ON COMPENSATION FOR

RISK AVERSION AND SKEWNESS AFFECTION IN WAGES

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Abstract

This paper presents extensive empirical testing of the hypothesis that greater post-schooling earnings risk requires higher expected returns. Expanding on this notion, on the basis of utility theory, we predict that workers not only care about risk but also about the skewness in the distribution of the compensation paid: workers exhibit risk aversion and skewness affection. To test these hypotheses, this paper carefully develops various measures of risk and skewness by occupational/educational classification of the worker and finds supportive evidence: wages rise with occupational earnings variance and decrease with skewness. In order to identify the discount rate and the degree of risk aversion, we also apply structural modelling of education and occupational choice and allow for non-lognormal wage distributions.

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1. Motivation

The notion that financially risky ventures will only be undertaken if there is a perspective on compensation is a commonplace. This also applies to the labour market. Indeed, as Adam Smith (1976:208) noted: "*The probability that any particular person shall ever be qualified for the employment to which he is educated is very different in different occupations. Put your son apprentice to a shoemaker, there is little doubt of his learning to make a pair of shoes; but send him to study the law, it is at least twenty to one if ever he makes such proficiency as will enable him to live by the business.*" Smith not only understood that in a competitive labour market wage differentials will compensate for differences in schooling length, he also singled out the probability of failure in an occupation as another factor that needs compensation to attract sufficient supply.

Ex ante, an individual deciding on schooling and occupation faces several kinds of uncertainty. She will not fully grasp the requirements of school and occupation, she will usually not even be fully sure of her own abilities and preferences. Most importantly, she will not know what the exact returns to her investment will be. In this paper, we acknowledge that an individual does not anticipate a given post-school wage rate but rather an entire wage *distribution*, without knowing where in that distribution she will end up. We estimate a standard Mincer earnings equation and group the residuals by their education-occupation classification. We take the within-group distribution of residuals as an indication of the uncertainty associated with the particular education-occupation combination. We then add the variance of these education-occupation residuals to the earnings function and we find that wages are indeed higher in education-occupation cells where the residual variance is higher. In fact, we even find that wages are lower in cells where the distribution is more right-skewed. We take this as evidence that the market responds to individuals' risk attitude: they dislike risk (variance), but they appreciate skew (the probability of obtaining a really high return). We identify the intensity of these preferences, and find that they are quite comparable to what is found in the literature on risk attitudes and in lifecycle consumption models.

Our basic approach has the virtue of simplicity: a two-stage estimation, where the residuals from the first stage Mincer equation give us the measures of variance and skew for the second stage risk augmented Mincer equation.[1] To be convincing, we have to face two key issues:

i. Is earnings risk relevant?

A key assumption of our approach is that individuals cannot insure the risk of their investment. This is hardly controversial: we simply do not observe individuals commencing a college education and buying insurance or an optimal investment portfolio that completely eliminates the risk of their venture. Davis and Willen (2000) compute optimal portfolios for some occupations and find completely unrealistic values. For example, a 40-year old truck driver (in 1982) should hold a portfolio of $550,000, including a short position in one portfolio of $141,000. Our view is shared by e.g., Blanchard and Fisher (1989:283), and also by Shaw (1996:626) who states: "The methods of reducing riskiness that are available in financial markets, namely, diversification, exchange, and insurance, are not options for reducing the riskiness of returns to human capital investments"

ii. Is residual dispersion the proper measure of individual uncertainty?

We assume that the distribution of residuals in an education-occupation cell for those already working provides all the information on earnings uncertainty that an individual will use. This ignores the potential effects of heterogeneity and selectivity. There are four arguments for taking this approach. The first is pragmatic: why not start with the simplest possible specification? The second argument is a perception

[1] The advantage of using residuals, rather than the distribution itself, is the correction for age (experience).

about what potential students know. Of course, the residual contains both individual heterogeneity and stochastic factors beyond the individual's control. But we are quite sceptical on the extent and precision of individuals' knowledge on their own abilities and future opportunities. Webbink and Hartog (2004) find that freshmen in university have a fairly accurate perception of mean starting salaries by education and some other characteristics, but they could not predict their own position within the distribution: predicted and realised starting salaries correlate at 0.06. Dominitz and Manski (1996) report a variance in individuals' own expected post-school earnings distribution that is larger than the actually observed variance of earnings. The third argument is analytical. Jacobs, Hartog and Vijverberg (2005) derive that self-selection by ability leads to a downward bias in the estimated OLS wage premium (risk is overestimated by confounding it with heterogeneous abilities, hence the coefficient is underestimated), self-selection by risk attitude generates no bias (compensation for the marginal worker is properly estimated), but that indeed heterogeneous risk will lead to an overestimate of the risk premium (of which we cannot assess the magnitude). It is an open question how large this bias might be. The fourth argument is empirical. Chen (2003) corrects observed wage volatility for high school graduates and two- and four-year college attendees and finds corrections for selectivity bias smaller than 10%. Berkhout, Hartog and Webbink (2005) condition risk and risk compensation on ability as measured by quartile of secondary school grades, and still find statistically significant results. Diaz Serrano, Hartog and Nielsen (2004) use a long Danish panel to distinguish permanent and transitory risk and find statistically significant compensation for transitory risk. In sum, it therefore appears that the issues of heterogeneity, self-selection and information possessed by potential students are relevant and interesting, and we will certainty continue to analyse them. But we have no indication that ignoring these issues renders our present results fatally flawed. We take residual dispersion as a meaningful indicator of the uncertainties in returns to schooling.

The earlier literature is small[2]. Skewness affection is a somewhat unfamiliar concept. However, it also holds in gambling at lotteries and horse racing[3] and is consistent with the Friedman and Savage (1948) utility function. The intuition is that, for a given mean and variance, individuals prefer a distribution that is skewed to the right, as they appreciate the small probability of a substantial gain. In the consumption-savings literature, there is strong support for the assumption of skewness affection, or prudence as it is called there (Gollier, 2001, p. 238).

Below, we first derive the basic wage equation with compensation for wage uncertainty. We then estimate reduced forms of these equations. Next, we estimate a specification that identifies preference parameters. We conclude by evaluating our findings; we relate them to the literature and discuss our neglect of unemployment risk. For details of derivations and estimation we refer to the longer version of this paper, available at our websites[4].

2 Formal modelling

2.1 Conceptual framework

We consider an individual who faces the option of going straight to work, and earn a fixed income Y_0 or go to school for s years and earn Y_s for the rest of working life. We assume that education is occupation-specific: it is characterised not only by the number of years it takes to complete but also by the curriculum that prepares the student for a particular set of occupations. The individual does not know Y_s when deciding on schooling: it will be revealed upon graduation, and will then remain

[2] King (1974), Feinberg (1981), McGoldrick (1995), McGoldrick and Robst (1996), Hartog, Plug, Diaz Serrano and Vieira (2003).
[3] Garret and Sobel (1999), Golec and Tamarkin (1998), Moore (1995).
[4] Wagerisk LabEcs longversion at www.utdallas.edu/~vijver and at

constant for the rest of working life. Y_s is the product of school output q_s (the individual's units of human capital) and the market price w_s. For educational production we have

$$q_s = q_{os} + \varepsilon_s \tag{1}$$

with q_{os} mean educational output and ε_s a random component that is unknown to the individual when entering school and becomes perfectly public information upon graduation. Thus, after completing school the individual will earn

$$Y_s = w_s\left(q_{os} + \varepsilon_s\right) \tag{2}$$

The unit price w_s is determined by the market equilibrium. Define N_s^g as the number of graduates from a particular schooling programme, equal to the number of school entrants *s* years ago (or some given fraction of that number). The stock of graduates is N_s^o (the stock may be related to past graduation cohorts, length of working life, etc., but this is immaterial for the present purpose). As we will focus on a stationary equilibrium, we will not subscript cohorts but simply assume a continual inflow of new graduates. Total demand for graduates with *s* years of schooling preparing for a specific set of occupations, measured in efficiency units produced in school, is a downward sloping function of the unit price w_s. Individuals are assumed to have identical tastes, and, in the presence of a suitable wage differential, to be indifferent between schooling and no schooling. We write this wage differential as a mark-off on the schooled wage:

$$Y_0 = (1 - M_s)Y_s \tag{3}$$

Below, we will determine M_s.[5] Stationary equilibrium requires an inflow of graduates N_s^g such that the demand price absorbing total supply exactly supports the wage mark-off M_s required by suppliers. Stated otherwise, total (and new) supply is determined at the intersection of the labour demand curve and the equilibrium wage rate as determined by the required wage mark-off.

As the mark-off M_s is determined by worker preferences and the equilibrium is stationary, dictating stability in this mark-off over time, a potential student is able to anticipate mean earnings with education *s*, but he is still uncertain about his own earnings because of the random component e_s. Before schooling is completed, the student's future productivity (and earnings) will be unknown; after completing schooling, he will be assigned his position in the output distribution and be paid according to the value of his productivity. Distributions are specific to each occupation-school curriculum type and exogenously given: in some trades output is simply more dispersed than in others.

Tying individuals to a given occupation throughout working life is restrictive. While individuals in many cases can switch occupations, there are also cases where transition costs are prohibitive: no one trained as a dentist will smoothly move into accountancy. We will leave that for future work.[6]

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[5] Note that there is a one-to-one correspondence between the unit price w_s and the mark-off M_s.

[6] Flyer (1997) indeed has estimated a complicated model of choice of first occupation after college, taking later switches into account (he did not analyse the actual moves). However, he found the option value of such moves insignificant for explaining choice of first occupation. With observations on a fine classification of educations, rather than occupations, we also find convincing support for risk compensation; see Diaz Serrano, Hartog and Skyt Nielsen (2004) and Berkhout, Hartog and Webbink (2005).

2.2 Compensation for earnings uncertainty

If individuals face non-stochastic incomes, Y_0 if unschooled and Y_s if schooled, we may derive the schooling premium M_s from imposing equal lifetime utilities, using a first-order Taylor expansion of U(Y_0) around Y_s:

$$M_s = \left(1 - e^{-d\,s}\right) \frac{U(Y_s)}{U'(Y_s)} \frac{1}{Y_s} \tag{4}$$

where $U(Y)$ is a standard utility function and d is the discount rate; utility while in school, with zero earnings, has been set equal to zero.

To find the compensation for earnings uncertainty, we assume the individual must choose between an occupation with fixed income Y^*, and an occupation with random income Y at an expected income of $E\left[Y\right] = m$. Define Θ as the generalized absolute risk premium: $\Theta = E\left[Y\right] - Y^* = m - Y^*$. We assume that switching occupations is not feasible, possibly because of licensing as in law and medicine or because the loss of specific human capital would be too costly.

With utility defined as a continuous differentiable function of income $U(Y)$, with $\partial U / \partial Y > 0$, we now also assume risk aversion $\partial^2 U / \partial Y^2 < 0$. Imposing equal (expected) lifetime utility in both occupations, applying a third-order Taylor expansion to the stochastic returns and expressing the premium relative to income, we may write

$$\Pi = \frac{\Theta}{m} = \frac{1}{2} V_r \frac{m_2}{m^2} - \frac{1}{6} V_r F_r \frac{m_3}{m^3} \tag{5}$$

where relative risk aversion V_r is given by

$$V_r = V_a m = -\frac{U''(m)}{U'(m)} m > 0 \tag{6}$$

and relative skewness affection F_r by[7]

$$F_r = F_a m = -\frac{U'''(m)}{U''(m)} m > 0 \tag{7}$$

where $U''(m) = \partial^2 U / \partial Y^2$ evaluated at $Y = m$, and $U'''(m) = \partial^3 U / \partial Y^3$ at $Y = m$, and with m_2 and m_3 defining the second and third moments of Y (the variance and the skewness) around m. We refer to the second moment as risk. Since, for a risk averter, V_a is positive and since F_a is positive if we assume decreasing absolute risk aversion (Arrow, 1971; Tsiang, 1972, 359), we conclude that the absolute risk premium Θ is positive in risk (variance) and negative in skewness. This motivates our terminology of skewness affection.

2.3 Towards an Empirical Model

We now combine compensation for schooling and for risk by writing the non-stochastic earnings option as a Mincer mark-up on the riskless no-schooling alternative. Thus, we write

$$E[Y_s] = m_s = (1 - \Pi_s)^{-1} (1 - M_s)^{-1} Y_0 \tag{8}$$

where Y_0 is the riskless income of those without any schooling (as in equation (3)). Disturbance terms are introduced by specifying $Y_s = m_s e^{h_s}$ and $Y_0 = e^{Xb+h}$, where X and h are observable and unobservable determinants of Y_0. Taking the logarithm of (8) yields an expression that is close to the familiar empirical model:

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[7] Gollier (2001, p. 238) calls this the index of absolute prudence.

$$\ln Y_s = X\,b - \ln\left(1 - \Pi_s\right) - \ln\left(1 - M_s\right) + e_s \tag{9}$$

and $e = h + h_s$ is a possibly heteroskedastic disturbance term combining random factors that are unobservable to the researcher with random fluctuations that are uncertain to the individual. Under CRRA simplification with

$$U(Y) = \frac{1}{1-r} Y^{1-r}, \tag{10}$$

it is straightforward to show that

$$M_s = \frac{1 - e^{-d\,s}}{1-r} \tag{11}$$

$$\Pi_s = \frac{1}{2}\frac{m_{2s}}{m_s^2}\,r - \frac{1}{6}\,r\,(r+1)\frac{m_{3s}}{m_s^3} \tag{12}$$

Next, connect (11) and (12) to (9) through Taylor expansions

$$-\ln(1 - M_s) = -\ln\left(1 - \frac{1 - e^{-d\,s}}{1-r}\right) \approx -\ln\left(1 - \frac{d\,s}{1-r}\right) \approx \frac{d\,s}{1-r} \tag{13}$$

$$-\ln(1 - \Pi_s) \approx \Pi_s \tag{14}$$

Furthermore, rewrite the second- and third-order terms in equation (12):

$$\frac{m_{2s}}{m_s^2} = \frac{E\left[\left(Y_s - m_s\right)^2\right]}{m_s^2} = E\left[\left(\frac{Y_s - m_s}{m_s}\right)^2\right] \tag{15}$$

$$\frac{m_{3s}}{m_s^3} = \frac{E\left[\left(Y_s - m_s\right)^3\right]}{m_s^3} = E\left[\left(\frac{Y_s - m_s}{m_s}\right)^3\right] \tag{16}$$

Then, under the assumption of CRRA, the earnings function would read

$$E(\ln Y_s) = \ln Y_o + \frac{d}{1-r} s + \frac{1}{2} r \frac{m_{2s}}{m_s^2} - \frac{1}{6} r(r+1) \frac{m_{3s}}{m_s^3} \tag{17}$$

which is a simple equation in schooling years, a variance term (15) and a skewness term (16). Hence with observations on relative variance and relative skewness we could estimate a Mincer earnings equation augmented with risk compensation. If we do not assume CRRA, the parameters of (17) will not be constant but depend on income levels. However, as a linearization, it would still be a good starting point for empirical work. This is exactly how we use (17) in section 3.

2.4 Adding a Profile to the Income Stream

Let us now introduce time dependence in the income profile. That is, let the income of a person with schooling level *s* at stage *t* of his/her lifecycle be a random variable Y_{st} with a mean m_{st} which follows a non-random profile denoted by a_t, i.e $m_{st} = a_t m_{s0}$. Then, to find the schooling premium M_s, assume that there is a riskless no-schooling income at age t, $a_t m_{00}$, and a riskless schooling income, $a_t (1-M_s)^{-1} m_{00}$. Hence, m_{00} is non-random, and the profile a_t is independent from s. Then, equating lifetime utilities, M_s has to be solved from

$$\int_0^\infty U(a_t m_{00}) e^{-dt} dt = \int_s^\infty U\{a_t (1-M_s)^{-1} m_{00}\} e^{-dt} dt \tag{18}$$

This does not easily simplify, and in general requires numerical methods to solve for M_s at given d and specified utility functions.

The risk premium, as before, is determined by the equality of expected lifetime utility of the risk free and risky income streams:

$$\int_s^{\infty} U\left(\left(1-\Pi_s\right)m_{st}\right)e^{-dt}dt = E\left[\int_s^{\infty} U\left(Y_{st}\right)e^{-dt}dt\right] \tag{19}$$

The same Taylor expansions as before yield the following equation for Π_s:

$$-\Pi_s\int_s^{\infty} a_t U'(a_t m_{s0})e^{-dt}dt = \frac{m_{2s0}}{2m_{s0}^2}\int_s^{\infty} a_t^2 U''(a_t m_{s0})e^{-dt}dt + \frac{m_{3s0}}{6m_{s0}^3}\int_s^{\infty} a_t^3 U'''(a_t m_{s0})e^{-dt}dt \tag{20}$$

a_t cannot be separated from m_{s0} and joined to e^{-dt}, so the integrals cannot be simplified.

3 Estimation

We will first turn to estimating our linearized reduced form, equation (17). We start by estimating

$$\ln W_{ji} = X_i b + e_{ji} \tag{21}$$

where *i* indicates the individual and *j* indicates the occupation-schooling group that the individual belongs to. Years educated is one of the variables in the matrix *X*. The wage profile is modelled as a quadratic function of age. We prefer age to potential experience because it is exogenous. Define s_j^2 as the variance of the disturbance e_{ji} in occupation/education cell *j*. Use the estimated parameter vector $\hat{b}$ and the estimated variance $\hat{s}_j^2$ to predict the wage rate for each individual through:

$$\hat{W}_{ji} = \exp\left(X_i\hat{b} + \hat{s}_j^2/2\right) \tag{22}$$

Finally, calculate wage deviations $W_{ji} - \hat{W}_{ji}$ and from these the relative variance R_j and relative skewness K_j, defined as

$$R_j = \frac{1}{I_j} \sum_{i=1}^{I_j} \left(\frac{W_{ji} - \hat{W}_{ji}}{\hat{W}_{ji}} \right)^2 \tag{23}$$

$$K_j = \frac{1}{I_j} \sum_{i=1}^{I_j} \left(\frac{W_{ji} - \hat{W}_{ji}}{\hat{W}_{ji}} \right)^3 \tag{24}$$

In (22), the variance term is added to the mean to reflect that the disturbances of the earnings distributions are approximately lognormal, as is commonly assumed. Were the distribution indeed lognormal, equation (22) would hold exactly.[8] *R* and *K* are the sample estimates of (15) and (16) and are added as regressors in equation (21).

Our data sources are the March 1998 round of the U.S. Current Population Survey, the 1-percent public use sample of the 1990 U.S. Census, and the 1995-1999 Merged Outgoing Rotation Group file that is derived from the monthly rounds of the U.S. Current Population Survey and is available from the National Bureau of Economic Research (which we shall refer to as the NBER-CPS data). We focus the analysis on full-time employees: the sample consists of individuals working between 30 and 70 hours a week, who are employed at least 4 weeks of work during the year. Individuals under 16 and over 65 years of age are excluded.

For CPS 1998 and Census 1990, hourly earnings are computed as the ratio of annual earnings and annual regular hours worked; in the NBER-CPS data, hourly workers report hourly wages themselves, but for salaried workers hourly earnings are computed from weekly earnings and hours. Relative variance and skewness are calculated for each occupation/education cell; we delete all cells with less than 6 observations. For most of the analysis, the detailed 3-digit occupational codes with its 500 listings are aggregated into one with 25 categories. The educational measure is categorical and is transformed into year equivalents. This yields 7 groups: = 10, 11, 12, 14, 16, 18 and 20. After omission of cells with too few observations, this still leaves 129 cells for men and 104 cells for women in the smallest (CPS 1998) sample, rather than the maximum of 7 x 25 = 175 cells. There is sufficient variation in R and K to search for effects on wages: the earnings distributions within cells are not simple scalar replicas of one standard distribution. The standard deviations of R and K are large relative to the mean, especially so for K and particularly so with the Census 1990 data.[9] Negative skewness is not uncommon, but most distributions are skewed to the right.

3.1 Preliminary Results

We start our testing with the Census 1990 and CPS 1998 data, which are representative of much applied work on earnings. Regression results indicate that the rate of return to education is around 9.5 percent for men and about 11 percent for women, and wages are concave in age.[10] Wages differ between regions and vary by race, without surprises. Earnings variability is compensated as theory predicts: wages increase with earnings risk and decrease with skewness. For both men and for women, significance levels are high, with the exception of the Census 1990 sample where R and K may not be measured as well.[11] Wherever feasible, t-statistics are based on bootstrapped standard errors, using

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[8] Below, we test for log normality and mostly reject it. Still, adding the variance reduces the bias in the estimate of the mean.

[9] As an example, for men in CPS 1998, the mean and standard deviation of R are 0.58 and 0.50, and those of K are 3.02 and 5.66. With the Census 1990 data, the latter values rise to 10.82 and 35.25 respectively.

[10] With the common specification in potential experience (age – 6 – schooling), the rate of return to education is about 2 percent points higher for both men and women. If the age at which schooling is undertaken does not vary across individuals, the effect of aging and postponing earnings cannot be separated. However, the choice of these specifications is immaterial for our results.

[11] When cells are defined according to the 500 detailed occupational categories instead of the 25 aggregated groups, the Census data generate better results. However, these estimates are still smaller than those from the CPS 1998 and NBER-CPS data, which again is indicative of measurement problems.

the method developed by Canty and Davison (1999).[12] The CPS 1998 results indicate that in an education-occupation cell where the relative variance of wages is one unit higher, male wages are almost 40% higher and female wages are 67 percent higher. If the relative skewness is one unit higher, wages are depressed by some 2 percent.[13]

Are these results robust to variations in modelling and econometric approaches? To start, we found that the estimates are insensitive to the inclusion of measures of job disamenities such as physical burdens or exposure to toxic conditions and the like. Second, one might wonder whether the use of R and K in the regression equation is improper since it is computed from first-stage residuals. However, deleting an individual's own first-stage residual from the computation of R and K has no effect on the estimated impact of these variables. Third, for women, restricting the sample to young women in order to allow for different supply behaviour between cohorts is immaterial.

What does matter, however, is how risk R and skewness K are measured, as they are very sensitive to outliers, measurement errors, etc. Results are sensitive to including or excluding a cell fixed effect in the first stage, and we include it henceforth.[14] At measurement level, the sensitivity of R and K relates to the definition of the data sample. For example, part-time workers may not earn the same wages as

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[12] Bootstrapping with weighted data requires an adjustment in the process of sampling with replacement from the original database. In particular, sampling weights that are attached to the resampled observations need calibration in order to simulate sampling from the overall population and therefore to minimize the impact of variation in the weights. We calibrate the sampling weights to the sampling proportions in the original database for each ethnic group, region, education group (less than or equal to 12 years, between 12 and 16 year, and more than 16 years), and age group (less than and more than the median age).

[13] Our specification differs slightly from McGoldrick (1995) who calculates variance and skewness of $\exp(e_{ji})$ in cell j, instead of the relative wage difference as given in equation (23) and (24). The approximate difference between the two expressions is equal to $\exp(s_j^2/2)$. The results are unaffected if we use the specification estimated by McGoldrick, except that the estimated effects of R and K are about 50 percent higher in our specification.

[14] Note that in the second stage analysis the fixed effects cannot be entered, because there would not be any within-group variation in R and K that could identify the impact of risk and skewness on the wage. Indeed the motivation for including fixed effects in the first stage is to, among others, remove systematic but to that point unmeasured contributions of risk and skewness.

full-time employees – or they may not recall their earnings and hours as accurately. It is noteworthy that the variation in *R* and *K* is the smallest in the NBER-CPS sample[15] where earnings and hours refer to the current job and the recall period is the shortest, and is the largest in the Census 1990 data where interaction with the respondent is minimal and the data describe earnings and hours over the previous calendar year.[16] Thus, as we desire to maintain our hypothesis of essential stability in the variability of earnings by education-occupation, it appears necessary to aim for a more "permanent" estimate of *R* and *K*, purged as much as possible from measurement errors. For this purpose we use the Merged Outgoing Rotation Group file that actually comprises CPS data files over a period of over two decades, and we use five years of data, namely 1995-1999.

3.2 The impact of stable measures of *R* and *K* on wages

As mentioned, the NBER-CPS data contain responses about hourly wages or weekly earnings of the current job. On such grounds, one may speculate that there is less measurement error in these data. For each cell, we calculate the five annual observations on *R* and *K*. An Analysis of Variance illustrates whether, allowing for separable effects of education-occupation category and time, there is any stability in the wage distribution for a given cell. In the case of mean wages, education-occupation and time explain over 99 percent of the variation, both for men and women and the effects of both variables are highly significant.[17] In the case of *R*, the two variables explain 39 and 45 percent of the variation for men and women, respectively, and the effect of both variables is significant at 5 percent or better. In the case of *K,* the two variables explain 21 and 23 percent of the variation (male/female), but the education-occupation effect is insignificant both for men and for women. However, removing *K* values greater than

[15] Compare footnote 12 with Table 1 below.

[16] CPS data are collected mostly by telephone, but with households being interviewed for several months in a row, 90 percent of the households in their first months are visited in person. Similar to the Census 1990 data, the CPS 1998 refers to earnings and hours over the past calendar year.

[17] The same picture of stability emerges from correlation of the education-occupation fixed effects over time: across the five years, they correlate better than 0.975, for both men and women.

5 (no more than 15 cases in some 600 observations) would already make both effects significant at conventional levels. (Of course, removal of outliers invalidates the statistical test, but this check indicates that insignificance is driven by a few outliers.) We conclude that education-occupation cell wage distributions have very stable, significantly different locations, and are significantly different in *R* and *K*. But *R* and *K* vary substantially over time. Concern over measurement errors is common (Abowd and Card, 1989; Davis and Willen, 2000; Carrol and Samwick, 1997). We aim for a more "permanent" characterisation of risk by using the median of the five annual estimates of *R* and *K*. Our annual data show low correlations between the various measures of *R* and *K*, but much higher values obtain for the median *R* and *K* of the NBER-CPS, ranging for *R* from 0.12 to 0.72 (males) and from 0.13 to 0.73 (females) and for *K* from 0.10 to 0.62 (males) and 0.01 to 0.70 (females). In all, therefore, the annual values appear highly variable, and the median looks to be more robust.[18]

Regression results with the more permanent five-year measures of *R* and *K* are presented in Table 1. Both for men and women, the mean of *R* is fairly stable[19] and the standard deviation is modest. The mean of *K* is however quite variable, with substantial dispersion even within samples. The regression results for men, based on the median, are quite robust: both for *R* and *K*, we find the sign as predicted by theory, high significance levels and only modest variation in the annual estimates. For women we only find similarly robust results for *K*. The coefficient for *R* is not significant. However, in the only year that it is significant, it does have the right sign. Using the "permanent" measures of *R* and *K* turns out to be essential. For each year of the five-year selection from the NBER-CPS data set, we also estimated the

[18] Measurement error in the data is also indicated by another feature in the correlation results. Within any given dataset, *R* and *K* are always highly correlated, but the value of *R* from one dataset is always little correlated with the value of *K* from another dataset. Thus, peculiarities (or outliers) in a given dataset appear more strongly reflected in the values of these uncertainty variables than the existence of risk itself. The impact of such peculiarities is lowered by our strategy of measuring *R* and *K* by the median of the annual values. Indeed, the correlation between this median-based *R* and *K* is lower, while at the same time the correlation with the annual values is higher than any of the correlations among the annual values.

risk augmented Mincer earnings function, with R and K each estimated from that year's sample itself. As the middle panel of Table 1 indicates, this produces poor results: mostly coefficients with the wrong sign, for both men and women.

The five year median value for R and K may still be a less than fully satisfactory measure of permanent variability because CPS and NBER processing put an upper limit on (implied) annual earnings, presumably because these very high values may be consequence of measurement error but also because of identifiability concerns. Hence, very high incomes are replaced by a maximum value. Calculations of R and K are affected by this top-coding. Using percentile-based statistics eliminates this effect; in particular, defining P_a to be the a^{th} percentile, let R be $P_{75} - P_{25}$, and measure K as $(P_{75} - P_{50})/(P_{50} - P_{25})$.

Table 1 around here

Table 2 around here

Table 2 is similar to Table 1, but now based on percentiles of the distribution; in this case we required a minimum education-occupation cell size of 20 observations. Again, results are supportive of theoretical predictions, perhaps even stronger than in the previous case: all the signs are as predicted, only the coefficient on R for men does not reach conventional significance levels. As before, using annual measures of R and K generates poor results: less stability in the coefficients and significantly wrong signs on R for men. In the annual measures, the means and the standard deviations of R and K are very stable, but the correlations over time between R and K are quite low (less than 0.4).

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[19] This within-sample stability across years exists despite of the fact that within-cell values across years vary

As an additional test on our results, we use the measures of *R* and *K* for women in the wage regression for men, and the measures for men in the regression for women. These opposite–sex measures are excellent instruments, as there is no reason to expect a direct effect on wages while the correlations between *R* and *K* across gender are high. The results for pooled data, reported in Table 3, lend strong support to the hypothesis of risk compensation: all coefficients have the right sign and are statistically highly significant.[20]

Table 3 around here

We conclude that there is more support for Adam Smith's theoretical argument than he believed himself. Smith judged that there was no fair compensation for risk: "*and that the lottery of the law, therefore, is very far from being a perfectly fair lottery; and that as well as many other liberal and honourable professions, are, in point of pecuniary gain, evidently under-recompensed*." To detect that support, it is imperative to focus on more permanent measures of wage variability, as measurement errors are pervasive. Using a permanent measure, like the five-year median, or the five-year percentile based measure, we have not found a single rejection of the prediction in the sense of a significant coefficient of the wrong sign and in particular with opposite-sex measures of *R* and *K* we find highly significant results. We did find cases where the coefficient was not significantly different from zero. This applied mostly to coefficients for *R* (medians for women, percentiles for men). In this sense, there is stronger support for the negative sign of *K* than for the positive sign of *R*. The importance of *K* is also stressed by another result. For all specifications we have run regressions

substantially, as highlighted above.

[20] We also examined annual (rather than pooled) opposite-sex measures of both moment-based and percentile-based values of R and K. Parameter estimates are more variable, as one would expect on the basis of the comparison

without *K* as a regressor. By far the dominant result is a significantly negative coefficient for *R*. Hence, the theoretically predicted positive coefficient for *R* is only found when *K* is included. This supports Samuelson's (1970) claim that restricting analyses of decision under risk to a second-order approximation (the Mean-Variance model) implies restrictions on the distribution of outcomes that may not be empirically valid. Two considerations are neatly in line with the powerful role of *K*. First, consider the argument of Adam Smith that supply is attracted to the "reputation of superior excellence": this refers to typically high-end outliers that catch the imagination. It is the exceptional success that has a strong impact on supply, and exceptional success of course mostly affects *K*. Second, it is known from experiments in decision theory that individuals typically tend to overestimate low probabilities and underestimate high probabilities (Camerer, 1995). This too, tends to give upper-end low probabilities a prominent role in affecting supply and, hence, wages.

4 Structural Specification of the Empirical Model

We now turn to estimates of equation (9) with expressions for Π_j and M_j (by education-occupation j) derived from explicit utility functions. Preliminary results based on CRRA results proved unconvincing. Mostly, the coefficient of risk aversion came out negative, and if not, the discount rate was negative, which is even more implausible. Lack of empirical support for CRRA is common (cf Dynan, 1993; Guiso and Paiella, 2000). If constant relative risk aversion is in doubt, it is better to estimate equation (9) with a more general utility function. Note that if *U* is CRRA, $U'(Y) = Y^{-r}$, or $\ln U' = -r \ln Y$. Thus, a suitable generalization of CRRA is the translog marginal utility (TLMU) function, written as:

$$\ln U' = r_1 \ln Y - 0.5 r_2 (\ln Y)^2 \qquad (25)$$

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between annual and pooled measures in Tables 3 and 4, but once again there is more consistency among the estimates themselves and in accordance with our hypotheses than for same-sex measures.

If $r_2 = 0$, TLMU reverts to CRRA, and r is estimated as $-r_1$. The TLMU assumption yields the following expression for the risk premium:

$$\Pi_s = -\left[\frac{m_{2s0}}{2m_{s0}^2}\int_s^{\infty} a_t U'(m_{st})\left(r_1 - r_2 \ln m_{st}\right)e^{-dt}dt + \frac{m_{3s0}}{6m_{s0}^3}\int_s^{\infty} a_t U'(m_{st})\left\{\left(r_1 - r_2 \ln m_{st}\right)^2 - r_1 - r_2 + r_2 \ln m_{st}\right\}e^{-dt}dt\right] / \left[\int_s^{\infty} a_t U'(m_{st})e^{-dt}dt\right] \tag{26}$$

Furthermore, since M_s depends on U as was shown in equation (4), we must find the utility function U that yields a translog marginal utility as in (25). This turns out to be:

$$U(Y) = \sqrt{\frac{2p}{r_2}}\ \exp\left(\frac{(r_1+1)^2}{2r_2}\right)\Phi\left[r_2^{1/2}\left(\ln Y - \frac{r_1+1}{r_2}\right)\right] \tag{27}$$

where Φ is the standard normal cumulative distribution function. Interestingly, this generalisation of the CRRA utility function leads to the welfare function of income derived by Van Praag (1968) from basic axioms on individual choice behaviour and strongly supported by a wealth of empirical studies (for a survey, see Van Praag and Frijters, 1997; for a review, Hartog, 1988). We have estimated our models for each of the years 1995 through 1999 on the NBER-CPS data. For each of these annual estimates, *R* and *K* are measured at their median values over the five-year period from a first-stage model that uses (age – 16) and (age – 16)^2, race and region dummies, with fixed effects for each occupation/education cell. The structural model is estimated by means of weighted non-linear least squares, using as a weight the inverse of the variance of the first-stage regression of the data proper.[21] Furthermore, one may note that equation (35) dictates the measurement of m_{st} at all *t*. Thus, for each individual, we compute his/her

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[21] We toyed with the idea of using the inverse of the median of s_j^2 as the weight, but this left too much heteroskedasticity in the model.

predicted wage on the basis of the first-stage analysis and use the first-stage estimates of the parameters to dictate his/her lifetime profile of wages.

Under normally distributed errors, whether U is CRRA or TLMU, the risk premium itself or the components of the risk premium are simple functions of s_j^2. However, test results indicate that residuals in the first-stage regressions are not normally distributed. This leaves the non-normal TLMU model as the preferred specification. It yields an estimated discount rate around 0.20 for men and 0.90 for women. Judged against intuition, these are high values. But intuition is not backed up by solid empirical evidence. Estimated discount rates cover a wide interval (Frederick et al., 2002) and high values are not uncommon in structural models (Lawrance, 1991; Carroll and Samwick, 1997). As to the risk aversion parameters, the exponential specification of our utility function implies that the marginal utility of income is always positive. However, other features are not imposed. Standard algebra applied to our utility function yields:

$$U'' = U'(r_1 - r_2 \ln Y)/Y \tag{28}$$

$$V_r = r_2 \ln Y - r_1 \tag{29}$$

$$F_r = 1 + V_r - r_2 / V_r \tag{30}$$

Hence, U'' will only be negative for $\ln Y > r_1 / r_2$. The same threshold holds for (relative) risk aversion to be positive. The unrestricted estimates for the non-normal TLMU model put these thresholds at fairly high values (an hourly wage of \$18.10 for men and \$14.86 for women in 1999). Such high thresholds imply that for a substantial portion of the sample marginal utility of income is increasing rather than decreasing. The positive sign of r_2 implies that relative risk aversion is increasing in income, a condition identified by Arrow as necessary for consistency with the theory of wealth accumulation (see

Guiso and Paiella, 2001:14, who also report increasing relative aversion in their own data).[22] As Dynan (1993) notes, utility functions with decreasing absolute risk aversion should have relative skewness affection larger than relative risk aversion: $F_r > V_r$. This requires that $\ln Y > 1 + r_1 / r_2$; this condition only applies for even higher values of the hourly wage.

One option is to follow common practice and simply impose declining marginal utility of income over a relevant range. Suppose, we require $U'' < 0$ for $\ln Y > 1$, a very low value for the hourly wage rate. This implies the condition $r_1 < r_2$. Given the estimation results we obtained, this will mean $r_1 = r_2$, thus yielding the restricted TLMU version of the structural model. Estimated parameter values for the five different years are very robust; the range is no more than 10% of the highest value.[23]

Table 4 around here

Typical results, for 1999, the most recent year in our dataset, are reproduced in Table 4. The estimated discount rate of 0.054 and 0.075 is quite reasonable. With equations (29) and (30) we can calculate the values of relative risk aversion and relative skewness affection at the sample means of ln*Y* (2.63 for men and 2.41 for women, NBER-CPS 1999). This yields the following results

	Unrestricted TLMU, non-normal		Restricted TLMU, non-normal	
	V_r	F_r	V_r	F_r
men	-1.60	2.63	0.64	1.03
women	-0.81	3.66	0.46	2.18

[22] Note that the significant value of r_2 also invalidates the CRRA specification.

[23] In fact, the variation in estimates across years is very small in all models, except for CRRA with normal disturbances, but this model is strongly rejected anyway.

The empirical literature on risk attitudes has not led to unambiguous conclusions on magnitudes. There is a wide variation in estimated values, and nasty puzzles remain. The observed long-term equity premium, over riskless assets, requires a high coefficient of relative aversion, at least 10, to be consistent with individual choice theory, but such high aversion rates are usually not found. Many analyses of individual asset holdings suggest a coefficient of relative risk aversion somewhere in the interval between 2 and 3 (Beetsma and Schotman, 2001). However, Dynan (1993) finds a relative risk aversion coefficient of about 10. In a direct survey approach, where an individual's measure of absolute risk aversion is derived from the stated reservation price for a specified lottery ticket, in three different datasets, the mean of absolute risk aversion multiplied by the mean income in the sample generates high values of relative risk aversion: 20, 65 and 93 (Hartog, Ferrer-i-Carbonel and Jonker, 2002). Using a similar approach, Guiso and Paiella (2001) find mostly lower values, with a median of 4.8. Ninety percent of the household cross-section observations are in the interval 2.2 to 9.9. Beetsma and Schotman (2001) analyse behaviour in a television game and find a coefficient of relative risk aversion of about 7. Dynan (1993) is one of the very few studies to report an estimated rate of relative skewness affection: about 0.3, with a 95 percent confidence interval from –0.12 to 0.75. The results we find for risk aversion and skewness affection are within the (wide) bounds of results found elsewhere. In our preferred specification, relative risk aversion appears on the low side. It might be a consequence of self-selection, where highly risk averse individuals shy away from high risk occupations.

The proper specification of the utility function is a matter for extensive empirical testing. Standard economic theory commonly assumes declining marginal utility of income throughout. Van Praag's empirically well-established lognormal Individual Welfare Function of Income has initially increasing marginal utility of income, although usually only up to a fairly low income level. The famous utility function introduced by Friedman and Savage (1948) has a stretch of increasing marginal utility of income, located in the middle income range. The utility function for bettors at horse racing estimated by

Weitzman (1965) has a positive second derivative throughout. The value function of income introduced by Tversky and Kahneman (1992) in prospect theory has increasing marginal utility of income below the reference level (i.e., in the loss range). Thus, it is not at all obvious that we should impose the restriction on our TLMU specification.

5. Conclusion

Considerable measurement error in wage data makes the measurement of risk rather difficult. Still, we find support for the hypothesis that the market compensates for differential risk by education-occupation, provided we apply “permanent,” longer-term measures of income variation. Annual measures are too noisy. In estimates based on explicit utility functions, we reject CRRA but find support for our Translog Marginal Utility function, which turned out to be identical to the firmly empirically supported welfare function developed by Van Praag.

We consider our results as sufficiently encouraging to propose further research along the lines initiated here. Measurement error in our dispersion variables is a major concern. We do believe, however, that permanent differences in earnings variability between educations and occupations exist. One argument is the finding, in the psychological testing literature, that the variability of individual output differs systematically between occupations: “Standard deviation of output is substantially higher in the more cognitively complex and better paid jobs” (see Hartog, 2001). Further research to purge earnings variability from measurement errors is important.

We have ignored possible compensation for the risk of unemployment. Unemployment risk may well be important in the perception of individuals and thus, supply reactions may generate a wage premium.

However, one may suspect the compensation for earnings variability to be much more important, simply because earnings variability is much larger**.** For example, in the CPS 1977-1984 data, the coefficient of variation is 0.24 for the hourly wage rate and 0.067 for annual hours worked (Murphy and Topel, 1987:109)**.** Suppose then that every individual faces an annual unemployment risk of 10% and, when unemployed, receives 70% of his earnings, and let us evaluate unemployment only in terms of lost income. Then, relative earnings risk m_2 / m^2 equals 0.008, from which, given the risk aversion coefficient V_r of about 0.5 (see the table above), equation (15) predicts an earnings premium of 0.2%. By contrast, our data indicate that relative earnings risk is in the order of 0.6, which would require a wage premium of 15%. Abowd and Ashenfelter (1981) estimate wage compensation for actually experienced unemployment in the order of 4%. Murphy and Topel (1987) find that a one standard deviation increase in the variability of weeks worked[24] would generate compensation in average annual earnings of about 0.5%. From these magnitudes, we are not inclined to give top priority to the measurement of possible compensation for the differences in unemployment risk on our list of further research.

[24] This risk compensation would be on top of the loss of expected income, i.e. .10 x .30 = 3 %.

Table 1: NBER-CPS: Sample Measures vs. Median Values of *R* and *K*

	Mean (*m*) and St.dev (*s*)				Estimated coefficients							
	R		*K*		Based on annual sample statistics				Based on median of 95-99			
	m	*S*	*m*	*s*	b_R	*t*	b_K	*t*	b_R	*t*	b_K	*T*
Males												
95	0.178	0.049	0.132	0.224	-1.139	16.68	0.054	3.52	0.452	4.21	-1.105	18.12
96	0.193	0.133	0.448	2.058	-1.170	22.34	0.061	17.33	0.631	5.08	-1.174	16.09
97	0.182	0.074	0.175	0.676	-1.336	22.80	0.095	14.23	0.459	4.20	-1.068	16.64
98	0.203	0.064	0.205	0.205	0.230	3.21	-0.252	13.51	0.882	8.04	-1.372	21.61
99	0.214	0.106	0.474	1.685	-0.223	5.16	0.003	1.27	0.799	6.35	-1.182	17.39
m	0.178	0.041	0.114	0.075								
Females												
95	0.203	0.096	0.646	1.492	-0.877	16.57	0.022	6.77	-0.123	1.79	-0.477	21.65
96	0.198	0.128	0.969	3.794	-1.132	20.31	0.024	13.61	-0.060	0.85	-0.462	23.73
97	0.178	0.052	0.199	0.242	-0.704	9.86	-0.107	6.78	-0.080	1.21	-0.440	22.47
98	0.193	0.072	0.303	0.428	-0.233	3.89	-0.067	7.72	-0.107	1.53	-0.407	19.86
99	0.193	0.094	0.382	0.978	0.047	0.83	-0.028	5.04	0.217	3.09	-0.491	25.04
m	0.179	0.050	0.190	0.168								

Note: *m* denotes the median over 1995-99. *t*-statistics are based on bootstrapped standard errors.

Table 2: NBER-CPS: Annual vs. 5-Year Measures of Percentile-Based *R* and *K*

	Mean (*m*) and St.dev (*s*)				Estimated coefficients							
	R		*K*		Based on annual sample statistics				Based on pooled data 95-99			
	m	*S*	*m*	*s*	b_R	*t*	b_K	*t*	b_R	*t*	b_K	*t*
Males												
95	0.494	0.081	1.294	0.293	-0.290	6.65	-0.080	6.78	-0.077	1.30	-0.168	7.17
96	0.497	0.085	1.306	0.371	-0.324	6.30	-0.021	1.54	0.049	0.79	-0.233	9.33
97	0.496	0.085	1.285	0.369	-0.303	6.05	-0.074	5.96	0.000	0.00	-0.219	9.86
98	0.499	0.079	1.344	0.419	-0.028	0.55	-0.005	0.40	0.033	0.56	-0.190	9.18
99	0.479	0.085	1.403	0.454	0.444	9.19	-0.102	10.57	0.091	1.51	-0.163	7.91
m	0.492	0.066	1.285	0.179								
Females												
95	0.465	0.106	1.396	0.420	0.630	12.84	-0.412	34.55	1.075	16.91	-0.593	31.10
96	0.472	0.104	1.422	0.436	0.661	12.53	-0.304	23.64	1.088	15.43	-0.577	29.06
97	0.471	0.096	1.389	0.398	0.371	7.03	-0.193	16.03	1.045	16.92	-0.568	30.80
98	0.473	0.092	1.515	0.680	0.371	6.48	-0.109	9.44	1.017	16.11	-0.539	26.93
99	0.462	0.101	1.339	0.419	0.719	13.85	-0.222	19.72	1.236	18.07	-0.543	27.75
m	0.469	0.085	1.362	0.250								

Note: *m* refers to values based on pooled data 1995-99. *t*-statistics are based on bootstrapped standard errors.

Table 3: Using opposite-sex measures of *R* and *K*

	Male wage equation with female *R* and *K*				Female wage equation with male *R* and *K*			
	b_R	t	b_K	t	b_R	t	b_K	t
A: Median-based measures of *R* and *K*								
95	0.774	13.54	-0.523	24.29	0.288	2.57	-0.949	14.21
96	0.940	15.96	-0.592	26.72	0.294	2.62	-0.920	14.17
97	0.932	16.18	-0.565	25.93	0.275	2.50	-0.845	13.08
98	0.902	15.35	-0.553	26.46	0.387	3.52	-0.921	14.55
99	0.894	15.44	-0.540	24.68	0.659	6.09	-0.981	15.34
B: Percentile-based measures of *R* and *K*								
95	0.808	20.22	-0.163	11.11	0.128	2.15	-0.362	15.36
96	0.965	23.50	-0.195	12.99	0.131	2.26	-0.338	14.39
97	0.967	24.05	-0.202	13.70	0.187	3.22	-0.352	15.13
98	0.904	21.28	-0.187	11.95	0.191	3.28	-0.349	14.92
99	0.943	22.92	-0.220	14.79	0.311	5.61	-0.304	13.73

Note: *R* and *K* values are based on pooled data 1995-99. *t*-statistics have not been bootstrapped.

Table 4: Estimates of the Structural Model (restricted non-normal TLMU), NBER-CPS 1999

	Males		Females	
Parameter	estimate	*t*-stat	estimate	*t*-stat
Intercept	1.870	173.06	1.795	160.00
(Age-16)	0.043	67.97	0.029	43.37
$(\text{Age-16})^2$ (x 100)	-0.066	-49.87	-0.046	-32.57
$r_1 = r_2$	0.392	31.21	0.330	36.22
d	0.054	26.56	0.075	47.74
Black	-0.146	-23.51	-0.055	-9.71
Indian	-0.097	-4.76	-0.076	-3.90
Asian	-0.101	-9.96	-0.040	-4.08
Hispanic	-0.201	-34.64	-0.129	-20.60
Mid Atlantic	0.009	0.90	-0.014	-1.50
East North Central	0.007	0.80	-0.054	-5.61
West North Central	-0.057	-5.28	-0.086	-8.52
South Atlantic	-0.045	-4.73	-0.067	-6.97
East South Central	-0.095	-8.35	-0.153	-13.46
West South Central	-0.063	-6.32	-0.117	-11.40
Mountain	-0.028	-2.56	-0.065	-6.01
Pacific	0.019	2.01	0.006	0.67
Number of observations	54774		45928	
log Likelihood	-32165.2		-24160.3	

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