The Health Returns to Education: A Cost-Utility Approach

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Structured Abstract:

Objective: To improve estimates of the education-health relationship by accounting for quantity and health-related quality of life.

Data Sources/Study Setting: We use secondary data from the 1985-2007 years of the Panel Study of Income Dynamics.

Study Design: We estimate OLS models of QALYs as a function of years of schooling and an extensive set of socio-demographic and family background covariates, and we also estimate sibling fixed effects models of QALYs.

Data Collection/Extraction Methods: We combine longitudinal survey data with frequent measurements of self-reported health status with data on month of death for the decedents in the sample. We use a previously validated algorithm for mapping self-rated health to health-related quality of life weights, along with the mortality data, to measure QALYs experienced over a 23-year period of time.

Principal Findings: Across our empirical specifications, an additional year of schooling is associated with an additional 0.20-0.38 QALYs over the 23-year study period. These estimates are considerably larger than looking at quality-unadjusted life years. Under various assumptions, we estimate that an additional year of schooling is associated with a discounted incremental value of $8,322-$18,624 of health.

Conclusions: Health gains associated with additional schooling are substantial, implying that increasing schooling may be a relatively cost-effective way to improve population health.

Keywords: Education, Health, Cost-Effectiveness, Cost-Utility

Introduction

Decades of research document a robust relationship between educational attainment and health outcomes. The positive relationship between education and health is observed for a diverse set of health outcomes (e.g., Cutler and Lleras-Muney 2008, Schoeni et al. 2005, Elo and Preston 1996). Although this relationship may result in part from reciprocal effects between educational attainment and health status, recent research suggests that education does indeed have a causal effect on health (e.g., Currie and Moretti 2003, Lleras-Muney 2005). These empirical results have led some experts in health policy to advocate for further investments in education as one of the most productive and cost-effective policy approaches to achieve the goal of improving population health (Mechanic 2007, Monheit 2007, Robert Wood Johnson Foundation 2009). The strength of these policy prescriptions, however, hinges on the value of health returns to education and how those returns compare to other possible interventions.

To date, little research has attempted to explicitly quantify the overall value of the health gains from education. Most research on the effects of education on health focuses on a single dimension of health, or on multiple health outcomes separately, without explicitly estimating the overall value of those health outcomes. Also, the value of health status has an important time dimension, since health status is both variable and valuable throughout the life span. Point-in-time estimates of health outcomes will not reflect the true health gains from education, since these gains accrue over an extended period of time. However, few existing data resources allow for the long-term observation of health outcomes.

One prior U.S. study attempts to explicitly estimate the monetary value of the health returns to education. Cutler and Lleras-Muney (2008) estimate OLS models of life expectancy using data from the National Longitudinal Mortality Study, modeling life expectancy as a function of age, sex, race, and education. They find that an additional year of education is associated with 0.6 additional years of life. Under the assumption that their estimates represent a causal effect and under various discount rates, they find that the marginal value of health due to a year of schooling is between \$13,500 and \$44,000 (assuming that a life-year is valued at \$75,000). While this is a useful starting point, it has several limitations. First (as the authors acknowledge) their estimates likely do not reflect causal effects, given their sparse model specification and the well known issues of endogeneity when estimating effects of schooling. Second, while longevity may be the most important health outcome, the quality of life-years gained is also highly valued. To the extent that schooling affects health-related quality of life along with longevity, their results may underestimate the health returns to schooling.

The goal of this paper is to construct more accurate estimates of the magnitude of the health returns to formal education. We build on the prior research in several ways. Our main innovation is in our measurement of health outcomes over an extended period of time. We use a 23-year longitudinal panel of data to combine survey data on health-related quality of life with information about longevity, thus capturing both quality and quantity of life. In addition, we are able to assess whether the association between education and health holds up under more rigorous econometric specifications, both by including extensive controls for family background characteristics and by estimating sibling fixed effects models. While we find that the health returns to schooling are substantial, we also find evidence that focusing only on longevity as a health outcome considerably underestimates the health returns to schooling. We also use our empirical results to derive estimates of the cost-effectiveness of increasing education, which has implications for the policy issue of whether investing in education is a relatively efficient way to improve population health.

Conceptual Framework

It is intuitive that people value both length of life and the health-related quality of life (HRQL) experienced while living. Conceptual models of health production (Grossman 1972) suggest that education can affect both quantity of life and HRQL. Education is hypothesized to affect longevity and HRQL through a number of mechanisms, including increasing income or occupational status, improving cognitive skills for acquiring and using health-promoting information (for a review, see Robert Wood Johnson Foundation 2009), or altering non-cognitive factors that could influence health investments (e.g., patience) (Becker and Mulligan 1997).

Thus, when assessing the value of health returns to schooling, the ideal measure of lifetime health status would integrate longevity with HRQL. This type of measure is commonly used, in the form of quality-adjusted life years (QALYs). An advantage of using QALYs is that a rich literature estimates the monetary value of QALYs, thus allowing for estimates of the effects of education on lifetime health status to be expressed in monetary terms (Hirth et al. 2000).

Methods

Data and Dependent Variables

Measuring the number of QALYs experienced over time involves three steps: measuring the HRQL (and assigning HRQL weights) over time, measuring longevity, and combining the information from the first two steps. We used data from the Panel Study of Income Dynamics (PSID) to follow those steps to measure health status over an extended period of time. The PSID is a nationally-representative longitudinal study that started following families in 1968, and has expanded to collect data from subsequent generations of the original sample families. The PSID has collected survey data on health status annually since 1984 (and biennially since 1997), for all designated household "Heads" and "Wives" in each wave. Our analytic sample consisted of individuals who were Heads or Wives in 1985, because some of the variables used in our analyses were not asked of both Heads and Wives until 1985. There were 11,180 Heads and Wives with a valid health status measurement in 1985. We further restricted the sample to observations at least 25 years old at the time of the 1985 survey to focus on individuals who have completed their education, reducing the initial sample to 9,952 observations.

To measure HRQL and assign HRQL weights over time, one would ideally want frequently-repeated measurements of general health status using a survey instrument that has been directly linked to HRQL weights by valuation studies using preference elicitation techniques (e.g., the EQ-5D, the HUI, and the SF-6D). The PSID, like other major panel studies, does not include survey instruments for general health status that have been directly linked to HRQL weights. However, the PSID includes other measures of health status, including the common five category self-rated health item (whether current health is excellent, very good, good, fair, or poor). To create measures of HRQL weights for each of the PSID years, we used the algorithm developed by Nyman and colleagues (2007). They used Medical Expenditures Panel Survey (MEPS) data to assign HRQL weights to each self-rated health category. A previous study linked the EQ-5D with HRQL weights using time trade-off methods (Shaw, Johnson, and Coons 2005). Nyman et al. (2007) were able to link the HRQL weights from that study to self-rated health because the MEPS included both the EQ-5D and self-rated health. For example, they estimated that the HRQL weight for someone with poor self-rated health is .511 lower than someone with excellent self-rated health. We used this algorithm to assign HRQL weights (η_t) to each year that the individuals in our sample are alive. For the PSID surveys that were biennial after 1996, we used linear interpolation to assign HRQL weights in the non-survey years. We also used linear interpolation to assign HRQL weights to years where an individual did not respond, but had another self-rated health measurement in a later year.

The next step in using the PSID to measure the number of QALYs experienced over time was to measure longevity. To measure longevity, we utilized data from the restricted-use PSID mortality file. This file contains the month and year of death for all PSID respondents with a documented death by the end of 2007. The PSID identifies respondents as deceased through National Death Index searches and also by periodically tracking long-term attritors. Mortality data were used to create variables ($Alive_t$) that measured whether each individual was alive in each of the 23 years. If an individual was alive (or dead) for the entirety of year t, $Alive_t$ equals one (or zero). If an individual died partway through year t, $Alive_t$ equals the proportion of the year that he or she was alive. We also used the mortality data to interpolate missing data between the last survey interview and death. We used linear interpolation to impute missing HRQL weights between the last recorded self-rated health measurement and death (where $\eta_t = 0$).[1]

The final step in using the PSID to measure the number of QALYs experienced over time was to combine the HRQL weights with the information on longevity. Our dependent variable is a measure of the number of QALYs experienced over a 23-year period and is computed as:

$$QALYs = \sum_{t=1}^{t=23} \eta_t * Alive_t \qquad (1)$$

For the sake of comparison, we also computed an alternative version of the dependent variable that counts the number of years lived over the 23-year period of observation, but does not adjust for HRQL. This variable, which can be thought of as quality-unadjusted life years, is computed as:

$$LifeYears = \sum_{t=1}^{t=23} Alive_t \qquad (2)$$

In our analyses, we dropped observations with missing data on the measure of 23-year QALYs or other covariates. A significant number of observations (3,685) were dropped due to these sample restrictions. A major reason for the size of this reduction is that because of budget constraints, the PSID reduced the number of core families in the 1997 sample by approximately 27% from 1996. The reduction is also accounted for by sample attrition due to serial survey nonresponse after 1985. This gives us a sample size of 6,267 observations.[2]

Study Design and Statistical Analysis

Any study that attempts to identify the causal effects of education on health faces several well-known impediments. First is reverse causality: while education may affect health, early life health conditions are also known to affect educational attainment. Second is that schooling decisions are endogenous and are correlated with other unobserved factors that may influence health in later life. For example, schooling decisions may be correlated with financial constraints that may be correlated with material resources that can influence health later in life, with cognitive abilities that lower the psychic cost of schooling and makes an individual a more efficient producer of health, or with noncognitive factors like time preferences which may be correlated with schooling decisions and health investment decisions that accrue benefits later in life. These factors can be difficult to measure and even when they are measured, there is still concern that there are other unobservable variables that are correlated with both schooling and health.

Given these complications, one would ideally want to exploit a natural experiment where there was plausibly exogenous variation in educational attainment. Unfortunately, no such variation is available given our data.[3] Instead, we took two approaches to deal with the problem of endogenous educational attainment. In the first approach, we utilized the very rich data available in the PSID to control for the family background characteristics that are plausibly correlated with schooling decisions and health outcomes. We estimated two sets of models. In the first set of models of health (equation 3, where health (H_i) refers QALYs or life years), we used a parsimonious set of covariates (somewhat similar to the specifications of Cutler and Lleras-Muney (2008)).

$$H_i = a + \beta E_i + \delta I_i + \varepsilon \qquad (3)$$

These models included education (E_i) measured as years of formal schooling and a vector of individual-level covariates I: age in 1985 and age-squared, sex, race/ethnicity (coded as white, black, Hispanic, and other), and a binary variable for whether the respondent reported having any health problems that began before age 18. This latter covariate was created using data from the 1978 PSID questions that asked for all individuals included in the PSID (including Heads, Wives, and other household members) about whether they have any physical or nervous condition that limits the type or amount of work they can do (or limits activity or schooling if the individual was younger than 18 in 1978) and when the condition began. Including this covariate reduced concerns that our results can be explained by reverse causation. To assess whether using a linear term for years of formal schooling accurately reflects the functional relationship between schooling and 23-year QALYs, we first estimated a semi-parametric model of 23-year QALYs. In this model, the covariates I were treated parametrically, while years of formal schooling were treated nonparametrically (DiNardo and Tobias 2001). The results of this model (available upon request) supported the use of a linear measure of years of schooling in our models.

Our second set of models (Equation 4) included an extensive set of family background characteristics that may be correlated with both schooling decisions and health outcomes.

$$H_i = a + \beta E_i + \delta I_i + \gamma R_i + \lambda C_i + \varphi N_i + \varepsilon \qquad (4)$$

In this model, *R* is a vector of variables that measure family socioeconomic resources, which were collected from Heads and Wives in 1985: whether the individual reports that his or her family was well-off, financially average, or poor while growing up; father's education; and mother's education (the latter two are categorized as less than high school, high school or more, or don't know). *C* is a variable that measures cognitive abilities in the family. This variable is a measure of IQ taken in 1972 that ranges from zero to 13 and is based on a 13-item sentence completion test. *N* is a vector of three measures of noncognitive abilities and characteristics of the family. The first is an index of ambition and aspiration, measured in 1968, and ranging from zero to nine with nine indicating a higher degree of ambition and aspiration. The second is an index of time horizons, measured in 1968, and ranging from zero to nine with higher scores indicating longer time horizons. The third is an index of risk avoidance, measured in 1968, and ranging from zero to nine with higher scores indicating greater risk aversion. For the variables in *C* and *N*, the data were collected from the household head. The individuals in our sample can be the original responding household head, the spouse, or one of the children of the original head, all of whom share the same values of *C* and *N*.[4] It would be preferable to have data on cognitive abilities that were measured for each individual, but such data are not available. Nevertheless, the family-level *C* and *N* variables may be reasonable proxies for individual-level characteristics, given the evidence on positive assortative mating based on intelligence and preferences, and on intergenerational correlations of cognitive skills and noncognitive factors (Black, Devereux, and Salvanes 2008, Dohmen et al. 2008, Feng and Baker 1994, Macie-Taylor 1989). In addition, we also included in equation 4 a dummy variable for whether an individual was the original household head respondent to these questions. For equations 3 and 4, we estimated heteroskedasticity-robust standard errors clustered on the 1968 family identifier. We did not use the PSID survey weights because there were a large number of Heads and Wives in 1985 with valid measures of the dependent variable but with weights of zero because they were not a member of an original PSID family. However, our results were not sensitive to whether or not we use the PSID weights.

In the second approach, we utilized the fact that the PSID tracks families from its original sample over time to estimate sibling fixed effects models of health returns to schooling. These models (Equation 5) used a more limited set of covariates, since family-invariant variables are absorbed by family fixed effects.

$$H_{if} = a + \beta E_{if} + \delta I_{if} + \gamma R_{if} + \theta_f + \varepsilon \tag{5}$$

In these models, I includes age, age-squared, sex, and whether there was a limitation before age 18. R_{if} includes whether the family was poor while the respondent was growing up, to allow for differences in childhood socioeconomic situations between siblings, and θ_f represents a set of family fixed effects. We calculated heteroskedasticity-robust standard errors that are clustered on the family.

The models described in equations 3-5 may not identify the true causal effect of education on health, unless we make possibly unrealistic assumptions. In equations 3 and 4, there are likely unobserved variables that may be correlated with schooling and health, even conditional on the family-background covariates included in equation 4. There are also well-known limitations to estimating effects of schooling using sibling models (Bound and Solon 1999). We lack data on individual-specific cognitive and noncognitive abilities that might allow our sibling model estimates to more credibly approximate the causal effect (Fletcher and Frisvold 2009). However, even with such data, problems due to measurement error that are magnified in sibling models could bias the estimates (Griliches 1979). As such, our results may be best characterized as detailed descriptive estimates of the association between schooling and 23-year QALYs.

The final part of our analyses is to construct estimates of the monetary value of the health returns to schooling, based on our estimates of 23-year QALYs. There are two issues to consider here. The first issue is the monetary value of a QALY. An extensive literature attempts to estimate the value of a QALY. We estimate the returns to schooling under two assumed values of a QALY: $75,000 per QALY and $100,000 per QALY. These may be conservative valuations, as Hirth et al. (2000) found that the median implied value per QALY from 35 value-of-life studies based on willingness to pay methodologies was $265,000 in 1997 dollars.

The second issue to consider is projecting and discounting health benefits over the post-education lifespan to calculate the present value of those benefits. We assumed that our main regression results pertain to an individual who is 50 years old at the start of the 23-year observation period, which is close to the sample mean age in 1985. We also assumed that we are considering individuals who start with perfect health (HRQL weight=1) at age 25 and for whom health returns to schooling start at that age. Our goal was to estimate the present discounted value of health benefits to schooling for a 25-year old, considering health benefits that accrue until age 73. We used a 3% discount rate, which is standard in the cost-utility literature (Gold et al. 1996).

We approached this problem in two parts. First, we estimated the marginal effect of a year of schooling on QALYs experienced between ages 25 and 49, assuming that there is no mortality before age 50, resulting in a conservative estimate of the health returns to education. To do this, we estimated the HRQL weight for all 1985 PSID respondents, using the same models as before. The results of these models (appendix table 1) show that a year of education is significantly associated with approximately .01 higher HRQL weight in 1985. We then interpolate HRQL weights for each year between age 25 and 50 using a quadratic interpolation.[5] Summing the difference in estimated HRQL weights between an individual with one year difference in schooling for each of those years gives the discounted value of a health return to a year of schooling for the ages 25 to 49.

Second, we estimate regressions of the same form as in our main analyses, except we adjust the dependent variable to represent the PDV of QALYs accruing between ages 50 and 73 for someone 25 year old at study start. This new measure is described by equation 6.

$$PDV = \sum_{t=26}^{48} (\eta_t * Alive_t)(V)^{-(1.03^t)} \qquad (6)$$

The first year of the PSID data (1985) is treated as being 26 years after age 25, and is discounted accordingly. Similarly, the last year of PSID data is treated as being 48 years after age 25, and is discounted accordingly. *V* represents the valuation of a QALY. To produce an estimate of the PDV of the effect of a year of schooling on QALYs from age 25 to 73, we sum the two parts.

Results

In our PSID sample, 32% of the subjects died between 1985 and the end of 2007 (Table 1). The sample mean for life years was 18.76 and the mean for QALYs was 16.76. The distribution of 23-year QALYs is shown in Figure 1.

Table 2 reports the results for the OLS models of health returns to education. Columns 1 and 2 show that with a limited set of covariates, a year of education is associated with an additional 0.24 unadjusted life years and an additional 0.38 quality-adjusted life years over the 23-year period. The coefficients on the education variable are both significant at the p<.001 level in both models.

After adding the family background covariates (columns 3 and 4), the coefficients on years of education diminish, but are still statistically significant. With the family background covariates included in the models, an additional year of schooling is associated with an additional 0.16 unadjusted life years and an additional 0.25 QALYs over the 23-year period. This result implies that an additional four years of schooling is associated with one additional QALY. We also find that both cognitive and non-cognitive family background factors are associated with health outcomes. Higher family IQ and greater risk avoidance are each significantly associated with more QALYs, while aspirations and ambitions have a significant negative association with QALYs.

We also test the sensitivity of our results to the functional form of the regression model. It is clear from Figure 1 that the distribution of QALYs has a large mass around the maximum (23) and a long left tail. To assess whether OLS does a poor job of modeling outcomes from this distribution, we also estimated generalized linear models (GLM). In this approach, we reversed the QALYs measure, so it has the interpretation of the number of QALYs *lost* over a 23 year period, and we estimated equations 3 and 4 using GLM with a log link and gamma family. The results of these models (not shown) suggest less precise, but still statistically significant ($p<.001$) coefficients for education.[6] The marginal effects from these models are nearly identical to those from the OLS models.

The results from the sibling fixed effects models are somewhat similar to the results of the OLS of models that included an extensive set of family background covariates (Table 3). We find that a between-sibling difference in a year of schooling is associated with a non-significant between-sibling difference in unadjusted life years, and with a significant difference in 0.199 additional QALYs. The magnitude of the difference between the two dependent variables is quite large – the coefficient for QALYs is four times the size of the coefficient for unadjusted life years.

Thus far we have demonstrated that health returns to schooling are substantially greater when considering HRQL along with longevity, compared to looking at longevity alone. We now describe the estimates of the present discounted monetary value of the health returns to schooling that were derived based on our main results.

In Table 4, we show these estimates under different assumptions. Assuming that a QALY is valued at $75,000, our estimates of present discounted health returns to a year of schooling range from $8,322 to $13,968. Assuming that a QALY is valued at $100,000, our estimates of present discounted health returns to a year of schooling range from $11,096 to $18,624.

These results can be used to estimate the cost-effectiveness of an additional year of schooling in producing health, if we provisionally assume that they represent causal estimates. It is difficult to estimate the incremental societal costs of a year of education, because that cost varies by whether one considers secondary or post-secondary education, and by the target population. For example, one might imagine that the costs associated with raising education through implementing and enforcing stricter compulsory schooling laws increase with the number of years of required education. With those caveats in mind, we compared our estimates of discounted health returns to a year of education for an individual who was 50 in 1985 with the total expenditures per pupil ($2,820 in real 2009 dollars (National Center for Education Statistics 2008a) for a year of public primary or secondary school in 1953-1954 (approximately when that cohort was finishing high school) as a measure of the incremental cost of a year of education. Our estimates suggest that increasing education by 5.37-9.01 years leads to one additional QALY for an individual age 50 in 1985, implying a cost-effectiveness ratio of $15,142-$25,414/QALY, which is in the range of what is considered “a bargain” in the medical cost-effectiveness literature. If we use more current levels of direct expenditures for secondary school per pupil ($11,663 in 2006-2006, expressed in real 2009 dollars (National Center for Education Statistics 2008b)), our estimates imply a cost-effectiveness ratio of $62,624-$105,107/QALY, still within the range that is generally considered “cost-effective” for health interventions (Hirth et al. 2000). Finally, we note that applying a 3% discount rate in deriving our estimates has a large effect on our estimates. If we did not discount the value of health returns, the cost-effectiveness ratios would range from approximately $24,500-$26,850/QALY based on 2005-2006 schooling expenditures.

Discussion

In this paper, we propose a new way to assess the value of the health returns to schooling that incorporates length of life along with health-related quality of life over time. Although the QALY metric is commonly used in cost effectiveness analysis and cost utility analysis to compare the relative efficiency of health services or policy interventions, we show how the metric can be applied more broadly by using panel data that include self-reported health status and mortality information. Under various econometric approaches and specifications, an additional year of schooling is associated with 0.20-0.38 more QALYs over a 23-year period of time. We also find that the association between schooling and QALYs is between 57% and 330% stronger in relative terms than the association between schooling and quality-unadjusted life years.

Our findings should be interpreted in the context of several limitations. As mentioned earlier, although we are able to control for many more factors than some of the previous literature, our estimates of the effect of schooling on health may nonetheless not be well-identified. Our estimates may overstate or understate the health returns to schooling. The presence of unobserved ability or motivational factors that are correlated with schooling and health may suggest that we overstate the results. Alternatively, most research that utilizes instrumental variables methods to estimate the effect of schooling on health actually finds stronger results from instrumental variables models, relative to OLS models (Currie and Moretti 2003, Lleras-Muney 2003). In addition, while we are able to observe our sample over an extended period of time, our measure is still far from the ideal, which would account for the total number of QALYs experienced after completing one's education.

Cutler & Lleras-Muney (2008) find that an additional year of schooling is associated with approximately $13,500 in discounted value of life expectancy if a life year is valued at $75,000. They note that relative to a present-discounted value of lifetime income returns to a year of schooling (approximately $80,000), their estimate implies that the overall returns to schooling are substantially underestimated if health returns are not considered. Our estimate of QALY returns to schooling that is based on a similar specification is strikingly similar to their estimate. However, their estimate is based on complete length of life data, whereas only 32% of our sample died over the observation period. Under the assumption that the patterns observed in our data will continue to hold as the sample ages further, our estimates likely understate the QALY returns to schooling.

Our findings have several implications for policy. First, our estimates of the cost-effectiveness of education do lend support to the argument that investing in education is a relatively efficient way to improve population health, compared to other possible interventions. Although average educational attainment rose in the U.S. throughout the 20th century, there is still much room for improvement as over 25% of youths do not complete high school (Snyder, Dillow, and Hoffman 2009). In addition, because educational attainment is a key component of socioeconomic status, policies that aim to improve educational attainment among relatively low-education populations may have the effect of making progress toward the policy goal of reducing socioeconomic differences in health (U.S. Department of Health and Human Services 2000). Our estimates of the monetary value of the health gains due to more education may also have broader policy implications. Because individuals value health status highly, our results suggest that conventional estimates of the returns to education that focus solely on earnings are biased downwards. As noted by Cutler and Lleras-Muney (2008), that might provide some rationale for further public or private investments in schooling.

Conclusion

We find that under several econometric approaches, schooling is associated with more QALYs, implying that the value of the health returns to schooling is substantial. Our method of measuring health returns in terms of QALYs has some clear advantages, but places high demands on data. Very few surveys collect longitudinal data on health status along with mortality data. Even the PSID currently only allows a 23-year period of observation, although that will grow as the PSID continues collecting health status and mortality data. Nevertheless, our method is one way to improve quantifications of health status that are multidimensional and vary over time, and could be applied to studying the returns to health inputs other than education.

Notes

1. We imputed only up to six years of missing HRQL data between last recording of self-rated health and death. While this decision is somewhat arbitrary, we wanted to limit the number of years that we linearly interpolate health declines before death. Our empirical estimates of the health returns to schooling were not sensitive to imputing fewer years of missing data.

2. Out of concern for non-random attrition bias in the dependent variable, we constructed non-missing QALY data propensity weights for the full initial sample of 9,952 observations. These weights were the inverse of the probability of having a nonmissing QALY measure, which was predicted by education, age, race, and sex using logit. When we estimated our main models using these weights, the results were virtually identical to our main results, eliminating concern that our estimates suffer from attrition bias.

3. We tried estimating instrumental variables models using changes in compulsory schooling laws as an instrument. However, changes in compulsory schooling laws were very weak predictors of educational attainment for our sample, which would have led to inconsistent estimates of returns to schooling.

4. We did not impute these variables for individuals who entered into the PSID in later years by marrying an original family member.

5. This approach is more conservative than linear interpolation, since it assumes that health declines more rapidly at older ages, and it more plausibly matches health trajectories among adults ages 25-50 than linear interpolation. Using linear interpolation, our estimates in Table 4 are several thousand dollars greater.

6. A loss of precision is to be expected in this instance since the log-scale GLM residuals are heavy-tailed, and that is known to lead to precision losses in GLM relative to OLS (Manning and Mullahy 2001).

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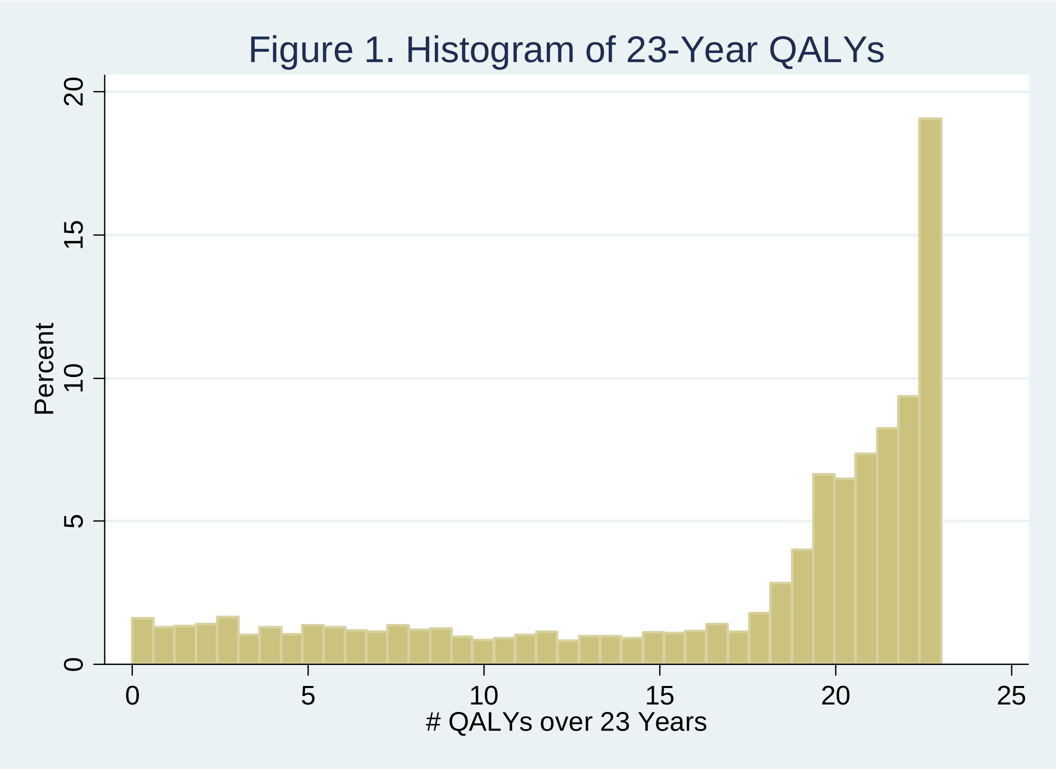

Figure 1. Histogram of 23-Year QALYs

Table 1. Sample Summary Statistics

Variable	Mean	SD	N
% died by 2007	0.328		6267
# QALYs	16.85	6.92	6267
# Life-Years	18.92	6.87	6267
Education	12.23	3.18	6267
Age	45.93	16.50	6267
Age-Squared	2381.32	1702.82	6267
Female	0.554		6267
White	0.687		6267
Black	0.272		6267
Hispanic-Latino	0.018		6267
Other Race	0.023		6267
Any health difficulty by age 18	0.014		6267
IQ Index	9.39	2.37	5453
Aspiration-Ambition Index	2.72	1.69	5453
Risk Avoidance Index	5.96	1.65	5453
Time Horizon Index	4.54	1.35	5453
Mother’s Education: less than HS	0.515		5453
Mother’s Education: HS or more	0.416		5453
Mother’s Education: don’t know	0.068		5453
Father’s Education: less than HS	0.605		5453
Father’s Education: HS or more	0.334		5453
Father’s Education: don’t know	0.061		5453
Parent’s Finances while growing up: Well Off	0.175		5453
Parent’s Finances while growing up: Average	0.381		5453
Parent’s Finances while growing up: Poor	0.411		5453
Parent’s Finances while growing up: Don’t know	0.033		5453

Table 2. OLS Models of Life-Years and QALYs over 23 Years

	(1) Life-Years	(2) QALYs	(3) Life-Years	(4) QALYs
Years of education	0.240***	0.377***	0.155***	0.248***
	(0.027)	(0.025)	(0.032)	(0.029)
Female	0.954***	0.562***	0.698***	0.355**
	(0.128)	(0.121)	(0.165)	(0.154)
Age in 1985	0.216***	0.0819***	0.253***	0.125***
	(0.026)	(0.025)	(0.030)	(0.028)
Age-squared	-0.004***	-0.003***	-0.005***	-0.004***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Black	-1.599***	-2.322***	-0.965***	-1.371***
	(0.178)	(0.169)	(0.225)	(0.209)
Hispanic/Latino	-0.637	-0.874*	-0.285	-0.290
	(0.524)	(0.529)	(0.545)	(0.554)
Other	-2.239***	-2.349***	-2.366***	-2.307***
	(0.512)	(0.480)	(0.603)	(0.559)
Any health limitation before 18	-1.663***	-2.581***	-1.446**	-2.189***
	(0.622)	(0.558)	(0.648)	(0.585)
Family Aspiration-Ambition Index			-0.128***	-0.120***
			(0.047)	(0.045)
Family IQ Index			0.101**	0.121***
			(0.042)	(0.039)
Family Risk Avoidance Index			0.334***	0.416***
			(0.055)	(0.054)
Family Time Horizon Index			-0.001	-0.005
			(0.060)	(0.057)
Mother’s Education: HS or more			-0.097	0.141
			(0.180)	(0.175)
Mother’s Education: don’t know			-0.900**	-0.762**
			(0.377)	(0.339)
Father’s Education: HS or more			-0.144	0.065
			(0.177)	(0.170)
Father’s Education: don’t know			-0.088	-0.265
			(0.350)	(0.315)
Parent’s Finances while growing up: Average			0.400**	0.416**
			(0.190)	(0.182)
Parent’s Finances while growing up: Poor			0.436**	0.144
			(0.218)	(0.206)
Parent’s Finances while growing up: Don’t know			0.573	0.533
			(0.449)	(0.428)
HH Head in 1968			-0.873***	-0.724***
			(0.233)	(0.217)
Constant	16.73***	16.60***	14.26***	13.59***
	(0.698)	(0.680)	(0.866)	(0.830)
Observations	6267	6267	5453	5453
R-squared	0.439	0.502	0.446	0.507

Heteroskedasticity-robust standard errors clustered on the family in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Sibling Fixed-Effect Models of Life-Years and QALYs over 23 Years

	(1) Life-Years	(2) QALYs
Years of education	0.046	0.199**
	(0.078)	(0.083)
Female	0.363	0.158
	(0.229)	(0.232)
Age in 1985	0.255	0.194
	(0.411)	(0.401)
Age-squared	-0.005	-0.005
	(0.006)	(0.006)
Whether any health limitation started before 18	-2.072	-2.509*
	(1.433)	(1.308)
Parent’s Finances while growing up: Average	0.210	0.0740
	(0.296)	(0.312)
Parent’s Finances while growing up: Poor	0.493	0.015
	(0.359)	(0.387)
Parent’s Finances while growing up: Don’t know	0.795	0.702
	(0.780)	(0.801)
Observations	2068	2068
R-squared	0.024	0.035

Heteroskedasticity-adjusted standard errors, clustered on the family, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Estimates of Present Discounted Value of Health Returns to Schooling

	(1) PDV (assuming QALY = $75,000)	(2) PDV (assuming QALY = $100,000)	(3) Cost-Effectiveness Ratio (assuming 1953-4 cost/pupil)	(4) Cost-Effectiveness Ratio (assuming 2005-6 cost/pupil)
OLS, limited covariates	$13,968	$18,624	$15,142/QALY	$62,624/QALY
OLS, extended covariates	$9,876	$13,168	$21,416/QALY	$87,572/QALY
Sibling Fixed Effects	$8,322	$11,096	$25,414/QALY	$105,107/QALY

Notes: All estimates apply a 3% discount rate to the health returns, with discounting starting at age 25.
The average per-pupil schooling costs used in columns 3 and 4 reflect schooling costs in the indicated years that are expressed in real 2009 dollars.
PDV, present discounted value; QALY, quality-adjusted life year