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ABSTRACT

Risk-Adjusted Returns to Education*

This paper looks at the joint impact of labour market risk and selection in to the labour market on returns to education. Accounting for non-employment risk leads to substantial changes in returns while wage risk has little impact. The risk- adjusted returns to both high school and college for males are larger than unadjusted returns. For females, risk leads to an increase in returns to high school but to a *decrease* in the returns to college while correcting for selection in to employment has large effects for females. The results suggest that failure to account for risk and selection in to employment when calculating returns to education leads to biased estimates.

JEL Classification: I26, J1

Keywords: education, risk, employment

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1 Introduction

The returns to education is one of the most widely researched topics in economics. However, despite the huge number of papers, very few incorporate risk. Education is an inherently risky investment and so it is surprising that such an important factor has not been given so much attention.[1] Furthermore, there does not exist any market that insures against low returns to education which makes this a very important topic to study. In this paper, I examine how non-employment risk and wage risk impact returns to education.

It is not clear how non-employment risk and wage risk will affect the returns to education. If higher educated individuals have lower risk of non-employment then their lifetime expected earnings will be higher and this will increase the returns to education. On the other hand, if increased education comes at the cost of higher wage risk then individuals will place less value on higher education and the returns will be lower. Investing in education does not guarantee that one will obtain a high paying job; indeed due to the skewed nature of the earnings distribution many people will earn significantly less than mean earnings.[2] Thus, it is likely that individuals care not only about the mean of the earnings distribution but also the variance.[3]

Higher educated individuals have higher levels of human capital, they are less likely to be fired due to higher training costs and in addition they can downgrade in times of economic recession, all of which contributes to a lower risk of unemployment. Despite the fact that the low educated have higher unemployment probabilities, they receive a relatively larger share of their pre-displacement income as unemployment benefits and this may be enough to negate the adverse effects of unemployment. Added to this, the existence of minimum wage laws provide a lower bound to the wage that one can receive and so this may make the risk-adjusted returns smaller than one may have previously

[1] An individual deciding whether to invest in education faces a huge amount of uncertainty concerning future labour market conditions, completion of schooling, future earnings and the fraction of time spent in employment.

[2] Income levels among observationally similar people may differ due to luck, social connectedness, illness, promotions, ability, different training opportunities or motivation and therefore there is a wide range of potential wage outcomes that may be realised.

[3] If returns are normally distributed this is enough to summarise the entire distribution.

thought.

While there have been many recent papers looking at this topic (see Hartog (2014) for a review), the papers closest in spirit to this paper include Pistaferri and Padula (2001), Brown et al. (2012) and Koerselman and Uusitalo (2014).[4] Pistaferri and Padula (2001) using both US and Italian data find the returns to education are significantly higher when accounting for both wage risk and unemployment risk. Brown et al. (2012) using US data find that returns to a high school degree increase when accounting for risk and that this is driven mainly by the relatively lower earnings volatility of high school graduates rather than being due to differential unemployment rates while they find that the risk-adjusted returns to college are actually slightly smaller than unadjusted returns. Koerselman and Uusitalo (2014) using Finnish data find that risk has little impact on the returns to college but that the entire return to vocational high school is due to differences in the degree of non-employment. Similar to these papers, I abstract from the endogenity of education as there was not a credible instrument available.[5]

Most papers examining returns to education focus on finding a credible instrument to deal with endogeneity of education and ignore the effect of selection in to the labour market and the impact of labour market risk. The conventional wisdom is that those who obtain higher education may have higher ability and so would have earned more regardless of their additional education. And, as a result, the estimates would be upward biased due to an ability bias. However, previous papers using instrumental variables to provide exogenous variation in education have found that the returns are actually larger and thus that the OLS estimate is downward biased (see Card, 1999).[6] In this paper, I abstract from using an instrument to correct for potential endogeneity of education and rather the purpose of the paper is to emphasize the impact of risk and of non-random selection

[4]Earlier papers looking at this include Weiss (1972) who found that risk is decreasing in education, Olson, Shefrin and White (1979) who found that risk adjusted returns to college are small but positive while Nickell(1979) found that unemployment had negligible impacts on the returns to education.

[5]Delaney and Devereux (2019) use the raising of the compulsory schooling age in the UK to look at the causal effect of education on labour market risk. They find that education leads to lower earnings volatility for younger aged men.

[6]This may be due to the fact that the estimate obtained from using an instrument represents a local average treatment effect rather than an average treatment effect.

in to the labour market. However, while there was no credible instrument available, the data does provide me with a rich set of controls including both mother's and father's highest education level. Conditioning on family background measures may help to pick up unobserved differences such as ability and tend to mitigate concerns of endogenous education.

All of the aforementioned papers estimate returns using the the whole life cycle and consider the impact of risk on estimating returns to education for both males and females. However, when looking at returns from a life-cycle perspective and in particular when looking at returns to females, it is likely that there is selection in to employment and failure to account for this may in itself induce a bias in the estimates.[7] There are some papers which do account for non-random selection in to the labour market when looking at returns to education, for example, Duraisamay (2002) does so when looking at returns to education in India and Asadullah (2006) when looking at the returns to education in Bangladesh but neither paper focuses on the impact of risk on the returns to education.

The main contribution of this paper is to show the impact on returns to education of adjusting returns for both wage risk and non-employment risk and simultaneously correcting for non-random selection in to work. The previous papers in the literature focus on either the impact of risk or that of selection in to employment but, to the best of my knowledge, this is the first paper to estimate returns to education accounting for *both* potential sources of bias. The paper also contributes to the literature by estimating the impact of risk on returns to education using UK data. In addition, unlike the previous papers, I perform a robustness check to understand whether risk measured in the data represents actual risk rather than picking up variability that can be predicted by the individual.

There are 3 main findings of the paper. Firstly, I find that the returns to high school for both males and females are significantly larger than the returns to college and this is mainly driven by the poor labour market attachment of men and women who are high school dropouts (college and high school graduates have much similar employment rates). Secondly, I find that the impact of wage risk is negligible for males. However,

[7]Most studies looking at the return to education focus on prime labour market participation ages when individuals are most likely to be in the labour market to avoid dealing with this issue.

for females, I find that adjusting for wage risk increases the returns to high school and decreases the returns to college and this is mainly due to larger transitory shocks for college educated females and much larger permanent shocks for females with less than high school graduation. Finally, I show that correcting for non-random selection in to employment has little impact on returns for males but leads to a large increase in the returns to college for females and a decrease in the returns to high school. However, overall the impact of risk outweighs the selection effect leading to an overall *decrease* in returns to college for females and an increase in returns to high school. For males, the combined effect of selection and risk leads the returns to both college and high school to increase suggesting that standard estimates of returns to education for males may be downward biased.

It must be emphasized that the risk observed by the econometrician may not actually represent risk if an individual can forecast some of this uncertainty in advance. Heckman, Cunha and Navarro (2005) find that individuals know at least 40 percent of the risk.[8] Therefore, the risk-adjusted returns will represent an upper bound on the amount of risk involved. However, in this dataset I perform a test for advanced information and find that individuals cannot forecast the risk involved.

2 Methodology

Individuals have CRRA preferences and choose schooling to maximize the expected utility of lifetime income

$$E_{t_0} \sum_{t=t_0}^{T} (1+\rho)^{t-t_0} \frac{y_{it}(s)^{\gamma}}{\gamma} \tag{1}$$

where $1-\gamma$ is the coefficient of relative risk aversion, ρ is the discount rate, E is the expectation operator conditional on information at time t_0 and T is the retirement age

[8]There is an important distinction between ex-post and ex-ante returns to education. If data were available on an individual's subjective expectations then one can credibly calculate the degree of ex-ante risk involved, however, data on subjective expectations covering the life cycle are hard to find.

which is assumed known with certainty at the beginning of life.[9]

Following Becker (1964) and Hanoch (1967) the internal rate of return (IRR) is defined as the discount rate that equates the present value of the discounted net lifetime earnings for two different schooling levels.

$$\sum_{t=t_0}^{T}(1+\rho^*)^{t-t_0}\frac{E_{t_0}[(y_{it}(s)^{\gamma}]}{\gamma} = \sum_{t=t_0}^{T}(1+\rho^*)^{t-t_0}\frac{E_{t_0}(y_{it}(s'))^{\gamma}]}{\gamma} \tag{2}$$

In this equation, t_0 denotes the school leaving age at which the lowest of the two schooling levels being evaluated is, while s and s' denote the two education levels being compared. I assume individuals with academic qualifications lower than a high school degree leave school at 16 and enter the labour market at age 17, those with a high school degree finish at 18 and enter the labour market at 19 while those with a college degree are assumed to enter the labour market at 22 allowing them to stay in college until age twenty one. It is assumed that the retirement age is independent of education level and is set at age sixty five.[10] I abstract from part-time work when in education and assume that individuals spend £5,000 each year in college which covers living costs and tuition.[11] I make no distinction between those who are unemployed and those who are out of the labour force and for simplicity I assume that those who are not in employment receieve an amount that is equal to the unemployment benefit. The unemployment benefit used is the standard weekly benefit for a single adult in 2012. This benefit differs depending on whether the individual is under 25 years of age or older and this is incorporated in to the analysis.[12]

[9] I abstract from consumption and thus implicitly assume that individuals care only about lifetime income. This would be the case if there were incomplete markets with no borrowing or saving. Although this may seem like a strong limitation of the paper, the literature on returns to education focus almost exclusively on the effect of education on earnings rather than utility and therefore my set up will be useful for comparisons with previous estimates.

[10] Heckman, Lochner and Todd (2006) find that allowing the retirement age to differ by education level does not lead to large changes since the earnings at the end of the life cycle are so heavily discounted.

[11] Given I am using data covering the period 1991-2008 I abstract from the recent increase in tuition fees in the UK. In 2008 tuition fees were capped at £3,000 per year. For simplicity, I assume £5,000 covers the fees in addition to living expenses (and taking in to account maintenance grants).

[12] Although the unemployment benefit is only given for a maximum of 26 weeks, after which it is means

This set up is advantageous over the standard Mincer regression in obtaining the IRR since the coefficient on schooling does not give an estimate of the IRR except under certain conditions which Heckman, Lochner and Todd (2006) find to be rejected in recent data.[13] An individual deciding whether to quit schooling and enter the labour market will be most interested in the internal rate of return which requires explicitly accounting for all costs and benefits associated with each schooling level.

The income process is estimated assuming income is log normally distributed $lny_{it} \sim N$ and the moments are converted back using standard log normal formulae:

$$E[y_{it}] = exp(E[lny_{it}] + 0.5var[lny_{it}]) \tag{3}$$

$$var[y_{it}] = exp(2E[lny_{it}] + var[lny_{it}])(exp(var[lny_{it}]) - 1) \tag{4}$$

In order to estimate the expected utility I use a second order Taylor approximation around mean earnings.[14]

$$EU_{wr} = \frac{E[y_{it}^{\gamma}]}{\gamma} \approx \frac{[E(y_{it})]^{\gamma}}{\gamma} + \frac{\gamma - 1}{2} var[y_{it}][E(y_{it})]^{\gamma-2} \tag{5}$$

I set the coefficient of relative risk aversion equal to 1.5 similar to Attanasio and Weber (1995). For each year the certainty equivalent value of the expected utility is calculated and used in the IRR calculation. Standard errors are calculated using bootstrap methods whereby I take 50 samples with replacement for each education by gender group (Efron and Tibshirani, 1993).

When calculating at the effect of unemployment on the IRR, the individual receives income with probability δ_{it} and unemployment benefit with probability (1-δ_{it}). Although δ_{it}, the probability of employment, is increasing in education, the replacement rate is

tested against household income including housing costs and household composition, for simplicity I assume that it is available for one year. Since one period corresponds to one year this also assumes that individuals are unemployed for the full year which may bias the results if the duration of unemployment varies by education.

[13] Rather, the Mincer approach gives an estimate of the growth rate of earnings with schooling.

[14] Risk neutrality occurs when γ is equal to 1 and the second part of the equation drops out and so utility is solely dependent on the mean of the distribution. When γ is equal to zero then it is a log utility function and the Taylor approximation is slightly modified.

significantly lower for the higher educated and this may be enough to offset any gains since risk averse individuals dislike large fluctuations in their income. The probability of employment is calculated from a probit regression of employment on a set of covariates including a quadratic in age, year dummies, dummies for parental education and a dummy denoting whether the individual is white or not. This is performed separately for each education by gender group.[15]

3 Wage Process

In the following wage specification, log net wages are regressed on a quadratic in age, year dummies, dummies for mother's highest education level, father's highest education level and a dummy denoting whether the individual is white or not.[16] Unlike many studies which use the standard Mincer regression, I use a quadratic in age rather than experience. There are two reasons for doing this: firstly, experience is endogenous and secondly, by controlling for experience the benefit to leaving education early via the effect on increased labour market experience is eliminated. Conditioning on family background will pick up unobserved differences such as tastes and possibly ability. The regression is performed separately by gender and education level. By estimating the regression separately by education level I allow all covariates to vary with education. This is necessary since earnings growth rates are not parallel across schooling levels.[17] One reason for non-separability would be differential on the job investment, for example, Mincer (1991) finds that the higher educated are more likely to receive training.[18] Log wages are defined

[15] I also examined the effects of using the mean value of employment and there was very little change in the results.

[16] I do not directly control for cohort but by using year dummies and a linear age variable, I am in effect allowing for a linear cohort trend. For robustness checks I include a quartic polynomial in cohort and the results are very similar.

[17] Migali and Walker (2011) and Heckman, Lochner and Todd (2006) find evidence against separability.

[18] Additionally, this set up is advantageous over earlier studies which included years of schooling as a dummy variable in the regression and thus imposed linearity in returns to schooling. The existence of 'sheep skin effects' whereby the returns to schooling vary with each qualification completed and therefore the returns to an extra year of schooling which does not warrant a qualification will be less than a year of schooling which does are captured by performing the regression separately by education level.

as usual net monthly pay multiplied by twelve. I use monthly pay rather than annual income as the latter is affected by periods of non-employment throughout the year and thus when I am computing the non-employment adjusted return, I would in effect be over estimating the impact of non-employment. Most papers use some measure of the gross wage as the dependent variable but with a progressive tax system this is not suitable since the individual will only receive a certain proportion of their income - that proportion decreasing with education - and therefore I use net wage. I do not include variables such as marital status, region or industry since these variables can be considered as intermediate variables in that they may be outcomes themselves of the education decision and thus by controlling for these variables, I would eliminate some of the pathways through which higher returns to education are realised.

The error term consists of a random walk and a purely transitory component. The transitory and permanent shocks are mean zero and serially uncorrelated.

$$lny_{it} = x_{it}\beta + \epsilon_{it} \tag{6}$$

The error component is composed of a permanent and transitory component:

$$\epsilon_{it} = u_{it} + v_{it} \tag{7}$$

The permanent component has a unit root such that

$$v_{it} = v_{it-1} + \zeta_{it} \tag{8}$$

Residual income growth is therefore[19]

$$g_{it} = \zeta_{it} + \Delta u_{it} \tag{9}$$

Thus the variance of the permanent and transitory components can be identified by the following covariances:

$$Cov(g_{it}, g_{it-1} + g_{it} + g_{it+1}) = var(\zeta_{it}) \tag{10}$$

$$Cov(g_{it}, g_{it+1}) = -var(u_{it}) \tag{11}$$

[19]Since the permanent component is calculated using the growth of the residual it is not affected by the inclusion or not of a fixed effect.

This earnings specification assumes that measurement error in earnings is negligible or subsumed by the transitory component. However, since I am only interested in comparing the returns at two different education levels, this should not be a problem if there is no systematic difference in measurement error across education levels.[20] I allow the variance to differ across ages as it is likely that the variance of wages will change across the life cycle due to an array of different reasons such as workers and firms gradually learning about the individual's productivity (Faber and Gibbons, 1997), differential investment in human capital and the increased occurrence of health shocks at the end of the life cycle.

4 Accounting for Selection in to the Labour Market

Almost all studies examining the returns to education use current earnings as a proxy for lifetime earnings. However, the use of current earnings will lead to inconsistent estimates because earnings vary systematically over the life cycle. Workers with high lifetime earnings tend to have higher earnings growth rates than workers with lower lifetime earnings and thus a comparison of earnings at the early stage of the life cycle will lead to a downward bias while comparing individuals late in life will lead to an upward bias in the estimates. Any attempt to overcome this problem by controlling for age or experience will not eliminate this bias because the result is due to heterogeneous variation around the central tendency of earnings growth (Haider and Solon, 2006).

Bhuller, Mogstad and Salvanes (2011) using Norwegian data find substantial evidence of a life-cycle bias in the returns to schooling. They find a strong positive relationship between the mean age in the sample and the returns to schooling and suggest that in order to minimize bias, the sample should be restricted to individuals aged 32 to 33. However, if there is differential selection in to employment at these ages there may still be bias in the returns. They also only estimate the life-cycle bias for males so the bias may be very different for females.

Given that female earnings growth rates are not as large as males, one might expect any bias to be substantially smaller. However, given the complexity of the interaction between female labour supply, childbearing years and education it is hard to pin point the

[20] Bound and Krueger (1994) find that measurement error is uncorrelated with education.

direction of bias. If higher educated females have children at an older age then comparing females at different stages of the life cycle would induce a 'child bearing' bias in addition to any life cycle bias. Therefore, it is important to look over the whole life cycle when calculating returns to education.

At younger ages it is likely that there is positive selection in to the labour market for the low educated if those with the least labour market value are hit with unemployment shocks. There may be negative selection for the higher educated if those with high earnings capabilities undertake MBAs or PhDs. At the end of the life cycle there is less attachment to the labour market for all education groups due to a variety of reasons including early retirement, unemployment and the fact that at the end of the life cycle the returns from investing in one's human capital are diminished due to the small amount of time left in the labour market to recoup the returns to experience (Shaw, 1989).[21]

Obviously many different hypotheses can be put forward regarding the way selection into the labour market works for each education level and for each gender; if there is positive selection of low educated workers then comparing returns at two different levels (assuming random selection in to employment of the higher educated) will lead to a downward bias in returns to education; on the other hand it could be that the average high educated worker is of higher quality than a potential high educated worker and in this case (assuming random selection in to the lower education level) returns will be overestimated. Correcting for non-random selection in to the labour market is very important if one wants to get an unbiased estimate of the returns to education. In order to address this issue, I use a Heckman selection equation. To avoid identification coming exclusively from the non-linearity of the inverse mills ratio, I use annual non-labour income net of annual means tested cash benefits as an instrument for labour market participation.[22] Non-labour income has been used before when looking at returns to education, for ex-

[21] Towards the end of the life cycle it is possible that there is positive selection in the labour market for the low educated if those who are hit with negative unemployment shocks or are discouraged from their low growth rates leave the labour market while there may be positive selection for the higher educated if those who have high earnings stay in the labour market as the opportunity cost of leaving is too great. Conversely, there may be negative selection for all education levels if high income individuals who have amassed enough wealth retire early.

[22] Low, Pistaferri and Meghir (2004) have used this as an instrument for participation.

ample, Duraisamay (2002), Asadullah (2006) and Asadullah and Xiao (2018).[23] This is valid as long as non-labour income significantly affects the decision to work (first stage) while having no direct effect on offered wages (the exclusion restriction). It is shown in Tables A2 and A6 that the first stage condition holds for both males and females. One cannot infer whether the second condition holds as it is fundamentally untestable given wage offers are not observed. On the one hand, it is likely that non-labour income affects labour force participation while having no impact on offered wages. For example, if an individual received a large lottery win then they may be less inclined to work but, all else equal, this would not affect the wages they are offered (as their productivity has not changed). On the other hand, individuals with higher non-labour income may also have unobservable characteristics that makes the wage they command in the labour market higher than someone with lower non-labour income. For example, highly-skilled individuals may be more likely to accumulate assets and investments and thus have higher non-labour income. If so, non-labour income would be correlated with offered wages and the instrument would not be valid. Given that I control for a rich set of covariates that correlate with wage offers (such as parental education), the exclusion restriction is more plausible in this situation than in many other cases where it has been used in the literature.

Denote the latent variable for labour market participation:

$$P_{it}^* = r_{it}'\theta + \pi_{it} \tag{12}$$

where

$$\begin{aligned} P_{it} &= 1 \quad \text{if} \quad P_{it}^* > 0 \\ P_{it} &= 0 \quad \text{otherwise} \end{aligned}$$

[23] I exclude means tested cash benefits to deal with the correlation between unemployment and work. Capital income makes up 82% of non-labour income and non-means tested cash benefits the other 18 percent. The first stage is significant and the inverse mills ratio also.

Assume the errors are joint normally distributed such that

$$\begin{pmatrix} \epsilon_{it} \\ \pi_{it} \end{pmatrix} \sim N \begin{pmatrix} \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\epsilon^2 & \rho_{\epsilon\pi} \\ \rho_{\epsilon\pi} & 1 \end{pmatrix} \end{pmatrix}$$

where ϵ_{it} is the unobserved component of the log wage equation and σ_π^2 has been normalised to 1.

Then

$$E[y_{it}|P_{it} = 1, x, z] = X_{it}\beta + \rho_{\epsilon\pi}\lambda(r'_{it}\theta) \tag{13}$$

$$Var[y_{it}|P_{it} = 1, x, z] = \sigma^2_{y_{i,t}} - \rho^2_{\epsilon\pi}\lambda(r'_{it}\theta)(r'_{it}\theta + \lambda(r'_{it}\theta)) \tag{14}$$

where

$$\lambda(r'_{it}\theta) = \frac{\phi(r'_{it}\theta)}{\Phi(r'_{it}\theta)} \tag{15}$$

Correcting the variance of the permanent component is slightly more involved since the permanent component is identified from the growth of residual earnings. Therefore, the permanent component is only identified if the individual is in the labour market for two consecutive time periods. However, assuming that the permanent error component is independent and serially uncorrelated across time periods then the variance of the permanent component can be identified from the following equations:

$$E[g_{it}|P_{it} = 1, P_{i,t-1} = 1, x, z] = \rho_{\zeta\pi}\lambda(r'_{it}\theta) \tag{16}$$

$$Var[g_{it}|P_{it} = 1, P_{i,t-1} = 1, x, z] = \sigma^2_{\zeta_{it}} + \sigma^2_{u_{it}} + \sigma^2_{u_{i,t-1}} + \rho^2_{\zeta\pi}\lambda(r'_{it}\theta)(r'_{it}\theta + \lambda(r'_{it}\theta)) \tag{17}$$

$$\sigma^2_{u_{it}} = -Cov(g_{i,t}, g_{i,t+1}) \tag{18}$$

5 Data

The data I use comes from the first 18 waves of the British Household Panel Survey (BHPS).[24] The BHPS started in 1991 and collected information on approximately 5,500

[24] The BHPS in 2009 became part of the new Understanding Society Survey. This the largest longitudinal survey of it's kind in the UK, sampling some 40,000 households.

households and 10,300 individuals in England. Supplementary samples covering Scotland and Wales each containing 1,500 households were added in 1999 while in 2001 some 2,000 households representing Northern Ireland were added. The BHPS contains rich information on education, income, family background, employment and consumption.

In the analysis I drop self-employed individuals, those who are still in full-time education and those who are older than 65 or younger than sixteen. Those with missing information on usual net monthly pay, highest education qualification, race, age or parental education are also dropped. The education variable I use is a derived variable in the BHPS denoting highest academic qualification. I group those with higher degree, first degree, higher national certificate (HNC), higher national diploma (HDC) or teaching qualification to the highest schooling level which I refer to as "College", those with A-levels comprise the schooling level which I refer to as "High School" and those with anything less than A-levels make up the lowest schooling level. Each parental education variable is categorised into no qualifications, some qualifications, further education, or university qualification and finally a variable denoting whether an individual is white or not is derived. The bottom and top 1 percent of earnings in each year are trimmed to eliminate any measurement error or outliers. All imputed earnings are set to missing. Earnings and consumption are deflated to 1991 prices using the UK retail price index (RPI).

6 Risk Differentials

There are quite substantial differences in employment levels across education groups. Employment is increasing in education for males with those with less than high school having significantly lower employment rates throughout the life cycle while the differential between high school graduates and college graduates is small.

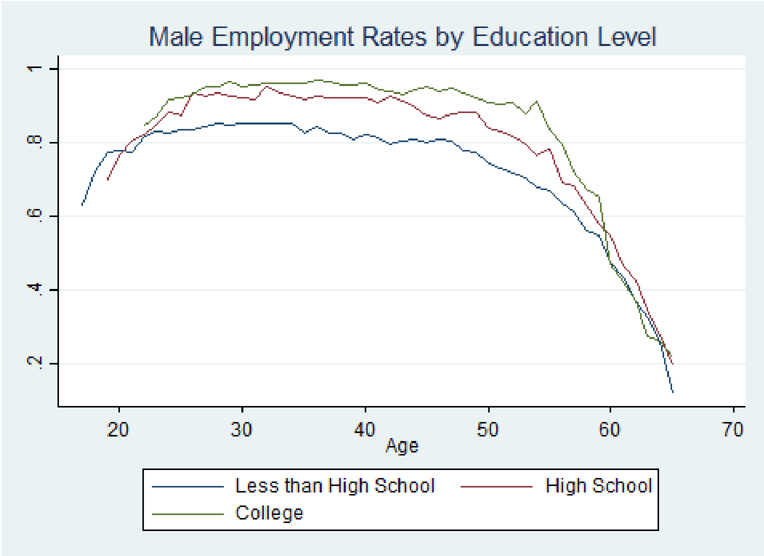

Figure 1: Male Employment Rates

Females are less likly to be employed than males and those with less than high school have particularly low employment rates while the differential between the two highest education groups is negligible. The lack of full employment highlights the importance to correct for non-random selection into the labour market.

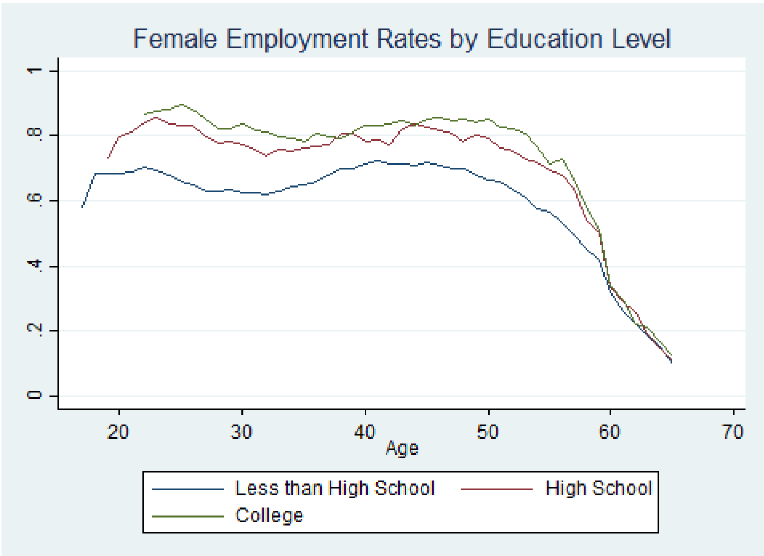

Figure 2: Female Employment Rates

Turning to the variance of earnings where variance is got by taking the square of the residual from a regression of log earnings on a set of explanatory variables, it appears that the variance is increasing in education level although there are some differences at earlier and later stages of the life cycle. For the majority of the life cycle, the variance is inversely related to education but after age 50, those with less than high school face a lower variance. However, in an IRR framework the end of the life cycle will be heavily discounted and so it is the earlier time periods which will have the most effect. Overall, Figure 3 shows that on average the earnings risk is decreasing in education.

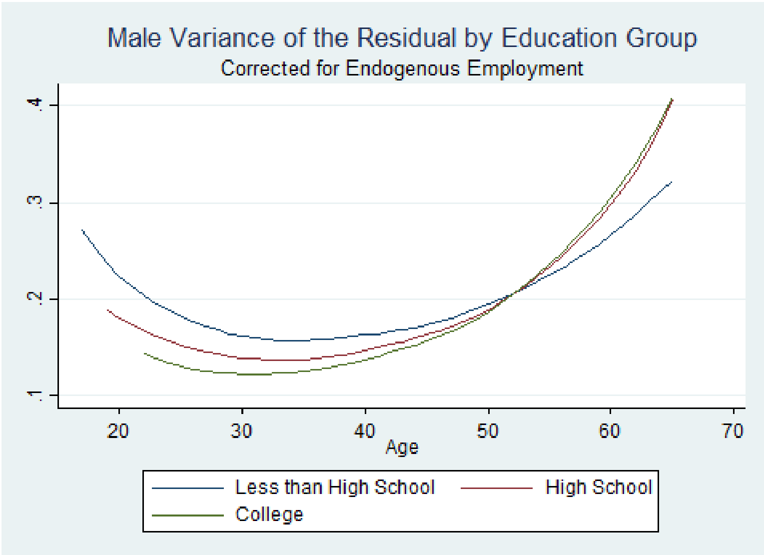

Figure 3: Male Variance of the Wage Residual

For females the variance is largest for the college educated and smallest for the high school graduates. This suggests that adjusting for wage risk will lead to an increase in returns to high school and a decrease in the returns to college.

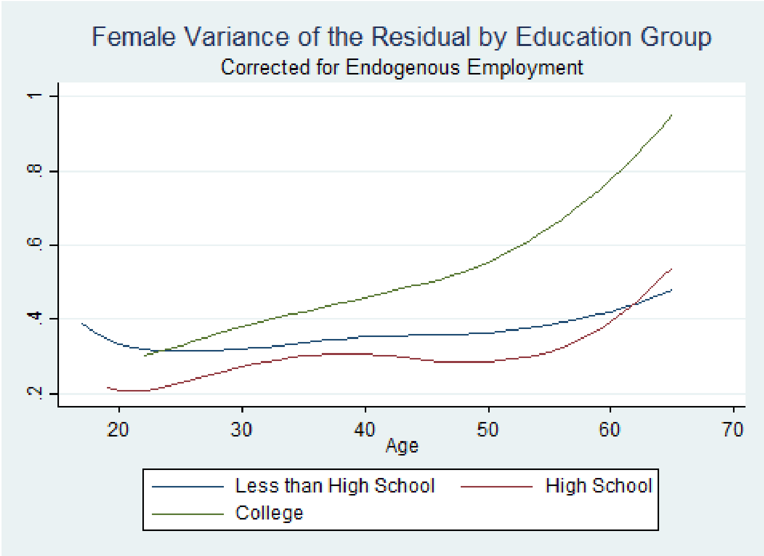

Figure 4: Female Variance of the Wage Residual

7 Results

7.1 *Males*

Table 1 displays the internal rate of return for both college and high school for males under risk neutrality. This leads to an IRR of 0.063 to college and 0.079 to high school. Adjusting for non-employment risk increases the return to college to 0.085 and to high school graduates to 0.132. Thus, as expected, the lower probability of non-employment for those with higher education leads to a higher return to schooling. The wage risk adjusted return to college is 0.063 while the adjusted IRR for high school graduates is 0.08. Thus the inclusion of wage risk does little to impact returns. The overall combined effect of both risks leads the returns to college to rise by 2.1 percentage points or roughly 33 percent while the returns to high school increased by 5.3 percentage points (67 percent). The main contribution to the increase in the risk-adjusted returns is non-employment risk.

Table 2 shows the results after correcting for selection in to the labour market. The first stage results which are shown in Table A2 in the Appendix show that non-labour income net of benefits has a significant negative effect on employment at all education levels. While the inclusion of the inverse mills ratio in the regression suggests that workers

Table 1: Male Internal Rate of Return

	No Risk	Non-Employment Risk	Wage Risk	Both Risk
College	0.063	0.085	0.063	0.084
	(0.023)	(0.024)	(0.036)	(0.026)
High School	0.079	0.132	0.080	0.132
	(0.021)	(0.018)	(0.027)	(0.021)

Bootstrap standard errors based on 50 samples with replacement are in parentheses.

are negatively selected in to employment at all education levels. This result could be due to negative selection in older ages outweighing positive selection at other stages of the life cycle.[25] Correcting for endogenous labour market participation leads to a fall in the IRR to college and high school with an IRR of 0.058 for both college and high school. The impact of non-employment risk is very similar to the baseline case without the employment correction with the effect of non-employment risk increasing the IRR at all levels. Wage risk increases the return to high school by almost 1 percentage point while slightly increasing the returns to college. This highlights the importance of accounting for selection in to employment as without this correction it would appear that wage risk has little effect on high school returns.

Table 2: Male Internal Rate of Return Corrected for Endogenous Employment

	No Risk	Non-Employment Risk	Wage Risk	Both Risk
College	0.058	0.080	0.059	0.081
	(0.023)	(0.022)	(0.018)	(0.020)
High School	0.058	0.123	0.066	0.128
	(0.018)	(0.018)	(0.012)	(0.017)

Bootstrap standard errors based on 50 samples with replacement are in parentheses.

[25] Interacting the inverse mills ratio with age and adding a quadratic in this interaction term shows the higher educated select positively in to the labour market but the estimate is not significant and adjusting the mean and variance for the additional selection terms leads to very noisy results and so I decide to use the standard approach and only include the inverse mills ratio in the regression.

7.2 *Females*

The returns to both college and high school are larger for females than for males with the returns being 0.071 for college and 0.098 for high school. Adjusting for non-employment risk leads the return to college to decrease to 0.045 and the return to high school to almost double to 0.187. The effect of non-employment risk on the return to college for females is very different to that of males and highlights that although the raw returns to college appear to be somewhat larger for females, once the effect of non-employment is accounted for, then the return to college for females is actually lower.[26]

Adjusting for wage risk slightly lowers the return to college by 0.4 percentage points while increasing the return to high school by almost 3 percentage points highlighting the u-shaped pattern in the variance across education levels.[27] Overall, the impact of both non-employment risk and wage risk results in a return to college of 4.2 percent and a return to high school of 19 percent.

Table 3: Female Internal Rate of Return

	No Risk	Non-Employment Risk	Wage Risk	Both Risk
College	0.071	0.045	0.067	0.042
	(0.003)	(0.016)	(0.007)	(0.011)
High School	0.098	0.187	0.126	0.190
	(0.032)	(0.020)	(0.017)	(0.012)

Bootstrap standard errors based on 50 samples with replacement are in parentheses.

Correcting for participation leads the return to college to more than double to 0.145 while the return to high school falls to 0.062. The large increase in the return to college

[26] The low return to college when non-employment risk is included suggests that given the likelihood that females may drop out of the labour market once they start a family and given that labour supply is the channel by which returns to human capital investment are reaped, it may seem that investing in college for females may not be such a worthwhile pursuit. However, if by going to college females marry college educated men this will tend to increase the overall returns.

[27] Although the returns to college are lower when adjustment is made for wage risk suggesting that college graduates face higher risk, Weisbrod (1962) stresses that the extra risk may not be considered as decreasing utility if going to college increases the potential occupations available to the individual.

could be due to the likelihood that college educated women who would earn the most if they participate in the labour market are married to high earning men and due to high levels of wealth decide not to participate in the labour market. Adjusting for non-employment risk decreases the return to college while more than doubling the return to high school. While correcting for selection in to the labour market increases the unadjusted returns to college, the effect is offset once risk is accounted for, resulting in a risk-adjusted return to college that is just 1.6 percentage points larger than the risk-adjusted return that does not account for endogenous employment; the corresponding change for high school is a decrease of 2 percentage points. Overall, comparing the naive returns that do not account for risk or selection in to employment, the adjusted return to college goes from 0.071 to 0.058 which represents a 22 percent decrease in returns to college; the corresponding figure for the adjusted return to high school is an increase of 63 percent.

Table 4: Females: IRR Corrected for Endogenous Employment

	No Risk	Non-Employment Risk	Wage Risk	Both Risk
College	0.145	0.082	0.102	0.058
	(0.031)	(0.017)	(0.027)	(0.018)
High School	0.062	0.163	0.097	0.170
	(0.027)	(0.035)	(0.026)	(0.025)

Bootstrap standard errors based on 50 samples with replacement are in parentheses.

8 Advanced Information and Insurance

8.1 Advanced Information

The previous section found a large effect of risk on returns to both college and high school. However, it is difficult to infer how much of this risk actually represents true uncertainty versus unobserved factors which can be predicted in advance by the individual. Heckman, Cunha and Navarro (2005) find that individuals know at least 40 percent of the risk due to heterogeneity and therefore neglecting this insight will lead to an overestimate of risk. They estimate the correlation between observed outcomes and the agent's schooling decision to infer the amount of risk that is known in advance. This could be due to individual's knowing their own ability, motivation, etc.

It is possible to test for advanced information if one has data on consumption. In the BHPS there is data for each year on usual weekly food expenditure.[28] The permanent income hypothesis predicts that consumption should only react to unanticipated permanent income shocks as it is assumed that agents can perfectly insure themselves against transitory shocks via savings.[29] It is likely that if one expects a promotion at the end of the term then this will be factored in to consumption decisions from today and although from the econometrician's point of view it registers as a shock when the agent gets promoted, this will not be a shock to the agent.

Following Blundell, Pistaferri and Preston (2008) I test for evidence of superior information. The basic idea is that if income is anticipated by the agent then future income growth should be correlated with current consumption growth. If there is a significant correlation between current consumption growth and future income growth then this implies that the agent has more information and such shocks that appear as risk may in fact be already known to the individual.

I regress the real values of log consumption and log earnings on a wide set of covariates including dummies for year of birth, year, household size, job status, number of children, region, marital status and race separately for each gender and education level and use the residuals from these regressions in the test. Tables 5 and 6 show that for those with college, the test of no correlation between current consumption growth and future income growth is rejected for both males and females. This adds support to the conclusion that the risk-adjusted returns do in fact represent risk and that the estimates are not over estimated.

[28] This includes takeaways but excludes meals eaten in restaurants. While it would be better to have consumption items such as expenditure on clothing, travel, and other non-durables, due to a lack of data covering these items, previous studies have also used food expenditure, for example, Zeldes (1989).

[29] Observing a muted response of consumption to permanent shocks to income could be due to advanced information or insurance. Van Rens and Primiceri (2009) attribute any observed change in permanent shocks which do not translate in to consumption changes as information that must have been known in advance. However, this assumes that there is no insurance available for permanent shocks.

Table 5: Males: P-values for test of null hypotheses of no correlation between consumption growth and future income growth for all years

	Less than HS	High School	College
Test $Cov(\Delta y_{i,t+1}, \Delta c_{i,t}) = 0$ for all t	0.197	0.286	0.112
Test $Cov(\Delta y_{i,t+2}, \Delta c_{i,t}) = 0$ for all t	0.202	0.745	0.921
Test $Cov(\Delta y_{i,t+3}, \Delta c_{i,t}) = 0$ for all t	0.593	0.502	0.604
Test $Cov(\Delta y_{i,t+4}, \Delta c_{i,t}) = 0$ for all t	0.694	0.747	0.669

Table 6: Females: P-values for test of null hypotheses of no correlation between consumption growth and future income growth for all years

	Less than HS	High School	College
Test $Cov(\Delta y_{i,t+1}, \Delta c_{i,t}) = 0$ for all t	0.456	0.996	0.268
Test $Cov(\Delta y_{i,t+2}, \Delta c_{i,t}) = 0$ for all t	0.091	0.853	0.219
Test $Cov(\Delta y_{i,t+3}, \Delta c_{i,t}) = 0$ for all t	0.607	0.070	0.413
Test $Cov(\Delta y_{i,t+4}, \Delta c_{i,t}) = 0$ for all t	0.111	0.642	0.878

8.2 Insurance

If there are mechanisms available that provide insurance against income shocks this will help to alleviate the negative impact of the shocks. The availability of insurance may differ across education levels and this will affect the internal rate of return. Possible insurance mechanisms include savings, borrowing, spousal labour supply, social networks and government transfers. It is likely that higher educated individuals would benefit most from the savings and borrowing channel since their high earnings mean they can afford to build up a buffer stock of precautionary savings to insure against adverse shocks while also making them more attractive from a lender's view point; furthermore, it is likely they have better credit history compared to the low educated who are more likely to default on loans.

There is large evidence that spousal labour supply can act as an insurance mechanism.[30] While this may differ across education levels, assortative mating (Neal, 2004) would imply that a higher educated spouse would command a higher wage and be more likely to get a job than a lower educated spouse. Similarly, if those who attend college have a social network that includes individuals who have also attended college then it is more likely that this channel would provide some benefit.

The role of government transfers is the most important and widely available avenue for providing insurance to individuals through unemployment insurance, disability benefits, etc. To the extent that government transfers are means tested, the lower educated will benefit the most from this insurance channel. Blundell, Graber and Mogstad (2012) using Norwegian data find that taxes and transfers play a substantial role in sheltering individuals from the adverse consequences of income shocks with particular benefit for the low educated. While the model used in this paper includes unemployment benefits, there are other government benefits available which were not included and may help to combat labour market shocks and mitigate the effect of risk on the returns to education.

Decomposing the variance of the earnings residual in to permanent and transitory components can offer insight in to the amount of insurable labour market shocks and how the magnitude may differ by education group. It is important to distinguish between these two components since they have very different welfare effects. Transitory shocks which are temporary and short lasting include a short illness, a bonus, overtime labour supply and any mean reverting shock. It is argued that transitory shocks average out over one's lifetime or can be smoothed through savings and so do not affect welfare; Cochrane (1991) and Blundell, Pistaferri and Preston (2008) find full insurance against transitory shocks.[31] Conversely, permanent shocks such as low productivity, disability, demotion, and skill biased technological change are less likely to be insured against and have persistent effects on a person's earnings and welfare.

Section A1 in the appendix contains figures and tables which show a depiction of

[30] Lundberg (1985) finds evidence that wife's labour supply increases in response to husband's negative income shocks, Devereux (2003) finds that a 10 percent fall in husband's wage leads to a 4% increase in wife's hours of work while Blundell, Pistaferri and Saporta-Ecksten (2012) find a 10% decrease in male wages leads to only a 4.4% decrease in household consumption due to an increase in spouse's labour supply.

[31] One way transitory shocks could affect welfare is if individuals faced liquidity constraints.

transitory and permanent shocks and how they differ by education level. For males the average variance of transitory shocks is decreasing in education while the variance of permanent shocks is u-shaped. Therefore, males with less than high school face substantially more transitory shocks in addition to permanent shocks and thus both insurable and non-insurable shocks. While college graduates face substantially less transitory shocks than high school graduates, there is no difference in permanent shocks which suggests that they face similar levels of non-insurable shocks.

The variance of transitory shocks for females is u-shaped in education. The quite substantial difference between the two highest education levels is not due to higher levels of non-employment given that they are very similar and so may be due to higher levels of mobility between jobs or differences in variation of hours on the intensive margin if higher educated females are more likely to move in and out of part-time employment.[32] The variance of permanent shocks, however, is decreasing in education. Therefore, although college educated females face larger short-term risk, they face less volatility in uninsurable permanent shocks which may lead to an increase in returns to education.[33]

9 Conclusion

The majority of studies investigating the return to education do not adjust returns to account for non-employment risk or wage risk which is equivalent to assuming that each risk is constant across education levels. This paper has provided evidence that there are significant differences in non-employment risk and to a lesser extent wage risk across education levels. It is shown that failure to account for these differences when estimating returns to education will lead to substantially biased estimates.

[32]It could also be due to the fact that higher educated individuals have children at older ages than their lower educated counterparts and given that the distribution of earnings is more dispersed at these ages due to differential growth rates, the variance of transitory shocks will be larger. This is assuming that maternity leave represents a temporary change in income and so that females do not stay out of the market for too long once they give birth.

[33]It should be noted that these results which use after tax pay will differ from those using gross earnings leading to lower variance of the permanent component but increasing the volatility of the transitory shocks because now tax changes become an additional source of uncertainty.

The returns to both high school and college for males increase substantially once non-employment risk is taken in to account while the impact of wage risk is negligible. For females, adjusting for non-employment leads the returns to high school to increase but leads to a *decrease* in the returns to college. Similarly, adjusting for wage risk leads to an increase in female returns to high school but to a *decrease* in returns to college.

Correcting for non-random selection in to employment results in large changes in the returns for females while the effect on males is not as substantial. It is imperative that future studies investigating the returns to education take into consideration the effects of risk, in particular non-employment risk, while those studies looking at returns to females should account for endogenous employment.

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Appendix

Table A1: Males: OLS Regression of Log Net Pay

	Less than High School	High School	College
Age	0.0816***	0.0877***	0.0942***
	(0.0031)	(0.0068)	(0.0080)
Age Squared	-0.0947***	-0.1002***	-0.1070***
	(0.0039)	(0.0087)	(0.0097)
Mother Some Qualifications	0.0669***	0.0784**	-0.0197
	(0.0214)	(0.0330)	(0.0272)
Mother Further Education	0.0633***	0.0564	-0.0217
	(0.0236)	(0.0390)	(0.0393)
Mother University	0.1386***	-0.0196	-0.0103
	(0.0487)	(0.0593)	(0.0517)
Father Some Qualifications	0.0054	0.0607*	0.0673**
	(0.0223)	(0.0364)	(0.0317)
Father Further Education	0.0174	0.0480	-0.0126
	(0.0205)	(0.0331)	(0.0290)
Father University	0.0567	0.1574***	0.0593
	(0.0408)	(0.0517)	(0.0453)
White	0.0453	0.0444	0.0732
	(0.0470)	(0.0995)	(0.0624)
Observations	18270	7406	7983
N_clust	2346	850	895

All regressions include year dummies. The base category for white is non-white and for mother's and father's education level it is no qualifications. Log net pay is defined as usual monthly earnings multiplied by 12. Standard errors reported in parentheses are clustered at the individual level. Significance levels: * 10%, ** 5%, *** 1%.

Table A2: Males First Stage Estimates: Probit of Employment using Non-Labour Income as an Instrument

	Less than High School	High School	College
Age	0.0488***	0.0310***	0.0231***
	(0.0030)	(0.0034)	(0.0039)
Age Squared	-0.0649***	-0.0411***	-0.0306***
	(0.0035)	(0.0042)	(0.0045)
Mother Some Qualifications	0.0231	0.0398*	0.0188
	(0.0229)	(0.0207)	(0.0116)
Mother Further Education	0.0024	0.0366**	-0.0057
	(0.0332)	(0.0176)	(0.0191)
Mother University	-0.0758	0.0355	0.0031
	(0.0574)	(0.0257)	(0.0306)
Father Some Qualifications	0.0166	-0.0058	0.0176
	(0.0227)	(0.0270)	(0.0132)
Father Further Education	-0.0027	-0.0348	0.0191
	(0.0248)	(0.0214)	(0.0122)
Father University	0.0670**	-0.0743	0.0128
	(0.0284)	(0.0605)	(0.0200)
White	0.0649	-0.0679***	-0.0444***
	(0.0551)	(0.0114)	(0.0099)
Non-Labour Income	-0.0508***	-0.0302***	-0.0290***
	(0.0043)	(0.0040)	(0.0031)
Observations	9748	4772	6001
N_clust	1984	739	897

All regressions include year dummies. The base category for white is non-white and for mother's and father's education level it is no qualifications. Standard errors reported in parentheses are clustered at the individual level. Significance levels: * 10%, ** 5%, *** 1%.

Table A3: Males: Including Inverse Mills Ratio in OLS Regression of Log Net Pay

	Less than High School	High School	College
Age	0.0736***	0.0724***	0.0684***
	(0.0069)	(0.0116)	(0.0120)
Age Squared	-0.0807***	-0.0812***	-0.0763***
	(0.0092)	(0.0150)	(0.0149)
Mother Some Qualifications	0.0525*	0.0334	-0.0180
	(0.0307)	(0.0505)	(0.0302)
Mother Further Education	0.0512	0.0147	-0.0610
	(0.0341)	(0.0529)	(0.0463)
Mother University	0.1550**	-0.1270	-0.0566
	(0.0785)	(0.0785)	(0.0586)
Father Some Qualifications	0.0128	0.0843*	0.0353
	(0.0342)	(0.0478)	(0.0356)
Father Further Education	0.0376	0.0415	-0.0605*
	(0.0288)	(0.0437)	(0.0322)
Father University	0.0508	0.2302***	0.0590
	(0.0571)	(0.0704)	(0.0543)
White	0.0407	0.0235	0.0356
	(0.0685)	(0.1262)	(0.0627)
Less than HS Inverse Mills Ratio	-0.3464***		
	(0.0788)		
High School Inverse Mills Ratio		-0.2354*	
		(0.1269)	
College Inverse Mills Ratio			-0.2532**
			(0.1154)
Observations	7157	3815	4833
N_clust	1537	625	771

All regressions include year dummies. The base category for white is non-white and for mother's and father's education level it is no qualifications. Log net pay is defined as usual monthly earnings multiplied by 12. Standard errors reported in parentheses are computed using block bootstrap method. Based on 500 replications and used to account for the pre-estimated Inverse Mills Ratio. Significance levels: * 10%, ** 5%, *** 1%.

Table A4: Males: Probit Regression of Employment

	Less than High School	High School	College
Age	0.0410***	0.0364***	0.0365***
	(0.0025)	(0.0034)	(0.0036)
Age Squared	-0.0582***	-0.0502***	-0.0491***
	(0.0030)	(0.0041)	(0.0041)
Mother Some Qualifications	0.0605***	0.0692***	0.0135
	(0.0179)	(0.0233)	(0.0145)
Mother Further Education	0.0456**	0.0334	-0.0043
	(0.0223)	(0.0229)	(0.0184)
Mother University	0.0426	0.0653***	-0.0214
	(0.0393)	(0.0247)	(0.0343)
Father Some Qualifications	0.0266	-0.0351	0.0074
	(0.0206)	(0.0340)	(0.0170)
Father Further Education	0.0199	-0.0421*	0.0197
	(0.0185)	(0.0242)	(0.0130)
Father University	0.0595*	-0.0551	0.0135
	(0.0360)	(0.0441)	(0.0209)
White	0.0673	-0.0455	0.0451
	(0.0418)	(0.0302)	(0.0478)
Observations	26728	9702	10178
N_clust	3035	994	1040

All regressions include year dummies. The base category for white is non-white and for mother's and father's education level it is no qualifications. Standard errors reported in parentheses are clustered at the individual level. Significance levels: * 10%, ** 5%, *** 1%.

Table A5: Females: OLS Regression of Log Net Pay

	Less than High School	High School	College
Age	0.0311***	0.0318***	0.0487***
	(0.0042)	(0.0102)	(0.0111)
Age Squared	-0.0429***	-0.0447***	-0.0587***
	(0.0054)	(0.0135)	(0.0141)
Mother Some Qualifications	0.0781***	0.0580	0.0219
	(0.0264)	(0.0455)	(0.0437)
Mother Further Education	0.1111***	0.1856***	0.0132
	(0.0309)	(0.0495)	(0.0478)
Mother University	0.3232***	0.1976***	-0.0690
	(0.0540)	(0.0750)	(0.0686)
Father Some Qualifications	0.0405	-0.0024	-0.0683
	(0.0292)	(0.0556)	(0.0482)
Father Further Education	0.0589**	-0.0590	-0.0164
	(0.0256)	(0.0439)	(0.0446)
Father University	0.0440	0.0436	-0.1045
	(0.0542)	(0.0698)	(0.0648)
White	-0.1650***	-0.0705	0.0117
	(0.0615)	(0.1284)	(0.0899)
Observations	24201	6577	7505
N_clust	3092	823	923

All regressions include year dummies. The base category for white is non-white and for mother's and father's education level it is no qualifications. Log net pay is defined as usual monthly earnings multiplied by 12. Standard errors reported in parentheses are clustered at the individual level. Significance levels: * 10%, ** 5%, *** 1%.

Table A6: Females First Stage Estimates: Probit of Employment using Non-Labour Income as an Instrument

	Less than High School	High School	College
Age	0.0537***	0.0277***	0.0445***
	(0.0036)	(0.0062)	(0.0066)
Age Squared	-0.0755***	-0.0417***	-0.0590***
	(0.0042)	(0.0073)	(0.0075)
Mother Some Qualifications	0.0387	0.0093	0.0635**
	(0.0258)	(0.0327)	(0.0298)
Mother Further Education	0.0558**	0.0314	0.0396
	(0.0283)	(0.0326)	(0.0307)
Mother University	0.0957*	0.0163	0.0932**
	(0.0529)	(0.0488)	(0.0376)
Father Some Qualifications	-0.0018	-0.0344	-0.0241
	(0.0312)	(0.0389)	(0.0406)
Father Further Education	-0.0179	-0.0133	0.0036
	(0.0235)	(0.0325)	(0.0319)
Father University	-0.0274	-0.0038	-0.0382
	(0.0502)	(0.0421)	(0.0479)
White	0.1311**	0.0535	0.0990
	(0.0612)	(0.0913)	(0.1186)
Non-Labour Income	-0.0417***	-0.0373***	-0.0406***
	(0.0044)	(0.0060)	(0.0058)
Observations	15382	4155	5723
N_clust	2822	705	886

All regressions include year dummies. The base category for white is non-white and for mother's and father's education level it is no qualifications. Standard errors reported in parentheses are clustered at the individual level. Significance levels: * 10%, ** 5%, *** 1%.

Table A7: Females: Including Inverse Mills Ratio in OLS Regression of Log Net Pay

	Less than High School	High School	College
Age	0.0240**	0.0393**	0.0069
	(0.0102)	(0.0157)	(0.0182)
Age Squared	-0.0349**	-0.0565***	-0.0045
	(0.0142)	(0.0211)	(0.0236)
Mother Some Qualifications	0.0172	0.0670	-0.0100
	(0.0376)	(0.0594)	(0.0593)
Mother Further Education	0.0351	0.2069***	-0.0083
	(0.0447)	(0.0593)	(0.0625)
Mother University	0.2910***	0.1573	-0.1226
	(0.0720)	(0.0986)	(0.0970)
Father Some Qualifications	0.0298	-0.0338	-0.0183
	(0.0402)	(0.0713)	(0.0641)
Father Further Education	0.0568	-0.1215**	-0.0131
	(0.0350)	(0.0620)	(0.0560)
Father University	0.0157	0.0020	-0.0742
	(0.0691)	(0.0938)	(0.0843)
White	-0.2395***	0.0229	-0.0941
	(0.0721)	(0.1359)	(0.1036)
Less than HS Inverse Mills Ratio	-0.1690		
	(0.1150)		
High School Inverse Mills Ratio		-0.1139	
		(0.1617)	
College Inverse Mills Ratio			-0.6755***
			(0.1742)
Observations	9860	3130	4040
N_clust	2064	600	745

All regressions include year dummies. The base category for white is non-white and for mother's and father's education level it is no qualifications. Log net pay is defined as usual monthly earnings multiplied by 12. Standard errors reported in parentheses are computed using block bootstrap method. Based on 500 replications and used to account for the pre-estimated Inverse Mills Ratio. Significance levels: * 10%, ** 5%, *** 1%.

Table A8: Females: Probit Regression of Employment

	Less than High School	High School	College
Age	0.0456***	0.0235***	0.0512***
	(0.0027)	(0.0052)	(0.0054)
Age Squared	-0.0631***	-0.0365***	-0.0679***
	(0.0031)	(0.0063)	(0.0062)
Mother Some Qualifications	0.0768***	0.0243	0.0484*
	(0.0177)	(0.0277)	(0.0264)
Mother Further Education	0.0955***	0.0335	0.0252
	(0.0204)	(0.0289)	(0.0273)
Mother University	0.1208***	0.0376	-0.0118
	(0.0413)	(0.0388)	(0.0410)
Father Some Qualifications	0.0276	0.0270	-0.0159
	(0.0208)	(0.0307)	(0.0335)
Father Further Education	0.0134	0.0348	0.0107
	(0.0170)	(0.0262)	(0.0275)
Father University	0.0151	0.0350	-0.0086
	(0.0375)	(0.0357)	(0.0371)
White	0.1678***	0.0842	0.0611
	(0.0432)	(0.0816)	(0.0794)
Observations	42208	9210	10664
N_clust	4187	946	1081

All regressions include year dummies. The base category for white is non-white and for mother's and father's education level it is no qualifications. Standard errors reported in parentheses are clustered at the individual level. Significance levels: * 10%, ** 5%, *** 1%.

A1 Variance of Earnings Residual

Table A9: Males: Average Life Cycle Variance of the Residual

	Baseline	Participation Correction
Less than High School	0.141 (0.004)	0.183 (0.006)
High School	0.140 (0.006)	0.159 (0.008)
College	0.144 (0.007)	0.154 (0.009)

Standard errors reported in parentheses are block bootstrapped at the individual level using 500 replications.

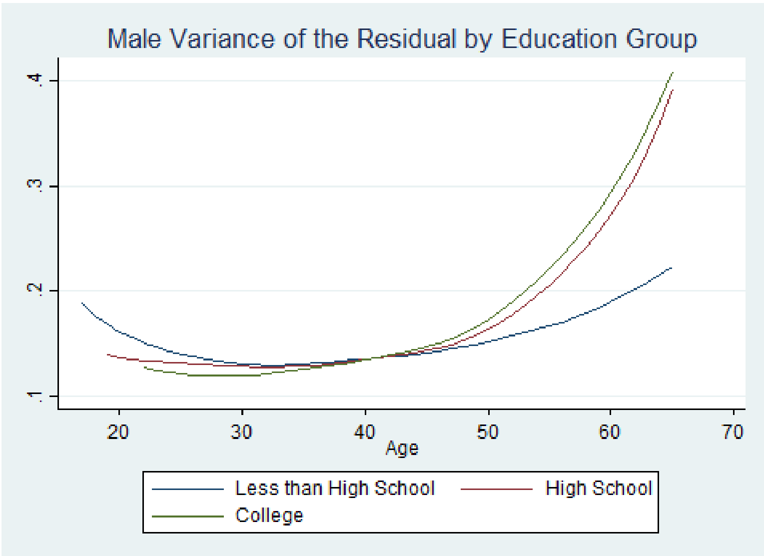

Figure A5: Male Variance of the Wage Residual

Table A10: Females: Average Life Cycle Variance of the Residual

	Baseline	Participation Correction
Less than High School	0.328 (0.007)	0.345 (0.010)
High School	0.283 (0.013)	0.281 (0.015)
College	0.293 (0.010)	0.477 (0.019)

Standard errors reported in parentheses are block bootstrapped at the individual level using 500 replications.

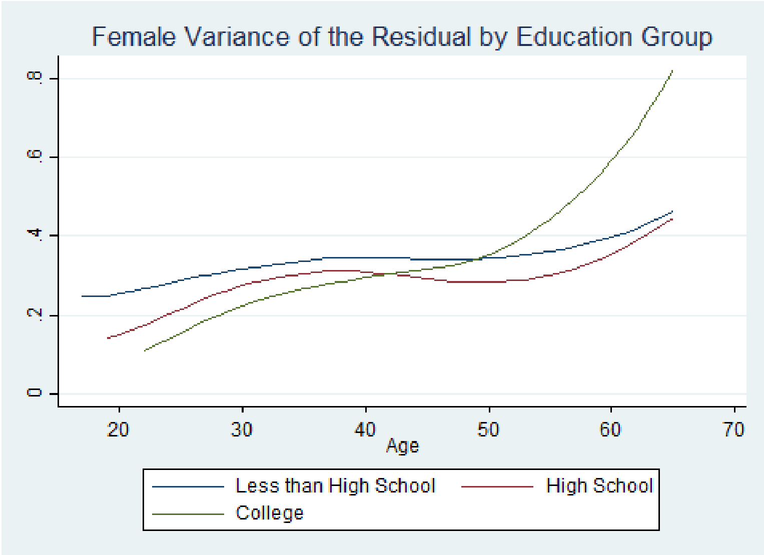

Figure A6: Female Variance of the Wage Residual

A2 Permanent versus Transitory Shocks

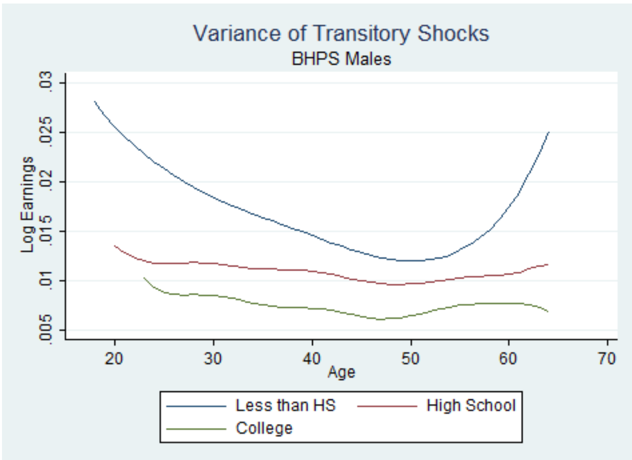

Table A11: Males: Average Life Cycle Variance of Transitory Shocks

Less than High School	0.015 (0.001)
High School	0.011 (0.001)
College	0.007 (0.001)

Standard errors reported in parentheses are block bootstrapped at the individual level using 500 replications.

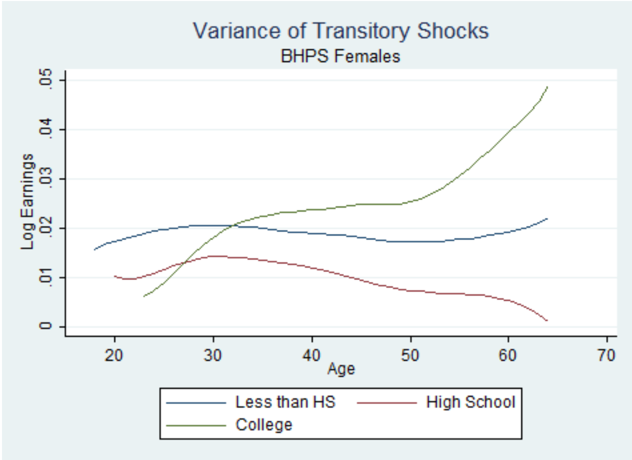

Table A12: Females: Average Life Cycle Variance of Transitory Shocks

Less than High School	0.019 (0.002)
High School	0.012 (0.002)
College	0.023 (0.004)

Standard errors reported in parentheses are block bootstrapped at the individual level using 500 replications.

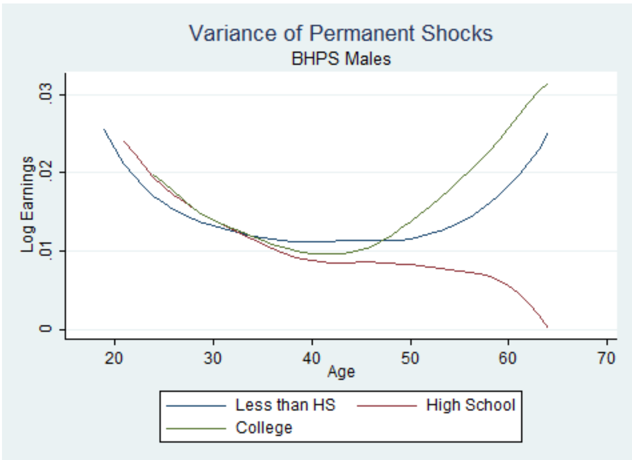

Figure A7: Male Variance of Permanent Shocks

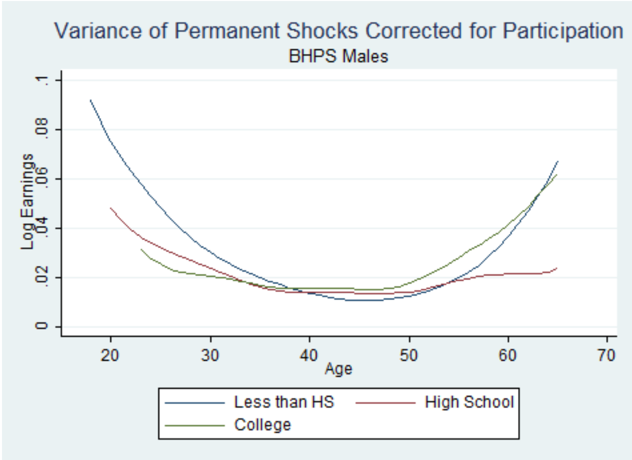

Figure A8: Male Variance of Permanent Shocks Corrected for Endogenous Employment

Table A13: Males: Average Life Cycle Variance of Permanent Shocks

	Baseline	Participation Correction
Less than High School	0.013 (0.001)	0.021 (0.003)
High School	0.010 (0.001)	0.016 (0.004)
College	0.012 (0.002)	0.017 (0.004)

Standard errors reported in parentheses are block bootstrapped at the individual level using 500 replications.

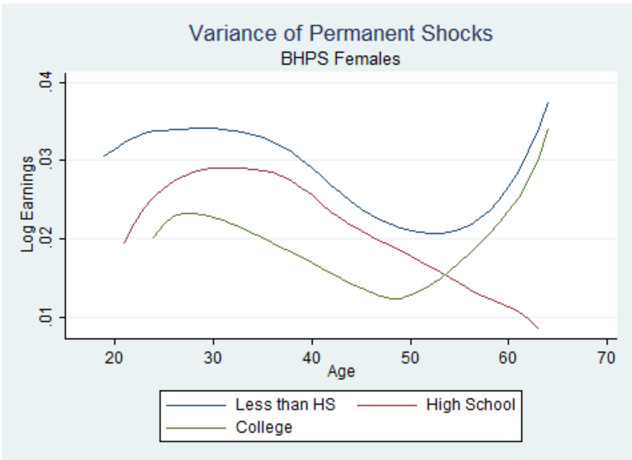

Figure A9: Female Variance of Permanent Shocks

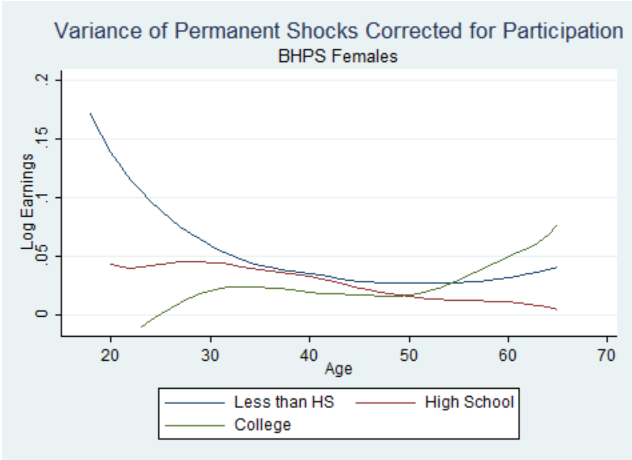

Figure A10: Female Variance of Permanent Shocks Corrected for Endogenous Employment

Table A14: Females: Average Life Cycle Variance of Permanent Shocks

	Baseline	Participation Correction
Less than High School	0.027 (0.002)	0.038 (0.004)
High School	0.027 (0.003)	0.034 (0.006)
College	0.018 (0.002)	0.022 (0.007)

Standard errors reported in parentheses are block bootstrapped at the individual level using 500 replications.