlled for in the estimating procedures. Indeed, models that attempt to explain differences in school attainment often do so by noting that costs and benefits from additional schooling are not the same for everyone. Individuals may differ by innate ability, motivation, organizational skills, entrepreneurship, time-management skills, and willingness to work hard. To the extent that these factors lead to higher earnings as well as higher education, and they are not accounted for in the statistical analysis, then omitting them from the estimating equation means that some of the higher returns to education may be reflecting the effect of these factors. That is, the estimated returns to education are biased because the higher education is capturing the economic returns to these omitted variables as well as the pure causal effect of education. Alternatively stated, higher-educated people may be a select group in terms of not only observable characteristics that can be controlled for in the regression analysis, but also unobserved traits as indicated above that are not conventionally controlled for in the analysis. The returns to education can reflect a return to these traits as well as to education itself.

The literature on estimating the causal returns to education has been a growth industry in recent years based largely on devising ways to control for this ability or selection bias, often involving imaginative ways of obtaining exogenous variation in education that is independent of ability or selection bias. The following illustrate such procedures.

Include proxy measures of ability

A number of empirical studies have been able to include proxy measures of ability such as IQ scores or test scores designed to measure innate ability. (Studies that deal with test scores as a measure of ability are referenced in Card (1999, 2001) and Griliches (1977)). Such studies tend to find the ability bias to be small in that the estimated return to education drops only by about 10% (e.g., from 0.10 to 0.09) after controlling for the effect of ability.

Family characteristics such as the education of a parent or sibling are also sometimes included to control for factors that may help a person obtain more education and affect their earnings. Such studies also generally find the return to education to drop very slightly (by around 0.01) after controlling for such family characteristics. (Family background controls are used in Ashenfelter and Rouse (1998); Ashenfelter and Zimmerman (1997); and Card (1995b)). Studies that have also examined how the return to education varies by the ability of the individual or his/her family background have yielded inconclusive results (Ashenfelter and Rouse (1998) and the literature cited therein).

Twin studies

Another way to control for ability bias and perhaps some of the other potentially important omitted variables is to use twins since they presumably have the same natural ability (especially if they are identical twins from the same egg as opposed to fraternal twins from two different eggs). Differences in their education are assumed to occur for random reasons (a possibly questionable assumption) and in this way this procedure approaches the ideal random-assignment procedure for estimating treatment effects (in this case the treatment being more education). Using same-sex twins also controls for the possibility that parents may favor one sex or the other in devoting family resources to them to improve their labor-market outcomes.

Studies that utilize differences in education between twins to identify education differences while controlling for ability and other differences generally lowers the return to education slightly (suggesting a slight upward ability bias) but this tends to be offset by the measurement error bias from mis-measuring education so that on net the true returns are about the same as those estimated in the conventional regression of earnings on education without controlling for ability bias or measurement error. Estimates of returns to schooling using US twins generally range between 0.06 and 0.12. (Earlier twin studies are reviewed in Griliches (1977, 1979) with more recent twin studies reviewed in Ashenfelter and Rouse (1998) and Miller *et al.* (2006)).

Natural experiments based mainly on features of the education system

A number of empirical studies have used institutional features of the education system or the environment to

generate differences in education that arise for reasons beyond an individual's control. A policy change that lowers the cost of college in one state, for example, affects some individuals but not others depending on when and where they are born. Forces that cause differences in education for reasons outside individuals' control are called exogenous. Using exogenous forces to estimate returns to schooling helps address ability bias because differences in education that arise from exogenous forces are unlikely due to differences in individual ability. Returns-to-schooling estimates from this approach apply only to individuals affected by the exogenous force (e.g., policy change). (Such studies are reviewed in Ashenfelter *et al.* (1999); Ashenfelter and Rouse (1998); Card (1999, 2001); and Carnoy (1997), and critically assessed in Heckman *et al.* (2006)). Exogenous variation can be caused by various factors:

- Geographic proximity to educational institutions can generate exogenous variation in education in that those close to a university are more likely to attend university and hence acquire more education than those who are far away from a university (e.g., Cameron and Taber, 2004; Card, 1995).
- Differences across regions or over time in financial costs to attending school (e.g., through tuition) can also lead to differences in education attainment (e.g., Kane and Rouse, 1995; Chen, 2009)
- The Vietnam draft lottery generated exogenous increases in schooling because many persons enrolled in school in order to defer military service (Angrist and Krueger, 1994).
- Local labor-market earnings for persons at the age of 17 years have generated exogenous variation in education in that higher earnings may increase the opportunity cost of education and thereby induce dropping out (Cameron and Taber, 2004).
- The GI bill in Canada gave rise to exogenous variation in education in that the cohort of males from English-speaking Ontario received additional education due to the GI bill and not to the decision, say, of higher-ability people to acquire more education. The earnings of this treatment group were compared to the earnings of a control group from French-speaking Quebec who were less likely to have served or to have taken advantage of the bill (e.g., Lemieux and Card, 2001).
- Day of birth can interact with compulsory school laws. For example, persons born earlier in a year (e.g., January) tend to have less education than those born later in a year (e.g., December) because they are older when they start school (from missing the school entry age cutoff) and hence reach the compulsory school-leaving age with a lower level of education, many of whom then drop out (e.g., Angrist and Krueger, 1991).

- Differences in compulsory school laws and changes to these laws over time can also generate differences in education attainment since some persons in jurisdictions with higher ages at which it is compulsory to remain in school will acquire more education because they cannot drop out until the compulsory age (e.g., Oreopoulos, 2006a, 2006b).
- Exogenous variation in education has also been found in situations where an additional year of schooling has been added or subtracted to the high school or university curriculum (Webbink, 2007; Krashinsky, 2007).

Studies using the natural experiments from features of the education system or environment to obtain exogenous variation in education tend to find such causal returns to education to be in the neighborhood of 0.06–0.15, and sometimes higher. As emphasized in Heckman *et al.* (2006: 392), however, the returns are often imprecisely estimated, with large standard errors. These estimates are somewhat higher than the returns when conventional years of schooling are used.

Heterogeneous Returns

It is important to view returns to schooling as being individual and context specific. Gains from schooling depend upon the individual's background, motivation, and the quality and type of schooling. An individual's decision to take more schooling depends on both expected gains and costs. Estimates of returns to schooling using exogenous policy variation can often be interpreted as average returns to schooling among individuals affected by the policy variation. Sometimes the policy variation identifies particularly interesting parameters, like the average gains to schooling among those forced to stay on in school because of more restrictive compulsory schooling laws, or the average gains to schooling among those who entered college because tuition costs were lowered. As discussed in Card (1999, 2001), many of the natural experiments used to estimate returns to education identify average returns for more disadvantaged groups. The fact that increase in the education of such persons tends to generate higher than-average returns suggests that increasing the education of such marginalized groups can have both desirable efficiency effects (high returns) as well as distributional effects (high returns to otherwise more-disadvantaged groups). This suggests the viability of increasing the education of such groups through policy initiatives such as increases in the compulsory school age, funding assistance, expansion of accessibility (e.g., by facilitating transfers from colleges to universities), and campaigns against dropping out.

A number of researchers have tried to model an individual's schooling decision by assuming more structure to

the decision-making process (e.g., schooling only affects wealth, people have rational expectations, and discount the future geometrically). The models are simplified enough to allow estimation of a few unknown parameters, like an individual's time discount rate and return to schooling. A correctly specified model with enough structure permits estimation of a wide set of returns-to-schooling measures for individuals under different circumstances (e.g., faced with different costs or benefits or different schooling-level decisions). The advantage of this approach is that it emphasizes the economic content of what is being estimated and offers a potential approach to measuring individual rates of return in situations where an experimental approach cannot. Studies using this approach typically estimate returns around 0.04–0.07, which are lower than those from experimental approaches (Bezil (2007) provides a review). If the assumptions of these models are incorrect, however, the returns-to-schooling estimates can be off significantly. Unfortunately, this is difficult to determine.

Annual Returns, Signaling, and Sheepskin Effects

An important issue to address is the extent to which the estimates of returns to schooling reflect not just the productivity-enhancing effect of schooling but an effect on earnings of the underlying set of skills that schooling signals. There is a fundamental difficulty in unraveling the extent to which schooling is a signal of existing productivity as opposed to enhancing productivity: both theories are observationally equivalent – they both suggest that there is a positive correlation between earnings and schooling, but for very different reasons. If the rate at which employers learn an employee's correct set of skills is slow, or if early job placements influence long-term job opportunities, the effects of signaling can be long-lasting.

The empirical literature generally finds evidence of such signaling or sheepskin effects (see Weiss (1995), Chatterji *et al.* (2003) for examples and reviews).

Ferrer and Riddell (2002) provide estimates of the credential effects and review much of the earlier literature, as do Heckman *et al.* (2006). The returns to an additional year of education that involves completion of a stage (e.g., graduating from high school, or university) is higher than the return to a year of education that does not involve the credential of the completion of a phase. For example, based on the 1996 Canadian census, Ferrer and Riddell (2002) estimate rates of return to an additional year of schooling to be 6% for males and 9% for females. These are averages of both the credential effects associated with milestones of completing various phases as well as the returns to years within the different phases. When the returns to completing the phases are calculated and annualized over the period of education necessary to complete the degree, the annual rates of return that are implied by completing university relative to high school are 9% for males and 11% for females.

While most researchers would agree that schooling affects earnings both by improving skills and by signaling skills, the relative importance of these effects is not well understood. One paper estimates that the contribution of signaling to the returns to schooling is less than 25% (Lange, 2007). Understanding the relative importance of signaling in explaining returns to schooling remains an important area for further research.

Trends and Some International Evidence

Returns to education in the US have been increasing steadily in recent years likely reflecting the widening skill differential in wages (Card and Lemieux, 2001), in spite of the dramatic increases in education that would normally be expected to depress returns. Returns have also been increasing in Canada and European even though the wage structure there is more compressed when compared to the US. (e.g., Bingley *et al.*, 2005). Obviously, the demand changes favoring higher-educated personnel have more than offset the supply changes.

International comparisons of the return to education are obviously difficult because of differences in the data sets and methodologies. In spite of this, reviews of the international evidence in general find similar results as those in the US and Canada. (The international generalizations given here are based mainly on Psacharopoulos and Patrinos (2004) (earlier studies are cited therein). Similar generalizations for some of the issues are given in Trostel *et al.* (2002) with further international evidence provided in OECD (1998)).

Summary

The following points sum up the returns to education:

- Returns to education tend to be in the neighbourhood of 10%, typically ranging from 6% to 15%. **Table 1** illustrates the main approaches used to estimate these returns and their general findings.
- Returns to education tend to be in the 6–10% range when based on ordinary least-squares (OLS) estimates from conventional schooling equations and the 10–15% range (and sometimes higher) when based on instrumental variables (IV) and other procedures used to identify exogenous variation in education. As such, the 10% estimate is at the upper end of the OLS range and lower end of the IV range.
- The returns tend to be higher for

Table 1   Illustrative estimates of returns to education using alternative approaches

Author	General method	Sample	Returns to education
Grilliches (1977)	Regress log median earnings of expected occupation at age 30 on schooling while using IQ score as additional proxy control for ability	17–27-year-old men in 1969 from US National Longitudinal Survey for Young Men, using log median earnings of expected occupation at age 30	0.059 (0.003)
Ashenfelter and Rouse (1998)	Regress difference in log earnings between identical twins on difference in schooling	1991–93 Princeton Twins Survey of identical twins	0.102 (0.010)
Card (1995)	Use indicator for whether living near a 4-year college as instrument for predicting schooling	US National Longitudinal Survey for Young Men	0.132 (0.049)
Chen (2008)	Use average tuition fees at the local college in county as instruments for predicting schooling	25–42-year-old men in 1979–2000 from US National Longitudinal Survey of Youth, 1979	0.133 (0.028)
Oreopoulos (2006b)	Use differences in state compulsory schooling laws as instruments for predicting schooling	25–64-year-old men and women in 1950–2000 US Censuses	0.142 (0.012)
Bezil and Hanson (2007)	Construct structural model on education-attainment decisions and estimate model along with returns to schooling	White males from the US National Longitudinal Survey of Youth	0.069 (average between grade 10 and 16)

1. females as opposed to males;
2. obtaining the credentials associated with completing phases like high school or university;
3. general academic streams compared to technical vocational streams; and
4. professional fields like engineering, medicine, business, and sciences and lower in social sciences and humanities and especially fields like fine arts.

- The returns tend to be increasing over time in spite of the large increases in the supply of educated persons, highlighting that the demand for education associated with the knowledge economy and the widening of the skilled–unskilled wage differential are outstripping the supply responses.

See also: Empirical Research Methods in the Economics of Education; Human Capital; Returns to Education in Developing Countries; School Quality and Earnings; Signaling in the Labor Market.

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