The Risk and Return of Human Capital Investments

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April 9, 2013

Abstract

Investing in human capital increases lifetime earnings, but these investments may involve substantial risk. In this paper we use panel data spanning over 22 years to predict the mean, the variance and the skew of the present value of lifetime earnings and to calculate certainty equivalent lifetime incomes in different levels of education. We find that university education is associated with about a half a million 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 incomes compared to compulsory education, and the entire difference is due to differential nonemployment.

1 Introduction

Hundreds of studies have demonstrated that higher education is associated with higher income. The estimates of the private rate of return to investments in education vary across countries and over time but are usually between 5 and 15 percent. (See e.g. Ashenfelter, Harmon & Oosterbeek, 1999; Card, 2001).

Much less is known about the risks associated with investments in human capital. Education can be considered as a risky investment because the variance of earnings is generally increasing in the level of education. On the other hand, the unemployment rate is inversely correlated with the level of education indicating that education is also an insurance against uncertain job prospects.

The risks involved in human capital investments can be measured at various frequencies. Education may affect both the transitory and the permanent component of earnings. In this paper we argue that since education is a long-term investment, a natural measure of risk is the variability of lifetime income.

We therefore estimate means, variances and skews of lifetime incomes conditional on education based on Finnish 22-year panel data. According to our estimates, university education is associated with higher mean, higher variance and higher skew in lifetime earnings. If individuals are risk averse, a higher variance reduces the value of education. However, commonly used utility functions also imply that for the same level of variance, higher skew increases the value of education. There empirical evidence supporting both variance aversion and skew affection (e.g. Golec & Tamarkin, 1998; Garrett & Sobel, 1999; Hartog, 2011). In the calculations presented in this paper we assume that utility funtion displays constant relative risk aversion (CRRA) and find that the risk-adjusted returns are comparable to unadjusted ones. According to our estimates, certainty equivalent labor income roughly doubles between vocational high school and university whether adjusting for risk or not. Disposable income increases by roughly two thirds to three quarters.

Our paper is related to multiple strands of literature. A number of papers starting with King (1974) and reviewed in Hartog (2011) estimate risk compensating earnings differentials between fields of education or occupations by including the variance and the skew of earnings in a log earnings regression. Risk averse individuals should demand higher wages if the variance of earnings in their occupation is high and accept lower wages in occupations where earnings have higher skew. In this literature, the risk measures are usually based on the residual variance of annual earnings after controlling for schooling and age or experience. Some related papers measure the effect of ducation on the distribution on earnings using quantile regression (Pereira Martins, 2002) or model the effect of education using a random coefficient model (Harmon et al., 2003).

More recently, there have been efforts to disentangle unobserved heterogeneity from uncertainty in residual earnings. Chen (2008) decomposes the residual variance of earnings into unobserved heterogeneity and uncertainty or risk. According to her model, observed variance in earnings on one hand underestimates the effects of education on inequality because of selection into schooling. On the other hand, not all inequality is risk, as individuals may have private information on their future wages. Risk may thus be either higher or lower than observed inequality. Chen finds that risk is increasing between some levels of education but decreasing between others.

Mazza, van Ophem & Hartog (2011) try to replicate Chen's methods using the same data, but find risk profiles that rise much more strongly in education. More importantly, they find that selection into schooling increases rather than decreases observed inequality. The same method applied to British data shows risk decreasing in education, while German data do not fit the model at all, and cannot be estimated. Cunha & Heckman (2007) survey a body of work by Heckman with various coauthors on uncertainty and heterogeneity in the returns to education. The authors find that over 50% of ex post variance is forecastable by individuals. The findings of Heckman and others stand in contrast with surveys indicating that students do poorly when asked to predict their own position in the future wage distribution within their level and field of education (Hartog 2011).

We conclude from the literature that whether unobserved heterogeneity can be separated from risk is still subject to considerable controversy. Observed residual variance can either over- or underestimate risk. In this paper, we do not attempt to identify private risks or identify the causal effects of education on the variance of lifetime earnings, but rather conduct a more descriptive analysis on the relationship between education and variability of lifetime income. Our possibilities to address selectivity issues in this paper are limited. However, for a subsample used in the analysis we can control for the cognitive test scores and parents' level of education. These controls shrink income difference between university and vocational high school graduates by 22% of the original difference. The reduction of certainly equivalent gains from education shrink with a similar proportion after adding these controls.

Most papers on risk in returns to education as well as papers on income dynamics use relatively short panels to decompose residual earnings variance into permanent and transitory parts. Among the exceptions are Björklund (1993) and Bönke, Corneo & Lüthen (2012), who compare distributions of annual and lifetime incomes. Bhuller, Mogstad & Salvanes (2011) measure the effects of earnings on directly observed lifetime earnings. Consistent with predictions by Haider & Solon (2006) they find that estimates of the return to education are sensitive to the age structure of the sample.

Our approach is most closely related to a recent working paper by Brown, Fang & Gomes (2012). There the authors analyze certainly equivalent gains from education accounting for risk preferences, earnings volatility and progressive taxation. They find that high school education is associated with higher lifetime earnings, reduced earnings volatility and lower risk of unemployment compared to less than high school. They also find that college graduates have higher lifetime earnings than high school graduates but college education is also associated with higher earnings volatility, reducing the value of education. Accounting for progressive taxation, unemployment insurance and social security further reduces the value of education.

While our basic approach is similar to that of Brown, Fang & Gomes, there are also some important differences. Brown, Fang & Gomes apply a standard time separable utility function to calculate expected lifetime utility. By contrast, we calculate the expected utility of discounted lifetime income. Hence we measure the risk related to human capital investments as the variation in lifetime earnings rather than period-specific volatility. Our approach also makes it easier to account for years with zero income, especially while in school and during other non-employment periods.

We add to the literature in a number of ways. First, we calculate the effect of education on the variance of income in a lifetime perspective where previous papers have typically used considerably shorter observation periods. Second, in addition to the variance, we also account for the skew in the earnings distribution, separating the upside risk from downside risks. Since our method is largely nonparametric, we do not have to log income measurements, and can therefore unproblematically include zeros in the calculations of 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 retirement age as these can be directly observed from the data.

2 Data

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

The key variables in the data contain information on the highest degree completed, on taxable earnings and on taxes paid. As most transfers are taxable in Finland they are also included in the data. All information is based on administrative registers. Educational attainment data are based on reports by schools to Statistics Finland and contains information on the date and type of degree according to the Finnish Standard Classification of Education. Information on earnings, taxes and transfers are based on tax records.

We restrict the sample to individuals aged 16–64 at the end of the calendar year. We define the level of schooling as the highest level of schooling achieved at age 30, and we therefore also have to exclude individuals who never turn 30 within the sample period. Furthermore, since we can only observe the date and level of the highest degree in the years between 1988 and 2009, we also have to exclude those who have received their highest degree after turning 30 but before entering the observation window because we do not know their highest degree at age 30. We focus on individuals with either compulsory education, vocational high school or a university degree as their highest level of education because these groups are comparably large, and the content of their degrees is consistent over time. We also discard immigrants by excluding persons who were citizens of a foreign country in any of the years that we have data on. The number of observations retained at each stage can be seen from Table 1. In total, we retain data 996471 individuals with on average about 17 yearly observations per individual.

Table 1: Sample selection.

	individuals	observations
between 16 and 64	1559554	22312681
excluding immigrants	1500141	21875181
schooling known	996471	16849188

Notes: the number of observations refers to the total number of yearly observations. The average number of years of data per individual in the final sample is thus about 17.

The age structure of the sample changes over time, and we need to make monetary variables comparable across time. To do this, we deflate all monetary variables to the 2009 level using the cost of living index from Statistics Finland. Since the cost of living was lower in earlier years, this effectively means inflating the earlier observations. 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 keep business cycle variation in the data while removing the average trend. Once observations have been made comparable across individuals, we add back 2% earnings growth to the moments of discounted lifetime income estimated below.

In this paper, we focus on labor income, which is reported directly in the data. All monetary variables in FLEED are top-coded at a nominal level of EUR 200 000 throughout the years. Because censoring affects less than 0.000522 of yearly observations, the effect of censoring on mean lifetime earned income is negligible. However, the higher moments are 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 taxes paid. Imputation of high incomes below the censoring threshold show that this method is accurate. Less than 0.000014 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 included 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 for all years. 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.

Table 2: Proportion of observations censored

	before imputation	after imputation
Taxable income	0.000521	0.000013
Labor income	0.000353	0.000011

We compare both lifetime earnings and lifetime disposable earnings across levels of education. We also separate earnings risks from employment risks by examining separately the subsample of individuals that are either employed or in school. An individual is included in this subsample when he or she is either registered as a student during the last week of the year, or is registered as employed during the last week, has not been unemployed for more than two weeks during the year, and whose annual real labor income has exceeded EUR 5000.

3 Schooling and Incomes in Finland

Finnish children start school at age 7. All children attend comprehensive school for nine years. At the age sixteen the students make first important choices regarding their education. Currently, about 45% of students continue to vocational secondary education that typically also takes three years to complete. After vocational school it is possible to continue at polytechnics or universities of applied sciences but for many, vocational school is their final education level.

The other 55% of students enter three year general secondary programmes ending in a matriculation exam which provides eligibility for tertiary education. In contrast to many other countries, university students are accepted directly to programs leading to a Master's level degree. University admission is competitive with less than half of applicants being admitted. Universities do not charge tuition fees and students receive relatively generous student grants.

Dropping out is common at all levels. Currently about 15% of thirty-year-olds have no education after compulsory school. In most cases these individuals have started in vocational education but never finished it. Dropping out of university is also common. In the data these persons are usually coded as having a general secondary education degree as the highest education level.

While the Master's level university education and secondary vocational education have remained reasonably similar over a long time, the structure of education has changed much more at other levels. For example, universities awarded Bachelor degrees in short university programs during the 1970s. In the 80s, thesse disappeared but in 90s they were re-created as vocational-oriented tertiary education at polytechnics. All these are coded as lower tertiary education degrees in the Standard classification of education but large changes in content make comparing cohorts born widely apart very difficult.

In this study we concentrate on comparisons between those with no post-compulsory education to those with vocational upper secondary education on the one hand and vocational upper secondary graduates to holders of Master's degrees on the other. These education levels are consistently coded across cohorts, and jointly make up a large share of individuals in each cohort.

As a first glance into the relationship between schooling and long-term income differences we plot the average annual incomes by the level of schooling in figures 1 and 2. In the figures we use data from the cohorts born between 1955 and 1964. For each individual in these cohorts we have calculated 22-year average income using data from the years from 1988 to 2009, and we display the 10th, 25th, 50th, 75th and 90th percentiles of these long-term average incomes. The figures also illustrate the size of the groups; the height of each box is proportional to the number of individuals at each education level.

As can be seen from the figures, compulsory education and vocational high school are the two largest education categories. With respect to earnings the Master's degree holders earn substantially more than vocational high school graduates, but vocational high school graduates do not make much more than those with compulsory school only. The figures also illustrate that the variance and the skew of long-term earnings are markedly larger for university graduates.

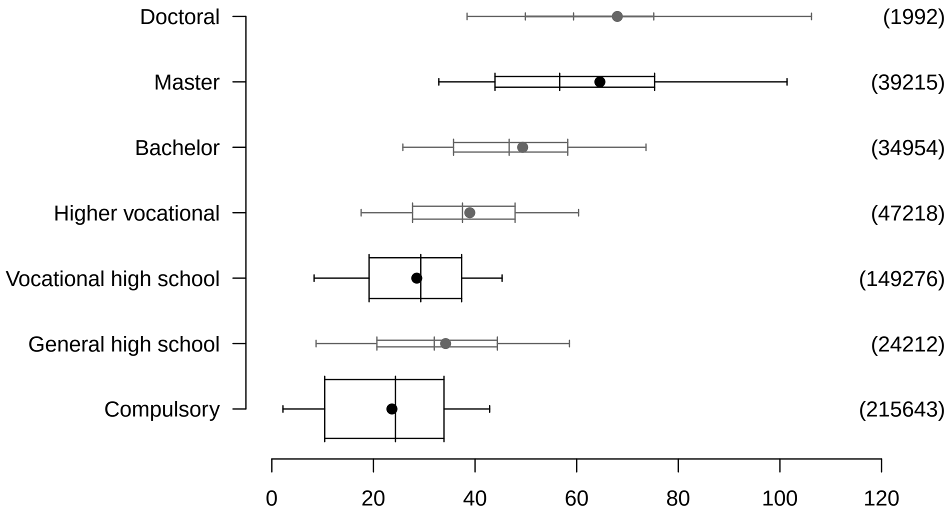

Figure 1: 10th, 25th, 50th, 75th and 90th percentiles of 22-year averages of annual labor incomes by education, men. Data cover cohorts born between 1955 and 1964. Earnings are observed from 1988 to 2009. The horizontal axis is in thousands of 2009 EUR. Dots indicate means. The heights of the boxes are proportionate to the number of individuals in the sample, which also have been added within parentheses on the right hand side of the figure. Boxes in grey indicate levels of education not used in the analysis.

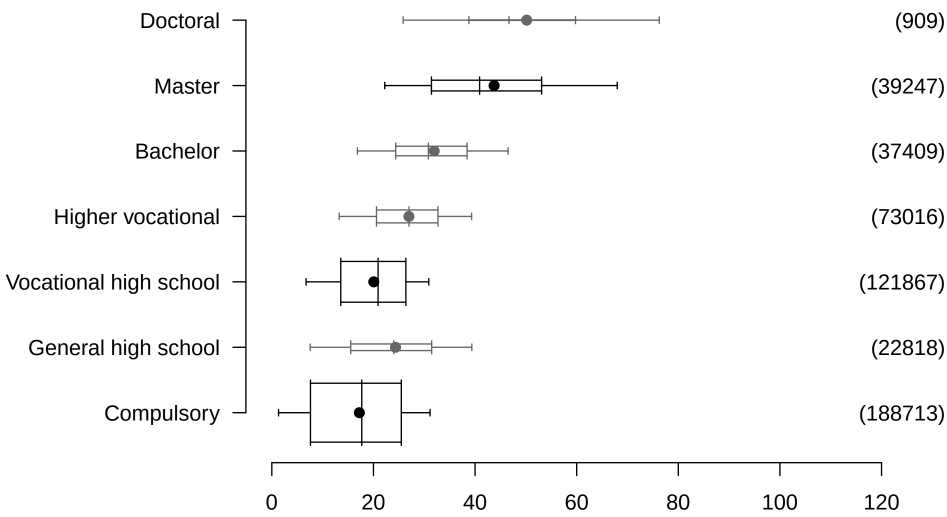

Figure 2: 10th, 25th, 50th, 75th and 90th percentiles of 22-year averages of annual labor incomes by education, women. See Figure 1 for details.

4 Methods

The relationship between education, age and mean earnings can be estimated based on a cross-section from a single year, and thus place relatively low requirements on the data. Calculating the variance of lifetime earnings is more demanding as it not only requires information about the variance of earnings at each age, but also about the covariance of earnings between different ages. Data sets spanning entire lifetimes are rare, but there are several data sets that span one or more decades. We demonstrate that such data can still be used to nonparametrically estimate the distribution of lifetime earnings in a straightforward manner. We do this in a way that accounts for the risk of having no earnings and does not impose strong assumptions on the shape of age-earnings profile, length of schooling or working life, nor on the relationship between age and variance of earnings.

We make two simplifying assumptions: that cohort effects can be ignored and that time effects can be accounted for by simple trends as described in the data section. Under these assumption the mean lifetime income for any exogeneously defined group can be nonparametrically estimated from cross-section or pooled panel data. Mean discounted lifetime income μ is simply the sum of the mean incomes w_t at each age t, discounted at rate r.

$$\mu = \mathbf{E}(Y) = \sum_{t=16}^{64} \frac{\bar{w}_t}{(1+r)^{t-16}}$$

In a similar way the variance of discounted lifetime income is the sum of the discounted elements of the variance covariance matrix describing the covariances cov of earnings between ages t and j.

$$\mathbf{E}[(Y-\mu)^2] = \sum_{t=16}^{64}\sum_{j=16}^{64} \frac{cov(w_t, w_j)}{(1+r)^{t-16}(1+r)^{j-16}}$$

For all the cells of the covariance matrix to be known, we would need a panel spanning over the length of working life, but in that case we could calculate the variance of lifetime incomes directly. For shorter panels, only part of the covariance matrix will be observed. In general, when estimating a covariance matrix ranging over A age groups with a panel of length N, $(A-N+1)(A-N)$ elements of the matrix will be unobserved. Since in our case $A = 49$ and $N = 22$, about 69% of the elements of the covariance matrix can be directly estimated. Fortunately these are also elements that make the largest contribution to the variance of lifetime earnings. The unobserved elements are small because the covarinces of earnings is the smaller the further away they are from the diagonal of the covariance matrix. Furthermore, discounting reduces the weight of missing elements.

We thus estimate nonparametrically covariances between residual incomes at age t and age $t+1$ through $t+N-1$, where N is the length of our panel. For the remaining correlations with residual income at higher ages, we impute it with the last covariance element that we could estimate, i.e. with the covariance of income at ages t and $t+N-1$. Under the assumption that covariances decrease monotonically from that point on, this will provide us with an upper bound of the missing covariances. As a robustness check, we repeat our analysis with imputed zeroes and with predictions from an AR(1) model instead. Because even at the upper bound only a small proportion of the total covariance is contained in the missing cells, these adjustments do not make a large difference in the results.

This method is easily extensible to higher moments, though the proportion of missing cells increases each time. For example, the skew of lifetime income is given by the sum of the discounted elements of the skew coskew tensor.

$$\mathbf{E}[(Y-\mu)^3] = \sum_{t=16}^{64}\sum_{j=16}^{64}\sum_{k=16}^{64} \frac{coskew(w_t, w_j, w_k)}{(1+r)^{t-16}(1+r)^{j-16}}$$

Because coskews drop off quickly away from the main diagonal, we make no attempts at imputing missing coskews, but simply set them to zero. This part of the analysis is also computationally intensive, since the skew coskew tensor has 49^3 cells for a working life of 49 years.

After having obtained the mean, variance and skew of lifetime income, we can enter them into an arbitrary utility function U in order to compress them into a single figure. We use the constant relative risk aversion family of utility functions, which is given by

$$\begin{aligned} &\frac{1}{1-\rho}Y^{1-\rho}, \qquad \rho \neq 1 \\ &\ln(Y), \qquad \rho = 1. \end{aligned}$$

where Y is lifetime income, and ρ the coefficient of risk aversion. Because we cannot observe the actual distribution of lifetime incomes, but have estimates of its moments, we follow Hartog (2011), and instead use a third order Taylor approximation of the utility function, into which we can substitute the first three moments of lifetime income.

$$U(Y) \approx U(\mu) + \frac{1}{2}(Y-\mu)^2U''(\mu) + \frac{1}{6}(Y-\mu)^3U'''(\mu)$$

With utility levels in hand, we can compute the certainty equivalent level of lifetime income (CE), which is the certain level of lifetime income which would yield the same expected utility as a risky draw from the estimated distribution of lifetime incomes.

$$Y^{CE} = U^{-1}[\mathbf{E}(U[Y])]$$

Instead of calculating certainty equivalent values at a fixed discount rate, it is also possible to calculate the discount rate at which the net present values for two levels of education are equal. This discount rate is closely related to commonly used internal rates of return or IRRs, but here defined over utilities instead of earnings so that it also accounts for risk.

$$\mathbf{E}[U(Y[r])]_{s=1} = \mathbf{E}[U(Y[r])]_{s=0}$$

Rates of return need not be unique, and so we perform a numerical search for the lowest positive discount rate just below which the higher level of education has the higher expected lifetime utility, and just above which the lower level of education has the higher expected lifetime utility. While none of the cases shown below have infinite rates of return, there are cases in which the lower level of education gives a higher expected lifetime utility level for any positive discount rate. When internal rates of return are very high, they effectively only take income at young ages into account. We therefore prefer to use CEs in our main analysis, and report only a subset of results as IRRs. Conclusions based on IRRs are however qualitatively similar.

We calculate the moments of lifetime income separately for men and women for three levels of education (compulsory, vocational high school, university). We also present separate estimates for labor income and disposable income and separate estimates for the employed only. We then calculate CEs for with different levels of risk aversion using both a second and a third order Taylor approximation. Finally, for the sake of comparison, we calculate IRRs for a subset of these combinations as well as a set of OLS estimates return to education based on Mincer equations.

4.1 Calculating standard errors

Calculating standard errors analytically for complicated nonlinear functions of experssions involving for example a $49 \times 49 \times 49$ skew coskew tensor is difficult. Bootstrapping would provide a simple solution but calculating hundreds of thousends of coskews on millions of observations would require much more computing power than what we have available, and hence is not a realistic option for us.

Instead, we follow Politis, Romano & Wolf (1999), and repeatedly draw (without replacement) 200 subsamples with 10 000 individuals in each subsample from each education×gender group of our original sample. We calculate all of our statistics from each draw. The standard deviation of the estimates from these 200 replications provides us a conservative estimate of standard error in the original sample. Assuming that our estimates converge at a rate of $\tau_n = n^{-0.5}$ we can then multiply the standard errors obtained from the subsample standard deviations by $b^{0.5} \cdot n^{-0.5}$, where b is the subsample size and n is the sample size for each education×gender group in the main sample. Tables with undeflated standard errors can be found in the appendix.

We also report standard errors for the differences in certainty equivalents between levels of education. Since these estimates of the certainty equivalents are independent by construction, these standard errors are simply given by

$$\sqrt{\hat{se_h^2} + \hat{se_l^2}},$$

where $\hat{se_h^2}$ and $\hat{se_l^2}$ are the estimated standard errors of the certainty equivalent lifetime incomes of the higher and lower level of education respectively.

5 Results

5.1 Moments and certainty equivalent income

In Figure 3 we plot our estimated age-earnings profiles. These earnings are discounted to 2009 price and real wage levels, but are otherwise simple arithmetic averages of earnings by age and education. Note that zero-earnings observations have been retained in the data used for calculating these averages.

From the figures we can confirm the conclusion from earlier Figures 1 and 2 that the university educated earn substantially more than those at the two other education levels, but that the differences between workers with vocational and workers with only compulsory education are not very large. Income for compulsory school graduates is initially slightly higher than for vocational school graduates, but that vocational school graduate incomes quickly overtake compulsory school graduate incomes. University graduates catch up with vocational school graduates after a few more years.

Figure 3 also shows that income is substantially higher than zero at ages when most individuals are still at school. This suggests that forgone earnings while at school do not seem to be very large, making education look less costly. After graduation the earnings of university graduates incresae rapidly. The growth of earnings among university graduates is much faster in both absolute and relative terms than at lower levels of education. The downward sloping part of the curves indicates early retirement, and the low levels of earnings at age 64 illustrate that we are not missing all too much labor income by ending the observation period to age 64.

Figure 4 shows the estimated covariances of labor income between difference ages for university educated men. On the diagonal we find the variances for labor income at each age. The variance is the highest at high ages when some men are retired while others still have high labor incomes. The volume under the lines represents the (undiscounted) variance of lifetime income. As can be seen from the figure, the missing covariances are only a small proportion of the total variance of lifetime income.

The coskews with age 40 labor income of university educated men have been plotted in Figure 5. Again, these are based on 2009 wage and price levels, and are thus not taking into account either discounting or real wage growth. The shown plane is one of 49 possible cross-sections of the skew coskew tensor. As can be seen from the figure, the coskews drop off quickly. We therefore feel confident in imputing the missing coskews with zeroes.

Table 9 shows the estimated moments of lifetime income. Looking at the results for the entire sample in the top two panels of the table, we see again that mean lifetime income is much higher for university graduates than for the other two categories. The coefficient of variation follows a U-shaped pattern, being lowest for vocational high school graduates. The skews are clearly higher for the university educated than for the other categories. The moments of lifetime income are predictably smaller after taxes and transfers. Finally, all moments are smaller for women than for men, but overall patters are similar across genders.

In the bottom two panels, we see the same measures calculated on a sample only including observations where the individual is either in school or working full time. Compared to the full sample, the coefficient of variation of lifetime income decreases and the relative skew increases quite substantially for the lowest two levels of education. More strikingly, compulsory school graduates have higher mean discounted lifetime incomes than those graduated from vocational high school once we condition on employment.

In Table 10, we combine the moments of lifetime income in different ways to

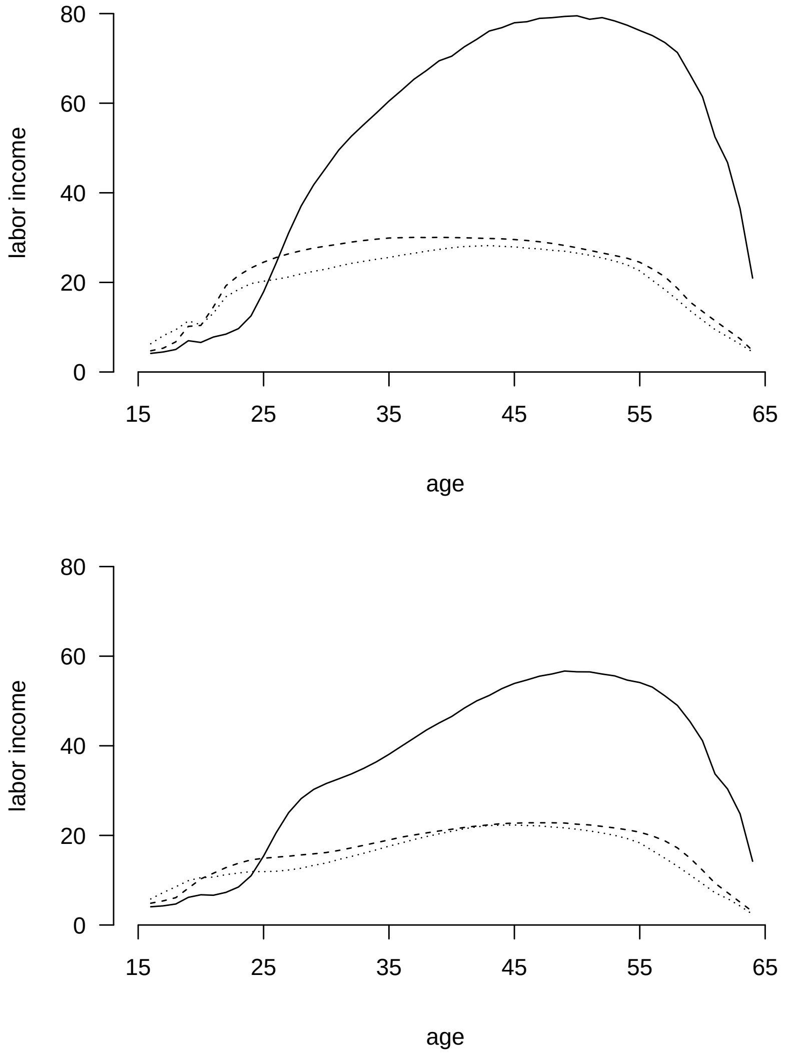

Figure 3: Cross-sectional labor income profiles in '000 EUR for university education (solid line), vocational high school (dashed line) and compulsory education only (dotted line): men (top panel) and women (bottom panel).

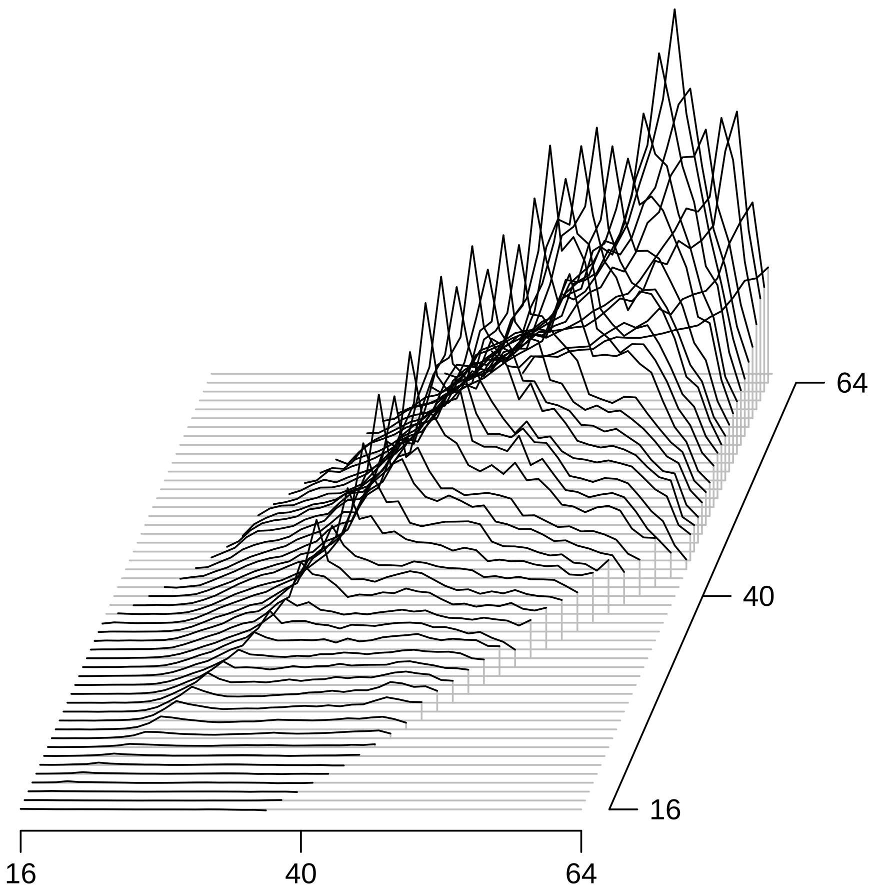

Figure 4: Covariances of residual labor income for university educated men. The volume under the lines represents the variance of lifetime income.

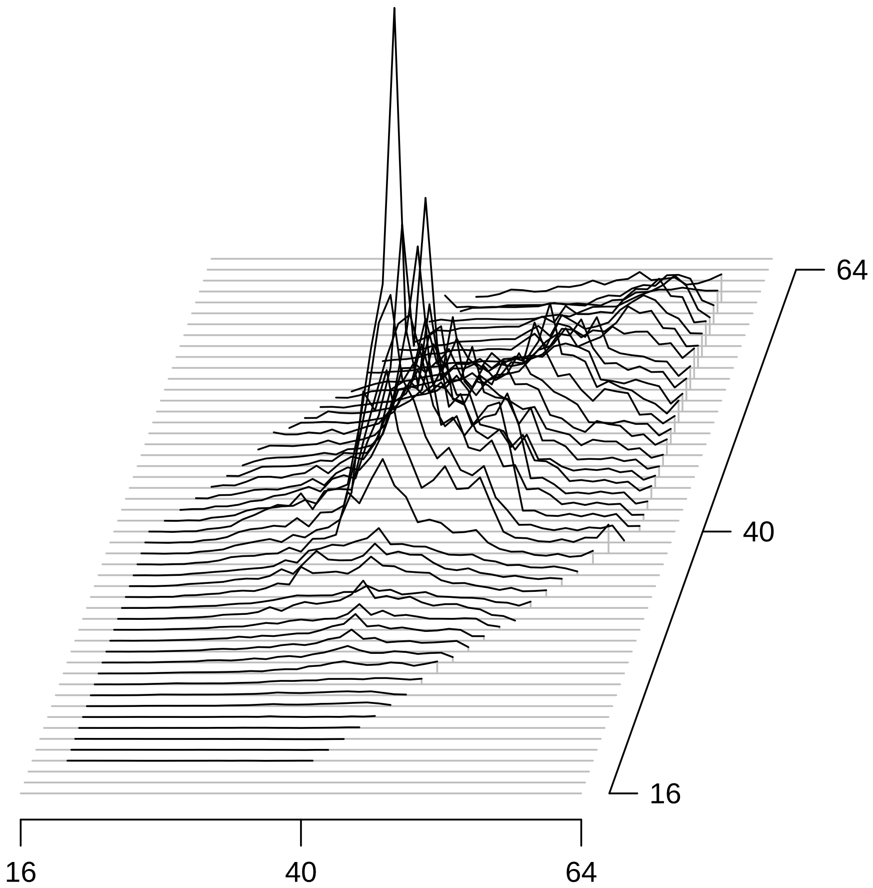

Figure 5: Coskews of residual labor income for university educated men. Shown is the cross-section of the skew coskew tensor at age 40. The joint volumes under the plots of the 49 possible cross-sections represent the skew of lifetime income.

arrive at certainty equivalent lifetime incomes. When assuming a coefficient of relative risk aversion ρ equal to 0, we are effectively calculating mean discounted lifetime income. When increasing the coefficient of relative risk aversion, the variances and skews of lifetime income gain in weight. As we saw before, university education is associated with substantially higher lifetime income than vocational high school. The difference is about one million euros for male labor income and about 700 thousand euros for female labor income. After taxes and transfers, these numbers are somewhat smaller, but still sizable at roughly 600 thousand euros and 400 thousand euros respectively.

One might think that the differences in mean lifetime incomes between university and vocational high school graduates are in fact compensating differentials for the higher variability of lifetime income for university graduates. After all, the coefficient of variation of lifetime income is higher for university graduates than for vocational high school graduates. However, when we look at the differences in CEs for higher levels of risk aversion, we see that they remain largely unchanged. This is because while variance enters the utility function negatively, skew enters it positively.

We have also calculated CEs based on means and variances only using a second order Taylor approximation of the utility function. These estimates can be found in Table 11. When we omit the skew, the differences between university and vocational high school graduates are indeed lower at higher levels of risk aversion, though still substantial. This illustrates how important it is to control for both variance and skew when evaluating risk. The higher variance for university graduates reflects a larger proportion of individuals with very high incomes but not a higher proportion of individuals with very low incomes. This higher variability is thus not detrimental to expected utility.

When we turn to the differences in CEs between compulsory and vocational high school graduates, we see differences in CEs that increase in the coefficient of relative risk aversion. This is an indication of the more attractive risk profiles that vocational high school graduates have. The differences in CEs conditional on employment turn negative. This suggests that the higher CEs for vocational high school graduates is due to differential employment. An interesting observation is that while taxes and transfers are a net working life loss for most individuals, the mean disposable lifetime income of women with compulsory education is higher than their mean lifetime labor income.

Table 3: Moments of discounted lifetime income.

	men, entire sample								
	Compulsory			Vocational HS			University		
	mean	CV	skew	mean	CV	skew	mean	CV	skew
labor income	798	0.55	0.50	886	0.46	0.52	1914	0.52	2.59
	2	*0.00*	*0.05*	*2*	*0.00*	*0.11*	*8*	*0.01*	*0.18*
disposable income	714	0.33	0.55	756	0.29	0.44	1311	0.39	2.48
	1	*0.00*	*0.07*	*1*	*0.00*	*0.12*	*4*	*0.00*	*0.16*
	women, entire sample								
	Compulsory			Vocational HS			University		
	mean	CV	skew	mean	CV	skew	mean	CV	skew
labor income	586	0.53	0.24	637	0.42	0.14	1327	0.45	1.61
	1	*0.00*	*0.03*	*2*	*0.00*	*0.02*	*6*	*0.00*	*0.19*
disposable income	598	0.28	0.24	614	0.24	0.15	1005	0.31	1.59
	1	*0.00*	*0.02*	*1*	*0.00*	*0.02*	*3*	*0.00*	*0.17*
	men, employed or in school								
	Compulsory			Vocational HS			University		
	mean	CV	skew	mean	CV	skew	mean	CV	skew
labor income	1205	0.29	1.68	1193	0.28	1.53	2120	0.47	2.78
	2	*0.00*	*0.18*	*4*	*0.00*	*0.26*	*9*	*0.01*	*0.18*
disposable income	878	0.23	1.60	884	0.22	1.06	1383	0.37	2.66
	1	*0.00*	*0.21*	*2*	*0.00*	*0.25*	*5*	*0.00*	*0.16*
	women, employed or in school								
	Compulsory			Vocational HS			University		
	mean	CV	skew	mean	CV	skew	mean	CV	skew
labor income	934	0.24	1.05	893	0.22	0.86	1511	0.39	2.08
	1	*0.00*	*0.12*	*2*	*0.00*	*0.07*	*7*	*0.01*	*0.20*
disposable income	738	0.19	0.62	718	0.17	0.45	1076	0.29	2.12
	1	*0.00*	*0.05*	*1*	*0.00*	*0.04*	*4*	*0.00*	*0.20*

Notes: Means are in '000 EUR. The coefficient of variation CV is defined as the standard deviation divided by the mean. The measure of skew reported is the third moment about the mean divided by the third power of the standard deviation.

Table 4: Certainty equivalent lifetime income, third order Taylor approximation.

	men, entire sample								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	798	705	654	886	811	764	1914	1889	2121
	2	*2*	*4*	*2*	*3*	*6*	*8*	*14*	*37*
difference				88	106	110	1029	1078	1357
				3	*4*	*7*	*9*	*14*	*37*
disposable income	714	680	655	756	727	704	1311	1276	1305
	1	*1*	*1*	*1*	*1*	*2*	*4*	*5*	*9*
difference				42	47	49	555	549	601
				2	*2*	*2*	*4*	*5*	*9*

	women, entire sample								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	586	515	471	637	586	547	1327	1260	1258
	1	*2*	*2*	*2*	*2*	*2*	*6*	*7*	*14*
difference				51	70	76	690	674	711
				2	*2*	*3*	*6*	*7*	*14*
disposable income	598	576	557	614	596	581	1005	973	958
	1	*1*	*1*	*1*	*1*	*1*	*3*	*3*	*4*
difference				15	21	25	391	376	377
				1	*1*	*1*	*3*	*3*	*4*

	men, employed or in school								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	1205	1170	1154	1193	1160	1142	2120	2092	2285
	2	*2*	*4*	*4*	*3*	*5*	*9*	*13*	*31*
difference				-12	-10	-12	927	932	1143
				4	*4*	*7*	*10*	*13*	*32*
disposable income	878	860	849	884	866	853	1383	1351	1382
	1	*1*	*2*	*2*	*2*	*2*	*5*	*5*	*9*
difference				6	6	4	499	485	529
				2	*2*	*3*	*5*	*6*	*9*

	women, employed or in school								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	934	913	896	893	875	860	1511	1459	1469
	1	*2*	*2*	*2*	*2*	*2*	*7*	*7*	*12*
difference				-41	-38	-36	618	584	609
				2	*2*	*3*	*7*	*7*	*12*
disposable income	738	726	716	718	709	700	1076	1050	1042
	1	*1*	*1*	*1*	*1*	*1*	*4*	*4*	*5*
difference				-20	-18	-16	358	341	342
				1	*1*	*2*	*4*	*4*	*5*

Notes: Values in '000 EUR, discounted to age 16 at $\delta = 0.03$. Utility is CRRA(ρ). Standard errors in italics.

Table 5: Certainty equivalent lifetime income, second order Taylor approximation.

	men, entire sample								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	798	685	612	886	798	733	1914	1669	1503
	2	*2*	*2*	*2*	*2*	*2*	*8*	*7*	*8*
difference				88	112	121	1029	872	770
				3	*3*	*3*	*9*	*7*	*8*
disposable income	714	676	643	756	725	697	1311	1215	1138
	1	*1*	*1*	*1*	*1*	*1*	*4*	*3*	*4*
difference				42	49	54	555	490	441
				2	*2*	*2*	*4*	*4*	*4*
	women, entire sample								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	586	509	457	637	584	542	1327	1199	1102
	1	*2*	*2*	*2*	*2*	*2*	*6*	*5*	*5*
difference				51	74	85	690	615	560
				2	*2*	*2*	*6*	*5*	*5*
disposable income	598	575	554	614	596	580	1005	957	916
	1	*1*	*1*	*1*	*1*	*1*	*3*	*2*	*2*
difference				15	21	26	391	361	336
				1	*1*	*1*	*3*	*3*	*3*
	men, employed or in school								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	1205	1154	1109	1193	1147	1107	2120	1895	1731
	2	*2*	*2*	*4*	*3*	*3*	*9*	*7*	*8*
difference				-12	-6	-2	927	747	624
				4	*4*	*4*	*10*	*8*	*8*
disposable income	878	855	833	884	863	844	1383	1291	1215
	1	*1*	*1*	*2*	*2*	*2*	*5*	*4*	*4*
difference				6	9	11	499	427	371
				2	*2*	*2*	*5*	*4*	*4*
	women, employed or in school								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	934	908	885	893	872	853	1511	1399	1309
	1	*1*	*2*	*2*	*2*	*2*	*7*	*5*	*5*
difference				-41	-36	-32	618	527	456
				2	*2*	*2*	*7*	*6*	*5*
disposable income	738	725	713	718	708	699	1076	1032	993
	1	*1*	*1*	*1*	*1*	*1*	*4*	*3*	*3*
difference				-20	-17	-15	358	324	295
				1	*1*	*2*	*4*	*3*	*3*

Notes: Values in '000 EUR, discounted to age 16 at $\delta = 0.03$. Utility is CRRA(ρ). Standard errors in italics.

5.2 Internal rates of return

In Table 6 we show a subset of the same results expressed in internal rates of return instead of in certainty equivalent income. Just as in the comparison of certainty equivalent income, we see that education is associated with a high internal rate of return for university. The returns to vocational education are now about as high as those to university (except for women when looking at disposable income) because at discount rates this high, incomes at higher ages are effectively ignored and the income differences between vocational education and compulsory education are more marked at younger ages

We also see again that the return associated with vocational high school is due to differential employment. Except when looking at the disposable income of men, there is no positive discount rate below which vocational high school yields higher discounted lifetime income once we condition on employment.

We omit rates of return based on other levels of the coefficient of relative risk aversion, but qualitative conclusions are the same as those drawn from the comparison of certainty equivalent income.

Table 6: Internal rates of return

men	Vocational HS		University	
	all	employed	all	employed
labor income	0.25	N/A	0.20	0.15
disposable income	0.18	0.04	0.19	0.15
women	**Vocational HS**		**University**	
	all	employed	all	employed
labor income	0.21	N/A	0.24	0.16
disposable income	0.09	N/A	0.19	0.15

Notes: Based on CRRA(0) utility. Vocational high school is relative to compulsory education only. University is relative to vocational high school. N/A indicates that there is no positive discount rate at which the net present values are equal, yet below which the higher level of education has the higher net present value.

The IRRs we find for university education are large compared to Mincer rates of return typically found for Finland. These differences exist for a number of reasons. First, comparing vocational high school to university gives a higher return than comparing all levels of education simultaneously. Second, Mincer rates of return are based on the incomes of the employed only, while we use all individuals in our baseline specification. Third, the Mincer specification assumes either infinite working lives, or working lives of equal length for different levels of education. We use actual labor market participation. Fourth, the Mincer specification assumes schooling of a fixed length, with zero income while in school. We use actual incomes and actual education durations.

In Table 7 we have tried to bridge the gap between Mincer estimates and our IRRs to show that they are consistent, and to see how important various assumptions are. The first row shows the result of a fairly standard Mincer specification regressing log labor income of full time employed individuals with ten years of predicted experience on predicted years of schooling. At 0.08 for men and 0.06 for women, the estimates are comparable to what others have found before us.

In the second row we compare log labor income of university graduates and vocational high school graduates only. This increases the rate of return to 0.10 and 0.09 respectively. The return increases further to 0.13 and 0.14 respectively when we drop the full time employment restriction and replace all incomes under EUR 5000 with EUR 5000. This reflects the higher employment levels of university graduates.

In the fourth and fifth row we calculate IRRs based on the moments of lifetime income while setting income during predicted years in school as well as more than 40 years after predicted graduation to zero. The fifth row includes adjustments for real wage growth. The estimated rates of return in the fourth row are close to that of the Mincer estimate in the third. The 2% real wage growth added in the fifth row naturally adds 2% to the IRR.

In the sixth row we drop the restriction of identical working life lengths and include earnings more than 40 years after predicted graduation. The difference is negligible because earnings later in life are discounted heavily under high rates of return.

The seventh row shows our baseline IRR which also includes income earned during predicted years in school. Since early earnings are weighted heavily at this high rates of return, this further increases the return.

5.3 Selection on observables

Though moments of lifetime income are both academically interesting and policy relevant of their own, it would also be good to have an indication of how much of the differences in moments are due to selection. This is a difficult problem even if suitable instruments for estimating causal effect of education on mean earnings were available. Unfortunately, we do not have reliable instuments for this sample.

Table 7: A comparison of Mincer equations and IRRs

method	education	nonemployed	wage growth	working life	income in school	men	women
Mincer	All	Excluded				0.08	0.06
Mincer	HS vs Uni	Excluded				0.10	0.09
Mincer	HS vs Uni	Included				0.13	0.14
IRR	HS vs Uni	Included	none	40 years	None	0.14	0.15
IRR	HS vs Uni	Included	0.02	40 years	None	0.16	0.17
IRR	HS vs Uni	Included	0.02	Empirical	None	0.16	0.17
IRR	HS vs Uni	Included	0.02	Empirical	Empirical	0.20	0.24

Notes: Mincer equations regress log labor income on predicted years of schooling at 10 years of predicted experience. Internal rates of return are based on the moments of lifetime labor income for university and vocational high school graduates in the full sample. HS indicates vocational high school, Uni university education.

A partial remedy is that test scores from verbal, math and logical reasoning tests administered to conscripts is available for a small number of male cohorts. For these cohorts also information on parents' education is available. The length of the panel is also more limited in this subsample: earnings can be observed for the years 1995 through 2003.

We take the 1965 cohort, for which we observe highest education at age 30 as well as incomes at ages 30 through 38. We sum these yearly incomes to end up with a proxy of lifetime income, and take the first three moments of the summed incomes by education.

We then repeat this exercise, but regress summed income on the three test scores and their squares as well as on dummy variables for each level of paternal and maternal education. From this regression we take the squared and cubed residuals and regress them in turn on the same covariates. Because we cannot impute censored incomes in this data set, we instead censor residuals at the 99th percentile for each level of education.

We then predict mean summed incomes by education using the first regression, holding the covariates fixed at their mean levels in the population. From the second regression we predict the variance of summed incomes, and from the third the skew of summed incomes. We then recombine these predicted moments into certainty equivalent lifetime incomes like before, and scale them relative to the certainty equivalent lifetime income for vocational high school graduates.

The results can be seen from Table 8. Panel (a) shows the unconditional differences in certainty equivalent lifetime income reported earlier, but this time reported as the proportional premium over vocational education. Panel

(b) shows the premia when we restrict our sample to the years 1995–2003. These are close to each other.

In panels (c) and (d), we show unconditional risk premia using the method described above; in panel (c) for the FLEED data set and in panel (d) for the army sample. These estimates are also close to each other. The premia for university education are likely lower than in the full FLEED sample because this sample is observed at a younger mean age.

Panel (e) shows educational premia conditional on test scores and parental education. As expected, these are smaller, reflecting selection into education based on observable characteristics. Panel (f) shows how much of each premium is due to selection on observables. The mean difference between university and vocational high school incomes is 22% smaller when holding covariates constant. It is 21% smaller when looking at certainty equivalent income using the CRRA(1) utility function, and 17% smaller using CRRA(2). A similar proportion of income differences between vocational secondary school graduates and compulsory school graduates can be explained away using observed covariates.

These results show that while the differences in lifetime income distributions documented in this paper are probably partially due to selection into education, the impact of selection seems to be about equally large with or without risk adjustments. The fact remains that income differences by education are large in Finland, and that adjusting for risk does very little to change this. At the very least, this calls into question the popular Finnish belief that education is a risky investment.

6 Conclusions

Education is an investment that has a very long pay-off period. To assess the profitability of human capital investments both their return and the risks involved should be meausred over the entire payoff period. In practise such evaluation requires measures of level and variation of lifetime earnings. Data streching over entire lifetimes of indivuduals do not usually exist. However, the moments of lifetime earnings can be estimated in a reliable way based on much shorter panels. Panel data sapnning from ten to twenty years exist in many countries, in particular in countries where such data can be collected from administrative registers.

Using such data from Finland, we find large mean discounted lifetime income differences between university graduates and vocational high school gradu-

Table 8: Relative unconditional and conditional observed certainty equivalent lifetime incomes for three levels of risk aversion, proportional difference to vocational incomes. Men only.

ρ	0	1	2
(a) FLEED baseline, unconditional			
compulsory	-10%	-13%	-14%
university	+116%	+133%	+178%
(b) FLEED 1995-2003, unconditional			
compulsory	-14%	-20%	-23%
university	+119%	+132%	+160%
(c) FLEED 1995-2003, 1965 cohort, unconditional			
compulsory	-22%	-27%	-29%
university	+ 91%	+ 98%	+106%
(d) army sample 1995-2003, 1965 cohort, unconditional			
compulsory	-20%	-25%	-27%
university	+90%	+100%	+117%
(e) army sample 1995-2003, 1965 cohort, conditional			
compulsory	-15%	-20%	-21%
university	+70%	+79%	+97%
(f) proportion of premium due to selection on observables $= (d - e)/d$			
compulsory	0.25	0.20	0.22
university	0.22	0.21	0.17

ates of up to about a million euros. These differences persist in certainty equivalent values after adjusting for the variance and skew of incomes. Moments of lifetime income are predictably smaller after taxes and transfers, but the major part of the income difference remains.

When we compare lifetime incomes of vocational secondary graduates to the incomes of those with compulsory school only, we find only small income differences. After controling for employment, compulsory school graduates have higher discounted lifetime income. This suggests that vocational secondary education is mainly a hedge against nonemployment in Finland.

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Appendix

Undeflated standard errors

Table 9: Moments of discounted lifetime income.

	men, entire sample								
	Compulsory			Vocational HS			University		
	mean	CV	skew	mean	CV	skew	mean	CV	skew
labor income	798	0.55	0.50	886	0.46	0.52	1914	0.52	2.59
	8	*0.01*	*0.25*	*9*	*0.01*	*0.43*	*17*	*0.01*	*0.35*
disposable income	714	0.33	0.55	756	0.29	0.44	1311	0.39	2.48
	4	*0.01*	*0.33*	*5*	*0.00*	*0.48*	*8*	*0.01*	*0.32*
	women, entire sample								
	Compulsory			Vocational HS			University		
	mean	CV	skew	mean	CV	skew	mean	CV	skew
labor income	586	0.53	0.24	637	0.42	0.14	1327	0.45	1.61
	6	*0.01*	*0.11*	*6*	*0.01*	*0.08*	*11*	*0.01*	*0.37*
disposable income	598	0.28	0.24	614	0.24	0.15	1005	0.31	1.59
	3	*0.00*	*0.08*	*3*	*0.00*	*0.07*	*6*	*0.01*	*0.34*
	men, employed or in school								
	Compulsory			Vocational HS			University		
	mean	CV	skew	mean	CV	skew	mean	CV	skew
labor income	1205	0.29	1.68	1193	0.28	1.53	2120	0.47	2.78
	8	*0.01*	*0.82*	*14*	*0.01*	*1.00*	*18*	*0.01*	*0.36*
disposable income	878	0.23	1.60	884	0.22	1.06	1383	0.37	2.66
	4	*0.01*	*0.98*	*8*	*0.01*	*0.97*	*9*	*0.01*	*0.32*
	women, employed or in school								
	Compulsory			Vocational HS			University		
	mean	CV	skew	mean	CV	skew	mean	CV	skew
labor income	934	0.24	1.05	893	0.22	0.86	1511	0.39	2.08
	6	*0.01*	*0.51*	*6*	*0.01*	*0.23*	*14*	*0.01*	*0.39*
disposable income	738	0.19	0.62	718	0.17	0.45	1076	0.29	2.12
	4	*0.01*	*0.22*	*4*	*0.00*	*0.14*	*7*	*0.01*	*0.40*

Notes: Means are in ’000 EUR. The coefficient of variation CV is defined as the standard deviation divided by the mean. The measure of skew reported is the third moment about the mean divided by the third power of the standard deviation.

Table 10: Certainty equivalent lifetime income, third order Taylor approximation.

	men, entire sample								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	798	705	654	886	811	764	1914	1889	2121
	8	*11*	*19*	*9*	*12*	*22*	*17*	*28*	*73*
difference				88	106	110	1029	1078	1357
				12	*16*	*29*	*19*	*30*	*76*
disposable income	714	680	655	756	727	704	1311	1276	1305
	4	*4*	*6*	*5*	*5*	*7*	*8*	*10*	*18*
difference				42	47	49	555	549	601
				6	*7*	*9*	*10*	*11*	*20*

	women, entire sample								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	586	515	471	637	586	547	1327	1260	1258
	6	*7*	*8*	*6*	*6*	*7*	*11*	*13*	*27*
difference				51	70	76	690	674	711
				9	*9*	*10*	*12*	*15*	*28*
disposable income	598	576	557	614	596	581	1005	973	958
	3	*3*	*4*	*3*	*3*	*3*	*6*	*6*	*8*
difference				15	21	25	391	376	377
				5	*5*	*5*	*7*	*7*	*8*

	men, employed or in school								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	1205	1170	1154	1193	1160	1142	2120	2092	2285
	8	*10*	*19*	*14*	*13*	*20*	*18*	*26*	*62*
difference				-12	-10	-12	927	932	1143
				16	*17*	*28*	*23*	*29*	*65*
disposable income	878	860	849	884	866	853	1383	1351	1382
	4	*5*	*9*	*8*	*7*	*9*	*9*	*10*	*18*
difference				6	6	4	499	485	529
				9	*9*	*12*	*12*	*13*	*20*

	women, employed or in school								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	934	913	896	893	875	860	1511	1459	1469
	6	*7*	*8*	*6*	*6*	*6*	*14*	*14*	*24*
difference				-41	-38	-36	618	584	609
				9	*9*	*10*	*15*	*16*	*25*
disposable income	738	726	716	718	709	700	1076	1050	1042
	4	*4*	*4*	*4*	*4*	*4*	*7*	*7*	*9*
difference				-20	-18	-16	358	341	342
				6	*6*	*6*	*8*	*8*	*10*

Notes: Values in '000 EUR, discounted to age 16 at $\delta = 0.03$. Utility is CRRA(ρ). Standard errors in italics.

Table 11: Certainty equivalent lifetime income, second order Taylor approximation.

	men, entire sample								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	798	685	612	886	798	733	1914	1669	1503
	8	*8*	*9*	*9*	*9*	*9*	*17*	*13*	*15*
difference				88	112	121	1029	872	770
				12	*12*	*13*	*19*	*16*	*18*
disposable income	714	676	643	756	725	697	1311	1215	1138
	4	*4*	*5*	*5*	*5*	*5*	*8*	*7*	*7*
difference				42	49	54	555	490	441
				6	*6*	*7*	*10*	*8*	*9*

	women, entire sample								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	586	509	457	637	584	542	1327	1199	1102
	6	*7*	*7*	*6*	*6*	*7*	*11*	*9*	*10*
difference				51	74	85	690	615	560
				9	*9*	*10*	*12*	*11*	*12*
disposable income	598	575	554	614	596	580	1005	957	916
	3	*3*	*4*	*3*	*3*	*3*	*6*	*5*	*5*
difference				15	21	26	391	361	336
				5	*5*	*5*	*7*	*6*	*6*

	men, employed or in school								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	1205	1154	1109	1193	1147	1107	2120	1895	1731
	8	*7*	*9*	*14*	*13*	*13*	*18*	*14*	*15*
difference				-12	-6	-2	927	747	624
				16	*15*	*15*	*23*	*19*	*20*
disposable income	878	855	833	884	863	844	1383	1291	1215
	4	*4*	*5*	*8*	*7*	*7*	*9*	*7*	*8*
difference				6	9	11	499	427	371
				9	*8*	*9*	*12*	*10*	*10*

	women, employed or in school								
	Compulsory			Vocational HS			University		
relative risk aversion ρ	0	1	2	0	1	2	0	1	2
labor income	934	908	885	893	872	853	1511	1399	1309
	6	*6*	*7*	*6*	*6*	*6*	*14*	*11*	*10*
difference				-41	-36	-32	618	527	456
				9	*9*	*9*	*15*	*12*	*12*
disposable income	738	725	713	718	708	699	1076	1032	993
	4	*4*	*4*	*4*	*4*	*4*	*7*	*6*	*5*
difference				-20	-17	-15	358	324	295
				6	*6*	*6*	*8*	*7*	*7*

Notes: Values in '000 EUR, discounted to age 16 at $\delta = 0.03$. Utility is CRRA(ρ). Standard errors in italics.