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Abstract

This paper studies the causal effect of education on income uncertainty using a broad measure of income which encompasses unemployment risk. To accomplish this, the variance of residuals from a Mincer-type income regression is decomposed into unobserved heterogeneity (known to the individuals when making their educational choices) and uncertainty (unknown to the individual). The estimation is done using Finnish registry data. The marginal effect of having secondary or lower tertiary level education decreases income uncertainty. University level education is found to have a small positive marginal effect on income uncertainty. The effect of education on income uncertainty is roughly similar for men when compared to women, but income uncertainty is larger for men than for women regardless of education. Contrary to some results from the U.S., the role of unobserved heterogeneity is found to be very small.

JEL: C35, J31

Keywords: earnings uncertainty, unobserved heterogeneity, permanent variance, transitory variance

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1 Introduction

Return to education is perhaps the most widely studied causal relationship in contemporary economic literature. A central message from this literature is that measuring monetary return to education is complicated by endogenous selection. Endogenous selection arises simply from the fact that people who choose different levels of education levels are likely to differ from one another in some dimensions unobservable to the researcher. Neglecting this unobserved heterogeneity may potentially introduce a large bias.

Monetary uncertainty in return to education has received much smaller empirical attention. Since the return to education is not constant among individuals and materializes possibly only several years after the choice of education has been made, educational investment has an inherent uncertainty to it. Analogously to estimating mean returns to education, endogenous selection also complicates the estimation of uncertainty in monetary returns to education.

The measure of earnings uncertainty used throughout this paper is the variance of yearly income. For example, a direct comparison of income variances between university and high school educated people might give an incorrect picture of the effect of education on income variance, because we cannot observe counterfactual income streams of the same people with different education levels. Consequently, the observed variance of income may not be a good measure of uncertainty, because it is comprised of two distinct components: unobserved heterogeneity and uncertainty. The intuition for this dichotomy follows from private information: wage uncertainty, or risk, is the part of the wage variance, which is not foreseeable by the decision-maker.

Unobserved heterogeneity (due to, for example, individual ability, motivation and general taste for education), on the other hand, is the portion of the wage variance which is known to – and acted on by – the individual, but not observed by the researcher. The unobserved heterogeneity is intimately related to private information on potential returns to education possessed by individuals. For example, if a person knows that her personal return from a given education level is particularly high, she will most likely choose that level of education. Disentangling unobserved heterogeneity (which stems from private information) from true uncertainty from the point of view of the agent making the schooling decision is instrumental when studying income uncertainty.

The question of how education affects income uncertainty is also of policy relevance. If, for example, more educated agents face larger income uncertainty, risk-averse agents might choose less education than would be socially optimal. This would suggest that income transfers supporting higher education are socially beneficial. On the other hand, if the earnings differences within an education group can be explained by unobserved heterogeneity rather than uncertainty, there might be less room for insurance against uncertainty.

This paper studies two interrelated decompositions. First, I correct for self-selection by modeling the selection of education level. Second, I decompose the uncertainty of income into a permanent component, which reflects fixed characteristics of individuals and a transitory component, which reflects idiosyncratic shocks to income streams of individuals. The transitory component is allowed to vary by time and by education level.

I follow Chen (2008) who extends the framework of Roy (1951) into more than two sectors. Chen disentangles potential variance and unobserved heterogeneity from one another, while taking into account the fact that the selection of agents into educational categories is endogenous. Chen estimates her model using data on U.S. males. She finds that the uncertainty-education profile is U-shaped; the most and least educated individuals face the highest income uncertainty. In addition, according to her model, unobserved heterogeneity is estimated to be up to 20 percent of the total earnings uncertainty.

The dependent variable in Chen's paper is average hourly wage. Her approach disregards perhaps the most important source of earnings uncertainty; namely, the risk of unemployment. Instead of hourly wages, this paper studies yearly total taxable income, which, in addition to income from employment, includes unemployment benefits and other taxable transfers. This measure arguably gives a more complete picture of the income uncertainty related to a level of education. This is particularly relevant because international evidence suggests that differences in unemployment risks between education groups may be substantial (Guiso *et al.*, 2002) and have widened in recent decades (Acemoglu & Autor, 2011). Using total taxable income as the measure of income also mitigates the problem of endogenous selection into employment, as people are observed even if they are not working. The model presented in this paper is estimated using Finnish data. An attractive featur e of the Finnish tax code for the current purposes is that virtually all of the income transfers, including unemployment benefits, are taxable and are therefore observed.

I also depart from Chen's approach in another way. Namely, I estimate separate models for men and women. In most similar studies attention is limited to men, because female workforce participation in most countries has been much lower until recent years. Nonetheless, the female workforce participation in Finland has been similar to male workforce participation already from the 1990s, which warrants doing a similar analysis also for females. Furthermore, since both female education and female workforce participation has also increased internationally, I find that calculating comparable measures for males and females is also interesting in its own right from an international perspective. As a result, I am able to test whether there are differences in the amount of uncertainty in career paths between men and women.

To ensure that the schooling and income equations are jointly identified, an appropriate instrument, which affects schooling but does not appear in the income equation, is needed. I use local differences in supply of education proxied by the region of residence in youth as an instrument. Even though I am able to control for a wealth of family background and individual characteristics, endogeneity of the instrument can not be ruled out. It turns out, that even an analysis using a possibly endogenous instrument is informative.

The association between mean earnings and its variance has been studied, among others, by Palacios-Huerta (2003), Hartog & Vijverberg (2007), Diaz-Serrano *et al.* (2008) and Schweri *et al.* (2011). The aforementioned papers do not find any robust relationship between education group income means and variances. This may be related to the fact that none of these papers address the possible selection effects.

In addition, the current paper nests two other prominent research themes. First, I explicitly allow for heterogeneity in the return to education. In this sense, the approach of paper is related to models used to study heterogeneous returns to schooling (e.g. Aakvik *et al.* 2010 and Abadie *et al.* 2002). Second, the approach chosen here is related to Cunha & Heckman (2008), Cunha *et al.* (2005) and Cunha & Heckman (2007), all of which study how the private information of individuals is related to their choice of education, but do not discriminate between permanent and transitory components. The approach of Chen (2008) is also applied in Mazza & van Ophem (2010) and Mazza *et al.* (2011).

As a preview of the results, I find that income uncertainty decreases up to the tertiary level of education. University educated individuals face slightly larger earnings uncertainty compared to people with a tertiary level education. For men, however, this effect is not distinguishable from zero. In addition, men face higher income uncertainty in comparison to women regardless of their education levels. Moreover, the estimates for the role of unobserved heterogeneity are found to be very small compared to estimates from the U.S.

The rest of this paper is structured as follows: Section 2 presents the details of the Finnish schooling system. Section 3 introduces the empirical model. Section 4 presents the data used. Section 5 presents the first and second stage estimates. In addition, Section 5 studies the robustness of the results to relaxation of parametric assumptions. I present the uncertainty estimates, compare them to the results acquired using data from the U.S. and discuss how possible endogeneity of the instrument affects the interpretation of the results in Section 6. Section 7 concludes the paper.

2 Brief description of the education system in Finland

The Finnish system of education consists of three stages. The first stage is compulsory education (9 years), which gives eligibility to apply for a secondary education. Secondary education (3 years) is provided by academically oriented upper secondary and vocational secondary schools. After completing secondary education, people apply to tertiary education (3-5 years), which is offered in universities (master's level) and polytechnic colleges (lower tertiary level).

There are two stages of selection. First one takes place after comprehensive school when students are about 16 years old. Students have an opportunity to apply to an academically oriented upper secondary school or to a more practically oriented vocational school. The second stage of selection takes place when people apply for tertiary education. In addition to upper secondary school graduates, also vocational school graduates are allowed to apply for tertiary education.

Tertiary education is offered in universities and polytechnic colleges. The focus of universities is research whereas polytechnic colleges are more practically oriented. Graduates from polytechnics are able to apply to universities to continue their studies. There are no tuition fees at any level. In addition, a student benefit of roughly EUR 400 monthly is offered to students over 18 not living with their parents.

I use a categorical education measure, S_i, with four distinct categories to capture the salient features of the Finnish education system. Each individual i, is placed into one of the schooling categories, which are

- $S_i = 1$; compulsory education,
- $S_i = 2$; secondary education (both vocational and upper),
- $S_i = 3$; lower tertiary education,
- $S_i = 4$; university level education.

As the data does not allow me to identify dropouts, I classify people according to their highest completed level of education.

3 Empirical model

3.1 Model for potential incomes

This section introduces the empirical model used in this paper. The setup is adopted from Chen (2008). It is an extension of the classic Roy (1951) model into more than two sectors.

The stylized model consists of two periods. In the first period, individuals choose their levels of education according to their tastes. In the second period, they face a yearly income stream which depends on the level of education they have chosen and gets an income stream which depends on personal characteristics (both observed and unobserved) and education and time specific transitory and permanent shocks. I observe a panel of N workers over T years. In the first observation year each worker has already chosen and completed their preferred level of education. The potential log-income of person i with schooling s in year t is given by

$$y_{sit} = y_{it} I\left(S_i = 1\right) + y_{it} I\left(S_i = 2\right) + y_{it} I\left(S_i = 3\right) + y_{it} I\left(S_i = 4\right), \qquad (1)$$

where $I\left(\cdot\right)$ is an indicator function having a value of 1 if $S_i = s \ (s = 1, 2, 3, 4)$ and 0 otherwise. The potential wage formulated in (1) gives rise to an income regression equation of the form:

$$y_{sit} = \alpha_s + x_{it}\beta + \sigma_s e_{si} + \psi_{st}\varepsilon_{it}, \ \forall \ S_i = s. \qquad (2)$$

In (2) α_s is the mean earnings for a schooling level and x_{it} is a vector of observables. The error term consists of two parts. The time invariant fixed effects are incorporated in $\sigma_s e_{si}$. $\psi_{st}\varepsilon_{it}$ denotes transitory shocks, which are assumed to be uncorrelated with both the observable characteristics and the fixed effect. The potential wage variance within a schooling level in year t is therefore $\sigma_s^2 + \psi_{st}^2$. Variation in σ_s^2 is the variance of individual specific fixed effects that are constant in time but may vary across schooling levels. $\psi_{st}\varepsilon_{it}$, on the other hand, may vary with both time and schooling level. e_{si} and ε_{it} are assumed to be $N(0, 1)$ distributed random variables.

It is assumed, that each individual chooses their level of education according to their preferences. This is formalized by a standard latent index model

$$S_i^* = z_i\theta + v_i, \qquad (3)$$

where S_i^* represents the optimal level of schooling chosen by individual i. The latent schooling factor v_i is a $N(0, 1)$ random variable. It summarizes the private information such as taste for education, unobservable ability and income expectations (including possible risk aversion), which are known to the individual but unobservable to the researcher.[1] z_i contains the elements in vector x_i and an instrument, which is assumed only to affect level of education but not income.

[1] In particular, v_i is assumed to capture both pecuniary and non-pecuniary utility components.

The predicted schooling level S_i depends on S_i^* by

$$\begin{aligned} S_i &= 1 \quad \text{if} \quad -\infty < z_i\theta + v_i \leq \kappa_1, \\ &\vdots \\ S_i &= 4 \quad \text{if} \quad \kappa_4 \geq z_i\theta + v_i > \infty. \end{aligned} \tag{4}$$

The cutoff value, $a_s = \kappa_s - z_i\theta$, is the minimal level of the unobserved schooling factor for which individuals choose s.

The model has three unobservable elements, e_{si}, ε_{it} and v_i. They are assumed to be jointly normal with the structure

$$\begin{bmatrix} e_{si} \\ \varepsilon_{it} \\ v_i \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 & \rho_s \\ 0 & 1 & 0 \\ \rho_s & 0 & 1 \end{bmatrix}\right), \tag{5}$$

where $\rho_s \in [-1, 1]$. Intuitively (5) implies that the unobservables in the schooling equation may be correlated with permanent earnings differences, but they are assumed to be uncorrelated with the transitory shocks. Therefore, the possible selection bias only contaminates the estimation of the permanent component. The transitory component captures macroeconomic shocks and institutional changes which affect all individuals symmetrically and are therefore uncorrelated with v_i. The structure of the unobservables is assumed to be common knowledge[2].

Correlation between the fixed effect and the unobserved schooling factor ρ_s has a central role in the model: it captures the selection effect. If $\rho_s > 0$, the unobservables in schooling and earnings equations are positively correlated, the selection effect is positive and workers with high income potential get more education. If $\rho_s < 0$, people with high income potential tend to enter labor markets at a younger age. Consequently, ρ_s also governs the magnitude and the direction of the bias in the OLS estimates: if $\rho_s > 0$, OLS overstates the true return to education and if $\rho_s < 0$, OLS understates the true return to education.[3]

From the point of view of an individual making her schooling decision, the expected log-income is given by

$$E\left[y_{sit} \mid s_i = s, x_{it}, v_i\right] = \alpha_s + x_{it}\beta + \sigma_s\rho_s v_i, \tag{6}$$

[2]The assumption of common knowledge of shock parameters is needed for the subsequent analysis. Even though this assumption might seem unrealistic, results from survey data (e.g. Schweri *et al.*, 2011 and Webbink & Hartog, 2004) and structural models (e.g. Charles & Luoh, 2003) support the assumption that students have at least some knowledge of their potential post-schooling income.

[3]Cameron & Heckman (1998) discuss, which types of economic models would rationalize the ordered structure given by Equations (3), (4) and (5). Most importantly, they conclude that v_i has to be independent of the level of schooling, i.e. $v_{si} = v_i \; \forall \; s$.

where the term $\sigma_s \rho_s v_i$ represents the channel through which individual schooling factors affect the potential wage.

Since agents are assumed to know their own draw of v_i, a proper measure of income uncertainty should account for v_i. The unforeseeable component of log-income, or income uncertainty from the point of view of an individual, is measured by the deviation of realized income from its mean conditional on unobservable v_i and observables x_{it} and S_i

$$\begin{aligned} \tau_{st}^2 &= Var\left[\sigma_s e_{si} + \psi_{st} \varepsilon_{ei} \mid x_{it}, S_i = s, v_i\right] \\ &= \sigma_s^2 \left(1 - \rho_s^2\right) + \psi_{st}^2. \end{aligned} \tag{7}$$

Equation (7) can be rearranged to $\sigma_s^2 + \psi_{st}^2 = \sigma_s^2 \rho_s^2 + \tau_{st}^2$. It shows that the residual variance of equation (2) consists of two parts: unobserved heterogeneity ($\sigma_s^2 \rho_s^2$) and uncertainty (τ_{st}^2). Income uncertainty is governed by the permanent and transitory components (σ_s and ψ_{st}) and the correlation between the unobserved schooling factor and permanent component ρ_s.

3.2 Identification of variance components

Equations (6) and (7) are not directly applicable for regression analysis because v_i is unobservable. To account for the effect of unobserved v_i, a multi-choice version of the Heckman selection correction model (Heckman, 1979) is used.

As a first stage, a latent index model (3) is estimated using ordered probit. The model is used to calculate generalized residuals of the schooling model[4],

$$\lambda_{si} = \frac{\phi\left(\kappa_s - z_i \theta\right) - \phi\left(\kappa_{s+1} - z_i \theta\right)}{\Phi\left(\kappa_{s+1} - z_i \theta\right) - \Phi\left(\kappa_s - z_i \theta\right)},$$

where $\phi(\cdot)$ is the probability density function of a standard normal distribution and $\Phi(\cdot)$ is the cumulative distribution function of a standard normal distribution. Adding λ_{si} as a regressor to (6) accounts for the correlation between unobserved schooling factor and education level. The expected value of observed wages from the point of view of the researcher can now be written as

$$E\left[y_{sit} \mid s_i = s, x_{it}, v_i\right] = \alpha_s + x_{it}\beta + \sigma_s \rho_s \lambda_i. \tag{8}$$

Calculating the difference between realized and expected wages gives

$$y_{sit} - E\left[y_{sit} \mid s_i = s, x_{it}, v_i\right] = \sigma_s - \sigma_s \rho_s + \psi_{st}. \tag{9}$$

Variance of (9) equals the measure of uncertainty, τ_{st}^2. Additionally, (9) implies that whenever $\rho_s \neq 0$, selection leads to a truncation of the observed income variance which, in turn, leads to an understatement of income uncertainty

[4]In the case of a binary schooling variable, the generalized residuals would boil down to Inverse Mills' ratios.

compared to the case we would observe if education was randomly assigned to individuals. The degree of understatement is given by [5]:

$$\delta_{si} = \lambda_{si}^2 - \frac{(\kappa_s - z_i\theta)\,\phi(\kappa_s - z_i\theta) - (\kappa_{s+1} - z_i\theta)\,\phi(\kappa_{s+1} - z_i\theta)}{\Phi(\kappa_{s+1} - z_i\theta) - \Phi(\kappa_s - z_i\theta)}.$$

The variance of transitory component can be identified from the residuals of the within-individual model,

$$(y_{it} - \bar{y}_i) = (x_{it} - \bar{x}_i)\,\beta - \left(\xi_{sit} - \bar{\xi}_{si}\right), \tag{10}$$

where bars denote time averages of the corresponding variables (note that time-invariant individual regressors, including λ_{si}, are subsumed in the fixed effects) and $\xi_{sit} = \psi_{st}\varepsilon_{sit}$. The procedure for estimating $\hat{\psi}_{st}^2$ is discussed in detail in Appendix A.

The regression coefficients $\hat{\alpha}_s$,$\hat{\beta}$ and $\widehat{\rho_s\sigma_s} = \hat{\gamma}_s$ can be identified using a between-individuals model

$$\bar{y}_i = \alpha_s + \bar{x}_i\beta + \gamma_s\bar{\lambda}_{si} + \omega_i. \tag{11}$$

The error term in (11) is, by equation (9),

$$\omega_i \quad = \quad \sigma_s e_{si} + \bar{\xi}_{si} - \gamma_s\lambda_{si},$$

and its variance is

$$Var\left[\omega_i \mid S_i = s\right] = \sigma_s^2 - \gamma_s^2\delta_{si} + \psi_{st}^2$$

Solving this for σ_s^2 gives the estimator for time invariant individual specific variance of wages for each schooling level,

$$\hat{\sigma}_s^2 = \widehat{Var}\left[\omega_i \mid S_i = s\right] + \hat{\gamma}_s^2\bar{\hat{\delta}}_s - \hat{\psi}_{st}^2, \tag{12}$$

where, again, bars denote averages over individuals. The second term $\hat{\gamma}_s^2\hat{\bar{\delta}}_s$ in equation (12) is needed to correct for the truncation of variances due to self selection. Each term in equation (7) is now identified:

$$\hat{\tau}_{st}^2 = \hat{\sigma}_s^2 - \hat{\gamma}_s^2 + \hat{\psi}_{st}^2 \tag{13}$$

4 Data

The data used in this paper is a random sample of 46321 individuals from a Finnish Census. I limit my attention to working males and females aged between 28 and 43. I assume that by the age of 28, people have finished their

[5] λ_i and δ_i are derived in Maddala (1987) under the assumption of joint normality.

education. An educational category of an individual is defined as the education they have at the youngest age they are observed in the panel. It is possible that individuals educate themselves further after the age of 28, but as my main interest is, how well individuals are able to predict their income in their youth, I interpret individuals' decision to re-educate themselves at later ages as a realized uncertainty, which should not be controlled for.[6]

The panel spans 1994-2009, adding up to a total of 244637 individual-year observations for men and 213840 for women. The composition of the sample is summarized in Table 1. The panel is constructed in a way that even the youngest cohort is observed for six years. I have limited my attention to individuals who were born after 1966 to make sure that an educational reform which took place in Finland in the early 1970's does not differently affect the cohorts under study.[7]

The educational categories are defined according to the standard classification of education. I do not discriminate between fields of education but only levels as the goal of this paper is to study the returns of an attained degree rather than returns to years of education. The specification used allows the marginal return to schooling to vary according to the level of schooling completed. Using the highest degree attained also mitigates the effect of measurement errors, since years of education are usually imputed using average years of education needed to complete a degree, which introduces measurement error.

As already mentioned, the risk of unemployment constitutes a considerable part of the total income uncertainty. The choice of the outcome variable reflects this; the dependent variable in income regressions is the log of total yearly taxable income which, in addition to wages and entrepreneurial income, includes taxable income transfers but excluding income from capital gains. As a result, the observed income streams allow for potential spells of unemployment.[8] However, if a person drops out of the workforce entirely, she only contributes to the estimation for the years when she is either unemployed or working. The variance of yearly total income is, by definition, comprised of three components, hourly wages, hours worked and the means-tested income transfers. Consequently, unless the covariances of the three components are very large and negative, the total variances will be higher than the variance of hourly wages (see, e.g. Abowd

[6] In practice this is rather rare. Only roughly five percent of individuals in the lowest education category get a higher degree during the time in the panel. For higher education categories, the proportion of people who re-educate themselves are in the order of 1 percentage.

[7] The goal of this reform was to standardize the quality of comprehensive education within the country. Consequently, people born before 1966 had a different school system from those born after 1966. In particular, before the reform, the quality of comprehensive education varied a great deal between regions. In addition, the reform resulted in removal of one educational tracking stage. For details about the reform, see e.g., Pekkarinen *et al.* (2009).

[8] Also (former) self-employed individuals are entitled to unemployment transfers.

& Card 1989).[9]

The income concept may introduce a problem of its own, since not working may be either voluntary or involuntary. To separate the involuntarily unemployed from voluntary workforce non-participants I include only the observations where the main type of activity of an individual is either working or unemployed in the estimation[10]. For example, if a women is on a maternity leave for one year, but is either working or unemployed for nine years, she contributes to the estimation for the years when she is not on a maternity leave.

The approach chosen leaves some (likely mis-classified) observations with zero income. I omit these observations. This does not affect the main results, because the proportion of zero-observations is very small (less than 2% of observations)[11]. To ensure comparability between years, the measure of income is deflated to EUR 2009 using the Consumer Price Index.

I do not have a reliable information on whether workers are part-time or full-time. Therefore, to some extend, the uncertainty measures also reflect voluntary part-time work. Nonetheless, the proportion of part-time workers is rather small in comparison to most developed countries. The proportion of part-time workers is 9.2% for men and 16.9% for women. Further, working part-time is virtually nonexistent in professional and management positions (where most peopleare likely in education categories 3 or 4) (Eszter, 2011).

The vector of controls in Equation (2) includes paternal and maternal education classified using the same four-level classification which is used for individuals' own education, a measure for family income calculated as the sum the income of mother and income of father and nine dummies for family socioeconomic status. Family background characteristics are measured at age 14 if possible. In addition, controls for first language, nationality and the region of residence in adulthood are included.

Estimation of Equation (11) necessitates an instrument excluded from the income equation (2). The region of residence in youth is used as an instrument.[12][13] The assumption is that the region of residence is correlated with individuals' access to higher education but not their income after controlling for

[9]Low *et al.* (2010) discuss a model which separates individual productivity and firm-worker match specific unemployment risks from one another in a structural framework. The dependent variable in this paper, total taxable income, should be interpreted as a combination of productivity and match specific risks, but measuring the respective contributions of these two parts is beyond the scope of this paper.

[10]In general, for an individual to be classified as unemployed (and be eligible for unemployment benefits), she must agree to accept a job if offered one.

[11]None of the results qualitatively change whether I exclude them or impute a small positive income value for these observations.

[12]Childhood information is collected from censuses. Censuses were administered in 1970, 1975, 1980, 1985 and yearly from 1988 onwards.

[13]A similar instrument is used, among others, by Suhonen *et al.* (2010) for Finland, Card (1993) for the U.S. and Bedi & Gaston (1999) for Honduras.

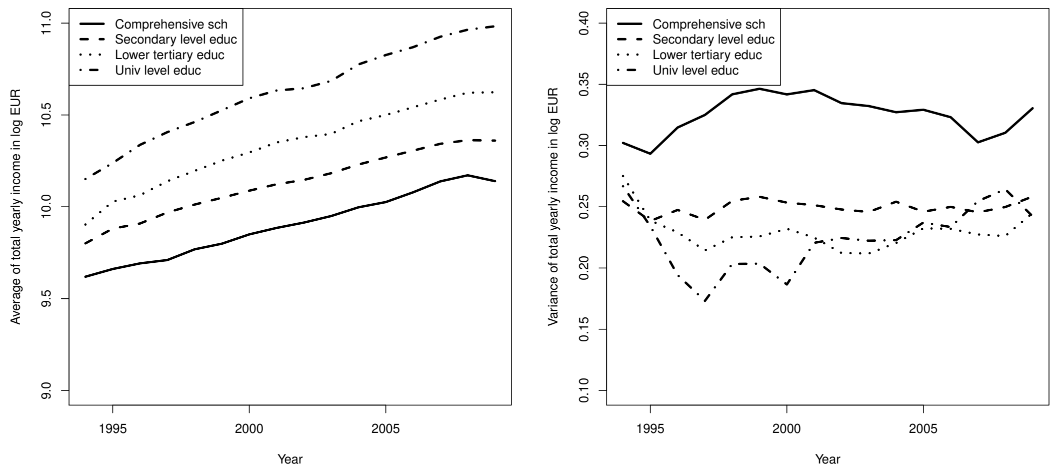
other observable characteristics. Consequently I need to exclude individuals who have no information on their place of residence at youth. The estimation results provided in Section 4.1 support the notion that the instrument is relevant.

As discussed by Card (1993), the place of residence in youth may affect income because of differences in local supply of education, but also because family background is correlated with place of residence. For this reason family background variables are controlled for. In addition, Card points out that differences in comprehensive schooling resources may affect subsequent income. In the case of Finland, comprehensive education is arranged in public schools with very small differences in resources and quality (Kirjavainen, 2009). In addition, international evidence suggests that the impact of school quality on learning (Kramarz *et al.*, 2009) and income (Betts, 1995) is rather small even in the context of less standardized comprehensive schooling. Finally, to control for differences in local labor market conditions in the presence of imperfect labor mobility, I control for job location in adulthood in the income equation. Despite controlling for family background and job location characteristics, it might still be the case that the instrument is correlated with the outcome. If this is the case, the estimates for ρ_s overestimate the true parameter value. I discuss this possibility in Section 6.

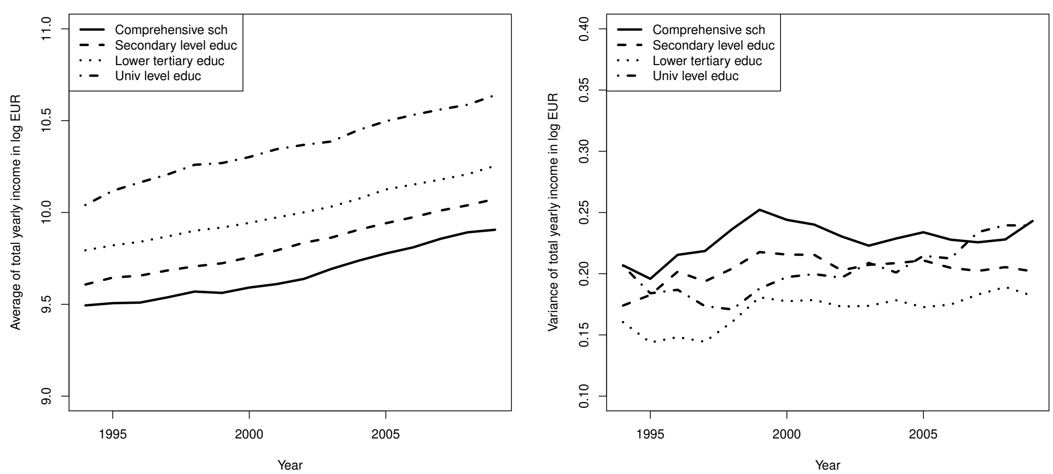
Figure 1 plots the estimated averages and standard deviations of log incomes for each panel year calculated from the sample described in Table 2. It is apparent that the mean income rises with education. Differences in the standard deviations of incomes are quantitatively much smaller, but some aspects can already be noted. First, people with only a compulsory education have the largest standard deviations of incomes. The standard deviation of male income in the lowest education category is especially large. The relative contribution of heterogeneity, permanent differences and transitory differences remains unclear. Using the method outlined in the previous section, it is possible to disentangle them from one another

Control variables, which capture the observed heterogeneity, are summarized in Table 2. Not surprisingly, the distribution of family background variables is virtually identical between sexes. There are larger differences in the distribution of education levels. The proportion of men with a basic or secondary education is larger than women. Conversely, there are more women with at least a tertiary level education.[14]

[14] The fact that women have overtaken men in terms of their education is a common finding in most industrialized countries (Barro & Lee, 2010).



(a) Men



(b) Women

Figure 1: Means (left panel) and variances (right panel) of yearly incomes by year for men and women.

Table 1: Sample sizes used in estimation.

Year of birth	Sample size (men)	Sample size (women)	Year-obs. (men)	Year-obs. (women)	Years
1966	2742	2543	38576	33335	1994-2009
1967	2696	2510	35330	30382	1995-2009
1968	2530	2501	31253	28601	1996-2009
1969	2318	2213	26752	23623	1997-2009
1970	2417	2211	25729	21475	1998-2009
1971	2118	2155	20589	19216	1999-2009
1972	2134	2056	18905	16643	2000-2009
1973	2100	1928	16462	13915	2001-2009
1974	2226	2146	15612	13739	2002-2009
1975	2492	2285	15429	12911	2003-2009
Total	23773	22548	244637	213840	

5 First and second stage estimates

5.1 First stage: schooling choice

Equation (3) is estimated by an ordered probit. The estimated model includes family background measures and the instrument for education. Table 3 shows the test statistics for the relevance of the instruments. The relevance of instrument using linear education as the dependent variable is also reported because there are no rule-of-thumb test statistic values for the relevance of instruments maximum likelihood models.. Educational categories are converted to years of education using average times-to-degree measured in full years.[15] This introduces noise to the dependent variable. Consequently the F-statistics reported in Table 3 might represent a lower bound for the effect of the instruments on education. Nonetheless, even the F-statistics of the linear model suggest that the instruments are highly relevant.

5.2 Second stage: average returns to schooling

This section presents estimates for the average returns to education. The reported estimates are based on the between model (11), where average yearly income of an individual is regressed on individual characteristics, schooling variable, mean age, mean age squared and the generated regressor λ_{si}.

To account for the fact that λ_{si} is a generated regressor, the standard errors are calculated using a block bootstrap procedure, where 200 samples of size N are drawn with replacement from the original population. For each bootstrap draw k, the estimates $\hat{\alpha}_s^k$,$\hat{\beta}^k$ and $\hat{\gamma}_s^k$ are calculated. Expected values and standard errors of the parameters are calculated from the distribution of these bootstrap draws.

The parameter estimates and their standard errors are presented in the second column of Table 4. The effect of education on income is nonlinear with

[15]These are 9 years for the compulsory level, 12 years for the secondary level, 15 for the lower tertiary education and 17 for the master's level education.

Table 2: Descriptive statistics of the explanatory variables.

	Men	Women		Men	Women
Time invariant variables			Family background		
Education			*Father's education*		
Compulsory education	0.18	0.15	Compulsory education	0.53	0.53
	(0.38)	(0.36)		(0.5)	(0.5)
Secondary	0.52	0.45	Secondary	0.25	0.25
	(0.50)	(0.5)		(0.43)	(0.43)
Lowest tertiary	0.21	0.25	Lower tertiary	0.15	0.15
	(0.41)	(0.43)		(0.36)	(0.36)
Bachelor or more	0.09	0.16	University	0.06	0.06
	(0.29)	(0.37)		(0.24)	(0.24)
First language			*Mother's education*		
Finnish	0.950	0.951	Compulsory education	0.52	0.52
	(0.218)	(0.216)		(0.48)	(0.5)
Swedish	0.048	0.048	Secondary	0.31	0.31
	(0.215)	(0.214)		(0.46)	(0.46)
Other	0.002	0.001	Lowest tertiary	0.15	0.15
	(0.040)	(0.032)		(0.36)	(0.36)
Nationality			Bachelor or more	0.03	0.03
Finnish	0.998	0.999		(0.17)	(0.17)
	(0.042)	(0.032)			
Other	0.002	0.001	*Family income (in 100 EUR 2009)*	394.23	393.401
	(0.042)	(0.032)		(253.06)	(253.01)
Instrument for education			Average ages in years		
Region residence in youth			1994	28	28
Uusimaa	0.20	0.21	1997	30	30
	(0.40)	(0.41)	2000	31	31
Varsinais-Suomi	0.08	0.08	2003	33	33
	(0.27)	(0.27)	2006	36	36
Satakunta	0.05	0.05	2009	39	39
	(0.22)	(0.22)			
Kanta-Häme	0.03	0.03			
	(0.17)	(0.17)			
Pirkanmaa	0.08	0.08			
	(0.27)	(0.27)			
Päijät-Häme	0.04	0.04			
	(0.2)	(0.2)			
Kymenlaakso	0.04	0.04			
	(0.2)	(0.2)			
Etelä-Karjala	0.03	0.03			
	(0.17)	(0.17)			
Etelä-Savo	0.03	0.04			
	(0.17)	(0.2)			
Pohjois-Savo	0.05	0.05			
	(0.22)	(0.22)			
Pohjois-Karjala	0.03	0.04			
	(0.17)	(0.2)			
Keski-Suomi	0.05	0.05			
	(0.22)	(0.22)			
Etelä-Pohjanmaa	0.05	0.05			
	(0.22)	(0.22)			
Pohjanmaa	0.04	0.03			
	(0.2)	(0.17)			
Keski-Pohjanmaa	0.02	0.02			
	(0.14)	(0.14)			
Pohjois-Pohjanmaa	0.08	0.07			
	(0.27)	(0.26)			
Kainuu	0.02	0.02			
	(0.14)	(0.14)			
Lappi	0.05	0.05			
	(0.22)	(0.22)			
Itä-Uusimaa	0.02	0.02			
	(0.14)	(0.14)			

Notes: Standard deviations in parentheses. Calculations are based on a random sample of individuals who are born between 1966–1975 and are between 28 and 43 years old. N is the sample size of time-invariant variables. Year-observations report the average number of years an individual is observed in the data.

Table 3: Test statistics for relevance of instrument.

		Men	Women
Dependent variable: categorical education	Likelihood ratio statistic	334.66	417.06
Ordered probit		[0.00]	[0.00]
Dependent variable: education in years	F-statistic	17.06	22.74
Linear model		[0.00]	[0.00]

Notes: P-values in brackets. Instrument for education is the region of residence in youth. Both models include controls for parents' education, family income, nationality, first language and year of birth.

respect to level of education. Most educated individuals accrue the highest marginal returns.

To facilitate comparability to previous literature on monetary returns to education, also IV estimates for the average return to education are reported in the third column of Table 4. They are reported for reference, but are not used when estimating uncertainty parameters. The IV estimates are somewhat larger than the corresponding estimates based on the selection model.

Without selectivity correction, the positive correlation between schooling of individuals and the residual in the income equation would result in an upward bias in the estimated returns to income. This bias arises if some of the unobservable characteristics (a high draw of e_{si}) are positively correlated with the schooling choice of an individual. This happens, for example, if the people with high income potential are also those who self-select into higher education (Griliches, 1977).

In the context of the current model, the correlation between income and schooling presents itself in positive values of the correction term γ_s. There is limited evidence of this: for men the estimate of the correction terms for lowest education categories γ_1 and γ_2 and for the correction term for the highest education category γ_4 for women are statistically significantly positive conventional significance levels. The correction terms for other levels of schooling are not statistically distinguishable from zero at conventional levels. Even the correction terms that differ statistically significantly from zero are qualitatively rather small. [16]

The error structure given in Equation (5) implies that $\gamma_s = \rho_s \sigma_s$ in conjunction with the finding my estimate for $\hat{\rho}$ is very small suggests that the unobservable heterogeneity for each education level is very small. This implies that, either, individuals have very little private information on their comparative advantage not captured by the observable characteristics, or, alternatively, individuals do not act on their private information on potential incomes.

A possible concern for the validity of the results of this paper is that they hinge on the assumption of joint normality of error terms and the linear depen-

[16] The fact that OLS and two-stage estimates are very close to one another, is a classic sign of a weak instruments (e.g. Bound *et al.* 1995). Notice, however that the first stage results point to instruments being highly relevant. The possibility that instruments are invalid, or correlated with the outcome, is discussed more closely in Section 6.3.

dence between mean incomes and the selection term. To shed some light on the concern, I have performed the test described in Vella (1998, pp. 137-138) and estimated Equation (11) where in addition to the Inverse Mills' Ratio, second and third degree polynomials of the Inverse Mills' Ratios are used as regressors. This allows me to test for possible deviations from joint normality of unobservables in schooling and income equations. The tests for the joint significance of the higher order polynomial always fail to reject the null hypothesis of linearity. This speaks in favor of the assumption of the joint normality.

Confidence on the distributional assumptions is further strengthened by the fact that the estimates of $|\hat{\rho}| < 1$ and $\hat{\delta}_{si} \in [0, 1]$ for all individuals, which is consistent with normality (notice that no restrictions on $\hat{\rho}$ and $\hat{\delta}$ are placed). Nonetheless, even though the assumption of normality is not immediately rejected, some caution should be exercised when interpreting the results, since they are obviously conditional on the distributional assumptions.

Table 4: Second stage estimates.

Men	Education categories			Years of education	
	Education	OLS	Corrected for selection	OLS	IV
	Secondary educ.	0.25***	0.25***	0.09***	0.13***
		(0.01)	(0.04)	(0.01)	(0.01)
	Lower tertiary educ	0.47***	0.45***		
		(0.01)	(0.04)		
	University	0.74***	0.73***		
		(0.01)	(0.07)		
	Selection correction term				
	Compulsory educ.		0.03**		
			(0.01)		
	Secondary educ.		0.02*		
			(0.01)		
	Lower tertiary		0.01		
			(0.02)		
	Bachelor or more		0.01		
			(0.03)		
Women	Education categories			Years of education	
	Education	OLS	Corrected for selection	OLS	IV
	Secondary educ.	0.22***	0.19***	0.08***	0.11***
		(0.01)	(0.04)	(0.01)	(0.04)
	Lower tertiary educ	0.37***	0.38***		
		(0.01)	(0.06)		
	University	0.77***	0.72***		
		(0.01)	(0.07)		
	Selection correction term				
	Compulsory educ.		-0.01		
			(0.02)		
	Secondary educ.		0.00		
			(0.01)		
	Lowest tertiary		0.00		
			(0.01)		
	Bachelor or more		0.04*		
			(0.02)		

Notes: Estimates are based on a between-individuals model. Standard errors in parenthesis. For the OLS and IV models, standard errors are based on the heteroskedasticity and autocorrelation consistent OLS covariance matrix. For the selection corrected model standard errors are based on 200 bootstrap replications. In addition to variables reported, both models include controls for parents' education, family income, nationality, first language and year of birth, age and age squared. In columns 1 and 2, the education is measured as a categorical education variable. In columns 3 and 4, the education categories are transformed into years of education using the typical time-to-education measures.

6 Uncertainty estimates

6.1 Main estimates

The estimates for the permanent and transitory components of income uncertainty at each education level are reported in this section. Standard errors of each variance component are again calculated from 200 bootstrap resamples. The uncertainty estimates are reported in Table 5. Since the error structure assumed implies that unobserved heterogeneity is not correlated with the transitory shocks, the total wage uncertainty is a sum of two components: transitory shocks and permanent earnings variance purged from the effects of private information.

I first discuss the transitory variance estimates. Since transitory shocks are time-varying, I start by reporting the time-means of the transitory component (denoted by $\bar{\psi}_s^2$). Among men, individuals in the lowest education group face the highest transitory income shocks. People with at least a secondary level education face similar transitory income shocks regardless of education. The estimation results are almost entirely opposite for women: transitory shock variances are almost constant among the three lowest education categories. The variances of transitory shocks are somewhat higher in the group with the highest education compared to other groups, even though the difference is qualitatively small. The differences between the transitory shocks of men and women are otherwise rather small, but men with only a basic level education face the highest transitory income shocks. The time-profile of the variance of transitory shocks can be seen from Figure 2; they are rather similar between education groups and sexes, which supports the idea that transitory income shocks are mostly driven by macroeconomic conditions in, for example, unemployment and job turnover.

Turning to permanent income variance, I find that education decreases permanent income differences considerably for men; having a secondary degree decreases permanent income uncertainty by 23%. Permanent income uncertainty decreases by another 15% with a tertiary level education. The difference between lower tertiary and university level education are statistically insignificant. In total, the permanent inequality is over 35% larger for the lowest education category in comparison to highest education category. The effect of education on permanent income variance is of similar magnitude for women and men. Having a secondary level education decreases permanent income variance by 30%. The uncertainty decreases further with a tertiary level education, but the differences between lower tertiary and university education is indistinguishable from zero for men and small and positive for women. Despite the marginal effects being similar, the level of permanent uncertainty is considerably larger for men than women regardless of the level of education. The differences in permanent incomes are twice as large for men than for women in the two highest education categories. Transitory and total income inequality levels are plotted in Figure 3.

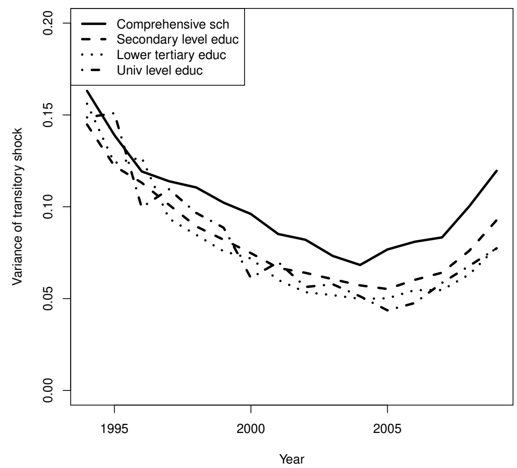
To get a better grasp of the effects of education on average return and uncertainty, Figure 4 plots the marginal effects of completed education on average income and income uncertainty. Completing a secondary education decreases income uncertainty of men more than that of women. A tertiary level education has a small negative effect on male and female earnings uncertainty. Completing an university level education increases uncertainty somewhat; this effect is, however, statistically significant for men but not for women. The returns-to-degree estimates are similar among men and women on all levels of education.

Table 5: Estimates of income variance components.

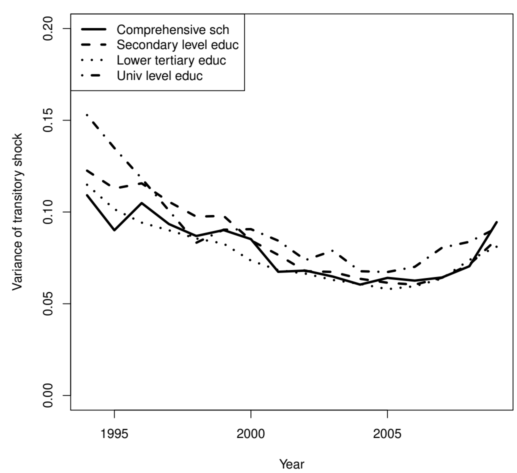
	Men Education category 1	2	3	4
Variance of transitory shock[1]	0.09	0.07	0.07	0.07
	(0.002)	(0.001)	(0.001)	(0.002)
Marginal effects[2]		-0.02***	-0.001	0.001
		(0.002)	(0.002)	(0.003)
Permanent component[3]	0.17	0.13	0.11	0.11
	(0.01)	(0.01)	(0.01)	(0.01)
Marginal effects[4]		-0.04***	-0.02***	0.00
		(0.006)	(0.006)	(0.01)
Effect of private information on permanent component[5]	0.00	0.00	0.00	0.00
	(0.06)	(0.04)	(0.04)	(0.06)
Total wage uncertainty[6]	0.26	0.20	0.18	0.18
	(0.005)	(0.003)	(0.005)	(0.009)
Marginal effects[7]		-0.06***	-0.02***	0.01
		(0.006)	(0.006)	(0.01)
	Women Education category 1	2	3	4
Variance of transitory shock[1]	0.07	0.08	0.07	0.08
	(0.002)	(0.001)	(0.001)	(0.002)
Marginal effect[2]		-0.002	-0.002*	0.005**
		(0.002)	(0.001)	(0.002)
Permanent component[3]	0.10	0.07	0.05	0.05
	(0.004)	(0.002)	(0.002)	(0.005)
Marginal effect[4]		-0.03***	-0.03***	0.01
		(0.005)	(0.003)	(0.01)
Effect of private information on permanent component[5]	0.00	0.00	0.00	0.00
	(0.04)	(0.02)	(0.02)	(0.04)
Total wage uncertainty[6]	0.17	0.15	0.12	0.13
	(0.003)	(0.002)	(0.002)	(0.005)
Marginal effect[7]		-0.03***	-0.03***	0.01
		(0.004)	(0.003)	(0.05)

1 $\bar{\psi}_s^2$
2 $\bar{\psi}_s^2 - \bar{\psi}_{s-1}^2$
3 σ_s^2
4 σ_s^2 - σ_{s-1}^2
5 γ_s^2
6 $\bar{\psi}_s^2 - \gamma_s^2 + \sigma_s^2 = \tau_s^2$
7 $\tau_s^2 - \tau_{s-1}^2$

Notes: Variance component decompositions are based on Equation (13) with region of residence in youth as an instrument. Standard errors from 200 bootstrap resamples in parenthesis. Education categories are: 1. compulsory education; 2. secondary education; 3. lowest tertiary education; 4. bachelor level education or higher.

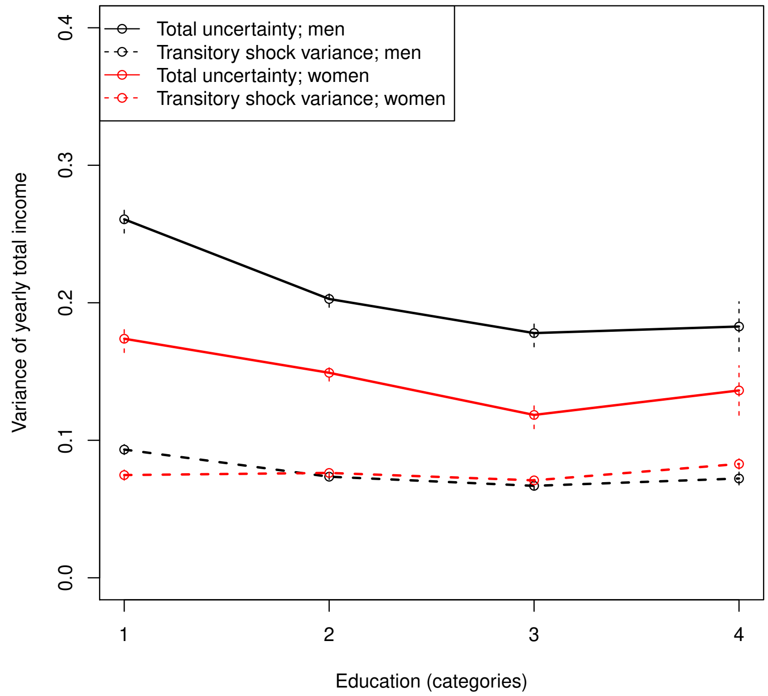


(a)
Men



(b)
Women

Figure 2: Transitory shock variances year by year.



decreases

Figure 3: Transitory (dashed lines) and total income variances (solid lines) for men and women by education categories. Dashed lines represent 95% confidence intervals calculated by bootstrap. Education categories are: 1. compulsory education; 2. secondary education; 3. lowest tertiary education; 4. bachelor level education or higher.

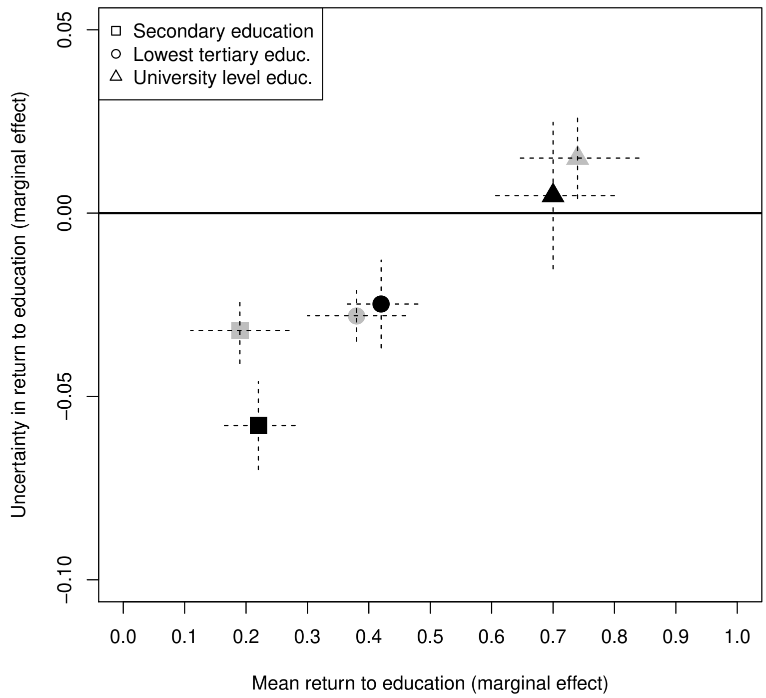


Figure 4: Marginal effects of completing a degree on mean income (horizontal axis) and uncertainty (vertical axis) for men (black symbols) and women (gray symbols). The dashed lines represent the bootstrapped 95% confidence intervals of return and uncertainty estimates on the corresponding axes.

6.2 Comparison to U.S. studies

My uncertainty estimates differ from those obtained in Chen (2008). Completing an education is found to decrease income uncertainty at lower education levels, but the effect is close to zero or even marginally positive for university graduates, whereas Chen's results suggest an U-shaped profile of income uncertainty where the highest and lowest education categories face the highest income uncertainty. Chen conjectures that the high income uncertainty of university graduates is related to the fact that they are able to choose their occupation from a wider pool of potential occupations, which is also reflected in their permanent income differences. It is possible that also Finnish university graduates are able to choose their occupation from a wider pool, but their income uncertainty is still smaller than that of lower educated individuals. It seems plausible that this is due to smaller risk of unemployment of more educated individuals.

Perhaps a more surprising finding is the very small unobserved heterogeneity. This is in stark contrast to the estimates based on data from the U.S.[17] For example, Cunha & Heckman (2007) conclude that up to 50% of the ex post variance in income of college graduates is attributable to unobserved heterogeneity, i.e. is foreseeable by individuals making their choice on whether or not to attend college. A potential explanation for the results is the choice of measure of income. The studies based on U.S. data use either a long period average earnings (Cunha & Heckman, 2007, 2008; Cunha *et al.*, 2005), or average hourly wage (Chen, 2008), which both arguably contain less variation than the yearly total income. Therefore, the correlation between residuals in schooling and income equations, which is used to identify unobserved heterogeneity, is mechanically smaller in absolute value.

A second partial explanation is that I target people in their youth. As the nine-year comprehensive school is mandatory, it may indeed be the case that young people making their choice on whether or not to attend higher education have limited information on their future incomes at the age of fifteen. In addition, early-career earnings are usually more volatile, or more uncertain. Since the Finnish comprehensive education is extremely standardized and allows for little differentiation in school curricula between skill groups, it may convey less private information to students about their future incomes and, therefore lead to a smaller unobserved heterogeneity, than a less standardized system would.

However, even though the unobserved heterogeneity is found to be smaller than in the U.S., this does not necessarily imply that people would have less information on their potential future income streams. Rather, it seems plausible, that, given the high amount of redistribution and collective bargaining in Finnish labor market, people would have a rather good perception on their potential future income, but this perception is not correlated with individual characteristics which are unobservable to the econometrician.

6.3 Sensitivity of results to the instrument

Even though I control for a variety of background characteristics in both first and second stages, the validity of the instrument is somewhat questionable. It is possible that the instrument has a direct effect on income even after controlling for the elements of x. To see the underlying intuition, note that the possibly

[17] Mazza *et al.* (2011) attempts to replicate the results in Chen (2008) using the same data but a different instrument, but they get very different results. In particular, their estimates for the unobserved heterogeneity are almost indistinguishable from zero regardless of education level and that the length of education and uncertainty are positively correlated. The same model applied to British data shows uncertainty decreasing with education and very small unobserved heterogeneity, while German data do not fit the model at all.

endogeneous instrument may affect the outcome through two distinct channels, through its independent effect on the probability of completing an education, and through direct effect of the instrument on income. More formally, the term γ_s in equation (11) can be written as

$$\gamma_s \lambda_{si} \left(z_i \theta, S_i = s \right) = cov(v_i, \omega_i \mid z,) + cov(z_i \gamma, \omega_i \mid S_i = s, x_i). \qquad (14)$$

The first term in the expression is the correlation between the unobserved schooling coefficient and the education. The second term is the covariance between income and the instrument when schooling and other observables except the instrument are kept constant. Equation (14) also provides a test for the exogeneity of the instrument; in a sub-sample, where schooling is constant, the instruments should have no predictive power on income after controlling for x. The tests for the joint significance of instruments are implemented separately for each schooling category and both sexes and reported in Table 6.

The instrument is found to have a direct effect to earnings in comprehensive schooling category for men and in the secondary education category for women. Consequently, for other education levels, the exogenous instrument assumption seems to hold. It should also be noted, that the endogeneity of the instrument biases the estimate of ρ_s *upwards* in absolute value. Therefore, it seems plausible that my estimates for $\hat{\rho}_s$ represent an upper limit of the true parameter value.[18]

To further study, to what extend the possible endogeneity of instrument drives the results, I have estimated the model without an exclusion restriction. The estimation results are presented in tables 7 and 8. The results are very similar to those reported in Tables 4 and 5. Since the two alternative specifications give very similar, and quantitatively small, estimates for the unobserved heterogeneity and, if anything, the main estimates are biased upwards in absolute value, it seems clear that unobserved heterogeneity is, indeed, very small.

Table 6: Test for the exogeneity of the instrument.

	Men	Women
Comprehensive education	1.67*	0.77
	[0.03]	[0.75]
Secondary education	1.499	1.47.
	[0.11]	[0.08]
Lower tertiary education	1.38	1.30
	[0.11]	[0.17]
University education	0.61	1.09
	[0.90]	[0.35]

Tests for the joint significance of instruments in samples with the same education. P-values in brackets.

[18] Also the IV estimates are somewhat larger than previous estimates from Finland (Uusitalo 1999). It should, however, be noted, that the earnings measures are not entirely comparable because the measure used in this paper consists of a compilation of earnings and unemployment risks. If education increases earnings and decreases the probability of being unemployed, this would lead to higher mean return to education.

Table 7: Second stage estimates (estimated without an exclusion restriction).

Men	*Education categories*			
	Return to education level	Corrected for selection		*Selection correction term*
	Upper secondary educ.	0.25***	Comprehensive educ	0.00
		(0.54)		(0.01)
	Lower tertiary educ	0.47***	Upper secondary educ.	0.00
		(0.05)		(0.01)
	University	0.73***	Lower tertiary educ	0.00
		(0.07)		(0.02)
			University	0.03*
				(0.02)
Women	*Education categories*			
	Return to education level	Corrected for selection	Comprehensive educ	0.00
	Upper secondary educ.	0.20***		(0.02)
		(0.05)	Upper secondary educ.	0.00
	Lower tertiary educ	0.39***		(0.01)
		(0.05)	Lower tertiary educ	0.00
	University	0.74***		(0.01)
		(0.06)	University	0.02
				(0.02)

Notes: Estimates are based on a model without an instrument. Standard errors in parenthesis. Standard errors are based on 200 bootstrap replications. In addition to variables reported, both models include controls for location of residence, parents' education and family income, nationality, first language and year of birth, age and age squared.

Table 8: Estimates of income variance components (estimated without an exclusion restriction).

	Men			
	Education category			
	1	2	3	4
Variance of transitory shock[1]	0.09	0.07	0.07	0.07
	(0.002)	(0.001)	(0.001)	(0.002)
Permanent component[2]	0.17	0.12	0.10	0.10
	(0.01)	(0.01)	(0.01)	(0.01)
Effect of private information on permanent component[3]	0.00	0.00	0.00	0.00
	(0.08)	(0.04)	(0.04)	(0.08)
Total wage uncertainty[4]	0.26	0.20	0.17	0.18
	(0.009)	(0.009)	(0.007)	(0.009)
	Women			
	Education category			
	1	2	3	4
Variance of transitory shock[1]	0.07	0.08	0.07	0.08
	(0.002)	(0.001)	(0.001)	(0.002)
Permanent component[2]	0.09	0.07	0.04	0.05
	(0.005)	(0.003)	(0.002)	(0.005)
Effect of private information on permanent component[3]	0.00	0.00	0.00	0.00
	(0.08)	(0.06)	(0.06)	(0.07)
Total wage uncertainty[4]	0.17	0.14	0.11	0.14
	(0.004)	(0.003)	(0.002)	(0.004)

[1] $\bar{\psi}_s^2$
[2] σ_s^2
[3] γ_s^2
[4] $\bar{\psi}_s^2 - \gamma_s^2 + \sigma_s^2 = \tau_s^2$

Notes: Variance component decompositions are based on Equation (13) estimated without an instrument. Standard errors from 200 bootstrap resamples in parenthesis. Education categories are: 1. compulsory education; 2. upper secondary education; 3. lowest tertiary education; 4. bachelor level education or higher.

7 Conclusions

This paper applies a simple model for identifying potential income distributions. The model is based on the residuals of the income regression equation. The variance of residuals is comprised of two components: uncertainty and unobserved heterogeneity. The uncertainty is further comprised of two components: permanent income differences and transitory shocks. Using a parametric model for selection, this paper disentangles the role of unobserved heterogeneity from permanent income differences. This paper departs from previous studies in two ways: in addition to wages, measure of income also includes transfers to people who are not working. This gives a possibility to include also the unemployed in the estimation allowing for a more complete picture of income uncertainty. Second, to facilitate comparison of earnings processes of men and women, separate models for men and women are estimated.

The results indicate that education is a good investment: in addition to having higher mean income, more educated individuals have smaller permanent income differences and face smaller transitory income shocks, even after correcting for selection. Moreover, my results indicate that men face considerably riskier income processes. For example, men with a basic level education is about 33% higher than women with a similar education. The results show that the higher male income variance is by and large driven by permanent earnings differences; no differences in unobserved heterogeneity are found. In addition, transitory shocks affect both genders and almost all education groups symmetrically. Only men in the lowest education category face larger transitory earnings shocks.

The estimates on share of unobserved heterogeneity in permanent income differences are qualitatively very small. This is a stark difference from previous studies, which mostly use data from the U.S. and find that the effect of unobserved heterogeneity may be up to 50% of permanent income differences. I argue that this result is likely driven by the choice of dependent variable or the relatively young estimation sample. Both of these factors increase the noise in the dependent variable compared to specifications typically used in studies using data from the U.S.

The estimation method applied in this paper take advantage of observed choices made by individuals to infer their information sets and, consequently, unobserved heterogeneity. A possible caveat in the analysis, is that if people know their expected incomes, but do not act on this information, the method which is based on their observed choices necessarily understates the unobserved heterogeneity. This may be a particularly relevant concern in the case of Finland, where higher education is entirely publicly funded.

The focus of this paper has been quantifying the effect of education on earnings uncertainty but the specific channel through which education affects earnings uncertainty is somewhat unclear. A classic explanation (e.g. Willis & Rosen, 1979) is that each level of education gives access to a distinct labor market with distinct income processes. In addition, education has been shown to have a variety of other positive effects on behavior. For example, it leads to a better health (Lleras-Muney, 2005) and reduces antisocial behavior (Lochner, 2004). Furthermore, these effects are found to be larger for men than for women. It is plausible, that at least a portion of the high earnings uncertainty of low educated males is attributable to these behavioral factors.

Since correcting for selection has only a small effect on the estimates of means and variances of incomes conditional on education level, it appears that, in the case of Finland, not correcting for selection has only a marginal impact on the estimated returns to education and uncertainty involved.

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Appendix A: Estimating $\hat{\psi}^2_{st}$ from the residuals of the within-model

Equation (10):

$$(y_{it} - \bar{y}_i) = (x_{it} - \bar{x}_i)\,\beta - \left(\xi_{sit} - \bar{\xi}_{si}\right).$$

Assuming that observations are missing at random and that ε_{st} and ε_{st-k} are independent for all $k \neq 0$, the residual variance can be written as

$$Var\left(\xi_{sit} - \bar{\xi}_{si}\right) = W_{st} = \left(1 - \frac{2}{T}\right)\psi^2_{st} + \frac{\Omega_{si}}{T_i^2},$$

where T_i is number of observation years of observation i and $\Omega_{si} = \sum_{t=1}^{T_i} \psi^2_{st}$. Summing both sides up over t gives

$$\sum_{t=1}^{T_i} W_{st} = \left(1 - \frac{2}{T}\right)\Omega_{si} + \frac{\Omega_{si}}{T}$$

and solving this for Ω_{si} gives

$$\Omega_{si} = \frac{\sum_{t=1}^{T_i} W_{st}}{\left(1 - \dfrac{1}{T}\right)}.$$

Plugging this back to the expression of $Var\left(\nu_{sti} - \bar{\nu}_{si}\right)$ and solving for ψ^2_{st} gives

$$\psi^2_{st} = W_{st}\frac{T_i}{T_i - 2} - \frac{\Omega_{st}}{T_i\left(T_i - 2\right)}.$$

Finally, replacing T_i's their sample average and W_{st} with its consistent estimate gives

$$\hat{\psi}^2_{st} = \hat{W}_{st}\frac{\bar{T}}{\bar{T} - 2} - \frac{\hat{\Omega}_s}{\bar{T}\left(\bar{T} - 2\right)},$$

where $\hat{\Omega}_s = \dfrac{\sum_{t=1}^{T_i} \hat{W}_{st}}{\left(1 - \dfrac{1}{\bar{T}}\right)}$.