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The risk and return of human capital investments

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HIGHLIGHTS

- We estimate moments of lifetime income by level of education using a 22-year panel.
- We find large differences in mean lifetime income by education in Finland.
- We adjust mean differences for variance and skew.
- Adjusted differences are no smaller.

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ABSTRACT

Human capital investments increase lifetime income, but may involve substantial risk. In this paper we use a Finnish panel spanning 22 years to nonparametrically predict the mean, the variance and the skew of the present value of lifetime income, and to calculate certainty equivalent lifetime income at different levels of education. We find that university education is associated with about a half a million euro increase in discounted lifetime disposable income compared to vocational high school. Accounting for risk does little to change this picture. By contrast, vocational high school is associated with only moderately higher lifetime income compared to compulsory education, and the entire difference is due to differential nonemployment.

1. Introduction

As any other investment, investment in human capital involves risk. Education produces skills that have market value in a limited set of occupations. As the future demand for these skills is uncertain, students investing in education end up with a risky portfolio of specific skills. These risks are not insurable, and cannot be easily diversified.

The value of an investment depends both on its expected return and on its risk. Hundreds of studies have demonstrated that higher education is associated with higher income. Much less is known about the risks associated with investments in human capital.

Education may affect both the transitory and the permanent component of earnings. Risks associated with the year-to-year volatility of earnings can to some extent be smoothed through saving and borrowing, but risks related to the variation in lifetime earnings cannot. Since education is a long-term investment, with returns to investment distributed over the entire career, we argue that a natural measure of risk is the variability of lifetime income.

In this paper we measure the variability of lifetime income by estimating means, variances and skews of lifetime income by level of education. We use administrative data from Finnish registers where we can observe individual earnings over 22 years — a substantial fraction of careers, though not entire lifetimes.

According to our estimates, higher education is associated with a higher mean, a higher variance and a higher skew of lifetime income. For a risk averse person, a higher variance decreases the value of education. The effect of skew is not discussed as often, but commonly used

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utility functions imply that holding other moments equal, a more positive skew, results in a higher level of utility. For a given variance, a higher skew implies that a larger part of the risk is upside risk. Empirical evidence supports both variance aversion and skew affection (e.g. Golec and Tamarkin, 1998; Garrett and Sobel, 1999; Hartog, 2011). In this paper, we use CRRA utility functions with varying assumptions on the degree of risk aversion to convert the moments of income distributions into certainty equivalent present values of lifetime incomes at different levels of education.

We find that risk-adjusted returns to education are comparable to unadjusted ones. According to our estimates, certainty equivalent lifetime earnings are about twice as large for university graduates as for vocational high school graduates, irrespective of whether we adjust for risk or not. Accounting for taxes and transfers by using disposable income instead of earnings reduces the returns to education, but even certainly equivalent lifetime disposable incomes are 60 to 80% higher for university graduates than for vocational high school graduates. On the other hand, the differences between vocational high school graduates and those with compulsory schooling only are much smaller, and are mainly due to the difference in non-employment risk rather than to the differences in the earnings distribution among those who are employed.

Our paper is related to multiple strands of literature. The risk/return trade-off has been evaluated in a compensating differentials framework at least since King (1974). Typically, the approach involves adding measures of variance to a log earnings regression. Hartog (2011) provides a recent survey of this literature. Among the alternative approaches are Pereira and Martins (2002), who examine the risk and return of education using quantile regression, Christiansen et al. (2007), who compare the risks and returns across different fields of education, and Harmon et al. (2003), who model the return to education using a random coefficient model. Because of our lifetime perspective, our paper is also related to papers which compare annual and lifetime income distributions (e.g. Björklund, 1993; Bönke et al., 2012), as well as to papers that evaluate the effect of education on lifetime earnings e.g. (Bhuller et al., 2011).

In a recent paper, Brown et al. (2012) also evaluate certainly equivalent gains from education after accounting for risk preferences, earnings volatility and progressive taxation. The key difference between their study and ours is that they use a time separable utility function and evaluate the sum of utilities at each age, while we directly evaluate the utility of lifetime income. Essentially, Brown, Fang, and Gomes assume that individuals are credit constrained while our approach assumes that there are no restrictions on saving and borrowing. One of the benefits of our approach is that it allows us to account for years with zero or negative income, e.g. while in school.

The analysis presented in this paper is descriptive in nature, and we do not attempt to uncover the causal effects of education on the distribution of earnings. We make no effort to distinguish between risk and heterogeneity, except by repeating the analysis for a smaller subsample where we can control for cognitive test scores and parents' level of education. Recent efforts to disentangle unobserved heterogeneity from uncertainty in residual earnings have resulted in conflicting conclusions (Cunha and Heckman, 2007; Chen, 2008; Mazza et al., 2013). Without suitable instruments we have little to add to this debate.

It would be straightforward to repeat our calculations by field of education to avoid mixing heterogeneity across fields with uncertainty in field-specific outcomes. In this paper, we are however primarily interested in aggregate comparisons across levels of education and follow a long tradition in economics of education examining differences across levels rather than across fields of education.

In short, we add to the literature in a number of ways. First, we estimate the effect of education on the variance of income in a lifetime perspective where previous papers have typically used considerably shorter horizons. Second, in addition to the variance, we also account for the skew in the earnings distribution, separating upside risk from downside risk. Since our method is largely nonparametric, we do not have to log income measurements, and can therefore include zeros in the calculations of all three moments. Third, we account for employment risk and social insurance. Our approach makes it easy to deal with issues such as duration of education and early retirement, as these can be directly observed from the data.

2. Data

We use the person file from the Finnish Linked Employer–Employee Data (FLEED) compiled by Statistics Finland. FLEED contains a one third random sample of individuals residing in Finland at any point between 1988 and 2009. Individuals are present in the data in each year that they are registered in the Finnish population register, and individual information can be linked across years using person identifiers.

FLEED includes information on the highest educational degree completed for each individual each year. These data are based on reports by educational institutions to Statistics Finland and contain information on the date and type of degree according to the Finnish Standard Classification of Education. We define the level of education as the highest level of schooling attained by age 30. The level of education at 30 cannot be observed for individuals who never turn 30 within the sample period. Furthermore, since we can only observe the date and the level of the highest educational degree the individual held during the years 1988–2009, education at 30 cannot be observed for individuals receiving their highest degree after turning 30, but before 1988. We therefore drop both groups from the sample.

Individuals who achieve a higher level of education typically also exit education at a higher age. Education thus involves an opportunity cost in terms of forgone income. A natural way to measure this cost is to include in our analysis the incomes of all educational groups from the end of compulsory education onward. We therefore retain yearly observations where the individual is as young as 16, even if most are still in school at this age, and even though we categorize individuals by their highest degree at 30.

Key income variables in the data are earnings, taxable income, and taxes paid. Income information is based on tax records. As most transfers are taxable in Finland, they are also included in the data. We compute disposable income by subtracting taxes from taxable income. We use gross taxable lifetime earnings and disposable lifetime income as the primary outcomes of interest in our analysis.

All monetary variables in FLEED are top-coded at a nominal level of EUR 200,000 throughout the years. Because censoring affects less than 0.06% of yearly observations, the effect of censoring on mean lifetime income is negligible. The higher moments are however more sensitive to censoring. We alleviate this problem using data on taxes. Because tax information is censored at the same nominal level as income variables, we can impute incomes for the observations that have censored incomes but uncensored tax variables using average municipal tax rates and municipal taxes paid. Imputation of high incomes below the censoring threshold shows that the accuracy of this method is more than satisfactory. Less than 0.002% of observations have censored municipal tax amounts, and for these we use the imputed amount at the municipal tax censoring threshold.

While municipal and church taxes are reported consistently in the data, state taxes are reported only in some years. To ensure that tax treatment is comparable across years, we impute state taxes for all years by applying each year's tax schedule to that year's taxable earnings. A comparison with the years for which state tax information is available shows that actual tax amounts are very close to those predicted by the tax schedule.

To make monetary variables comparable across time, we deflate all money amounts to 2009 prices level using the cost of living index from Statistics Finland. On top of that, we account for real earnings growth by deflating with an additional 2% per year, a figure that comes close to average real earnings growth both over the sample period and over longer time frames. In this way, we remove trend growth in