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ABSTRACT

Do Wages Really Compensate for Risk Aversion and Skewness Affection?*

Utility theory suggests that foreseeable risk should increase the compensation for work. This paper expands on this notion: on basis of utility theory, people should care not only about risk but also about the skewness in the distribution of the compensation paid. In particular, because the degree of risk aversion ought to decrease with income, people should appreciate a small chance of a substantial gain; they should exhibit an "affection" for skewness. 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.

JEL Classification: D8, J3

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1. Motivation

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.

Adam Smith (Wealth of Nations, p. 208) not only understood that in a competitive labour market wage differentials compensate for differences in schooling length, he also singled out the probability of success 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. First, when embarking on an education, the individual does not know whether she will be able to complete it. The education may prove more difficult or less interesting than anticipated, and the individual may lack the ability or perseverance to complete it. Second, even after completing education for a particular trade or profession, the graduate may still lack the ability to become a successful practitioner. There may be a wide dispersion of performance or productivity in the job, and the individual may not know his true competence when entering the trade. On top of that, there is uncertainty on the market value of output. The returns in an occupation may fluctuate, due to fluctuations in product demand, the general business cycle, etc. Such effects will be greater in, for example, managing car sales than managing health services. These are all foreseeable risks, in the sense that individuals will have a perception on the probability distribution of potential earnings when they make their decision on entering the field. And foreseeable risks normally require compensation in expected returns. In this paper we try to discover whether this is indeed the case. Adam Smith was quite sceptical about the empirical validity of his own argument. He 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.” Sufficient supply was nevertheless forthcoming in those occupations, he argued, because of the “desire of the reputation of superior excellence” and because of common overestimation of success in particular by young people (their “contempt of risk and presumptuous hope of success”).

The empirical literature on compensation for imperfect predictability of rewards for education and occupation is virtually non-existent. Yoram Weiss (1972) has considered the variance of earnings by schooling level and corrected estimated rates of return to education under alternative presumed degrees of relative risk aversion, assuming lognormal earnings distributions. There is a small, mostly unnoticed literature that seeks to test for risk compensation, in a simple, straightforward framework:[1] add a measure of earnings variation in the individual’s choice set to a standard Mincer earnings function and see if the coefficient is positive. However, a measure of earnings variance alone is not enough if earnings distributions are characterized by more than two parameters. McGoldrick and Robst (1996) added skewness. Theory predicts a positive sign for the variance and a negative sign for skewness, as we will demonstrate below. This is indeed

[1] King (1974), Feinberg (1981), McGoldrick (1995), McGoldrick and Robst (1996).

what McGoldrick (1995) finds. In a replication study for Germany, The Netherlands, Portugal and Spain we also found strong support for this conclusion (Hartog, Plug, Diaz Serrano, Vieira, 1999). Wage variance in an individual's education-occupation has a positive effect on the wage; wage skewness has a negative effect. While risk aversion is a routine assumption in many analyses, skewness affection is a less familiar concept, except in the context of lifetime wealth accumulation modelling, where it is called prudence. Skewness affection, however, is also found to hold in gambling at lotteries and horse racing.[2] Such results are consistent with the utility function as specified by Friedman and Savage (1948). The intuition is that, for given mean and variance, individuals prefer a distribution that is skewed to the right, as they appreciate the small probability of a substantial gain (we provide the formal argument in section 3).

In this paper, we attempt a more thorough approach to the analysis of uncertainty in financial rewards to educations and occupations. We start with the theory of choice of education and occupation under uncertainty, and derive basic wage equations that include compensation for wage uncertainty. We then estimate reduced forms of these equations. After finding sufficient support for the approach, we derive a structural specification and estimate the relevant parameters. We conclude by evaluating our findings and relate them to other evidence available in the literature. The basic problem that we face is to find a proper measure of the ex ante earnings risk of the individual when deciding on education and occupation; we discuss this in section 3, and throughout the empirical sections. We will only try to measure the effect of uncertainty in the earnings flow, and ignore the risk of unemployment.[3] We discuss this omission in the concluding section.

2 Formal modelling

To analyse choices in a world with uncertain earnings prospects, we will first consider schooling choice under utility maximisation rather than earnings maximisation (which is unavoidable if we analyse uncertainty in a utility framework). In the next stage we will examine earnings uncertainty proper.

2.1 Utility maximization

Individuals face two alternatives: go straight to work, and earn an annual non-stochastic income Y_0 for the rest of their working life, or go to school for s years, and then after school earn a non-stochastic income Y_s for the rest of their working life. We assume individuals have an uninhibited choice between alternatives. In equilibrium, lifetime utility should be equal. We seek to derive the premium M_s that accomplishes equilibrium, hence

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[2] Garret and Sobel (1999), Golec and Tamarkin (1998), Moore (1995).

[3] Wage compensation for unemployment risk is analysed and estimated by Abowd and Ashenfelter (1981) and by Murphy and Topel (1984).

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

i.e. M is the mark-off on Y_S to equate lifetime utility. Discounting at a rate d and setting utility of zero income while in school at zero, we get

$$\int_0^\infty U(Y_0)e^{-dt}dt = \int_s^\infty U(Y_s)e^{-dt}dt \tag{2}$$

where $U(Y)$ is a standard utility function. With time-independent income (and utility) this solves into

$$U(Y_0) = e^{-ds}U(Y_s) \tag{3}$$

A simple first-order expansion of $U(Y_0)$ around Y_S generates

$$\begin{aligned} U(Y_0) &= U(Y_s) + (Y_0 - Y_s)U'(Y_s) \\ &= U(Y_s) - M_s Y_s U'(Y_s) \end{aligned} \tag{4}$$

Combining (3) and (4) yields the solution for M_S:

$$M_s = \left(1 - e^{-ds}\right)\frac{U(Y_s)}{U'(Y_s)}\frac{1}{Y_s} \tag{5}$$

Clearly, this is a generalisation of Mincer's earnings function. The last two terms jointly are the inverse of the income elasticity of utility. Under earnings maximization, $U(Y)=Y$, and (5) reduces to the term in parentheses, implying $\ln Y_s = \ln Y_0 + ds$, the standard Mincer equation.

Assuming a constant income elasticity of utility simplifies equation (5). Specifically, with Constant Relative Risk Aversion (CRRA)

$$U(Y) = \frac{1}{1-r}Y^{1-r} \tag{6}$$

we get

$$M_s = \frac{1-e^{-ds}}{1-r} \tag{7}$$

In an expected utility framework, monetary returns will be depreciated by the declining marginal utility of income.

2.2 Risk Aversion and Skewness Affection

Consider an individual who can choose between two occupations, one with a fixed income Y^*, the other with random income *Y*, at expected income $E[Y]=m$. Define Θ as the absolute risk premium: $\Theta = E[Y] - Y^* = m - Y^*$: an individual in the risky occupation receives an income that exceeds the income of the riskless occupation by an amount of Θ. 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.

We seek to establish the equilibrium risk premium Θ, i.e. the gap between expected income in both occupations at which a utility maximizing individual is indifferent between the two occupations. Utility is defined again as a continuous differentiable function of income *U*(*Y*), with $\partial U / \partial Y > 0$. We also assume risk aversion $\partial^2 U / \partial Y^2 < 0$. Indifference requires

$$U(m - \Theta) = E[U(Y)] \quad \text{with} \quad E[Y] = m \tag{8}$$

To solve for Θ, we follow Pratt (1964, his equations (4) to (7)). For the left-hand side of (8) we write

$$U(m - \Theta) = U(m) - \Theta U'(m) \tag{9}$$

where $U'(m)$ is $\partial U / \partial Y$ evaluated at $Y = m$. For the right-hand side we retain one more term than Pratt did in his Taylor series expansion:

$$U(Y) = U(m) + (Y - m)U'(m) + \frac{1}{2}(Y - m)^2 U''(m) + \frac{1}{6}(Y - m)^3 U'''(m) \tag{10}$$

where $U''(m) = \partial^2 U / \partial Y^2$ evaluated at $Y = m$, and $U'''(m) = \partial^3 U / \partial Y^3$ at $Y = m$. Hence

$$E[U(Y)] = U(m) + \frac{1}{2} m_2 U''(m) + \frac{1}{6} m_3 U'''(m) \tag{11}$$

since $E[Y]=m$, and with m_2 and m_3 defining the second and third moments of Y (the variance and the skewness) around m. Equating (9) and (11), we are now able to solve for Θ:

$$\Theta = \frac{1}{2} V_a m_2 - \frac{1}{6} V_a \frac{U'''(m)}{U''(m)} m_3 \tag{12}$$

where $V_a = -U''(m)/U'(m)$ is the degree of absolute risk aversion. If, by analogy to risk aversion, we define absolute skewness affection as $F_a = -U'''(m)/U''(m)$, we may write

$$\Theta = \frac{1}{2} V_a m_2 - \frac{1}{6} V_a F_a m_3 \tag{13}$$

Equation (13) is the standard equation for a risk premium as derived by Pratt (1964) and Arrow (1965), but now expanded with skewness affection.

The sensitivity of absolute risk aversion to income (or wealth) Y can be derived as

$$\frac{d}{dY}\left[-\frac{U''}{U'} \right] = \frac{-U'U''' + (U'')^2}{(U')^2} \tag{14}$$

As Arrow (1965) argues, increasing absolute risk aversion is an absurd assumption, as it would imply investing less in risky alternatives if income (wealth) increases. Assuming the same holds for choice in the labour market, we require *decreasing* absolute risk aversion, i.e. a negative sign for (14). Then, a necessary but not sufficient condition is $U''' > 0$, as was first pointed out by Tsiang (1972, p. 359): "Thus, if we regard the phenomenon of increasing absolute risk aversion as absurd, we must acknowledge that a normal risk-averse individual would have a preference for skewness in addition to an aversion to dispersion (variance) of the probability distribution of returns." Since, for a risk averter, V_a is positive and since F_a is positive if we assume decreasing absolute risk aversion, we conclude from (13) that the absolute risk premium Θ is positive in risk (variance) and negative in skewness. This motivates our terminology of skewness affection.

As will be clear in the next subsection, the empirical model derives more naturally when the compensation for uncertainty is expressed through a relative, rather than absolute, risk premium. It is straightforward to rewrite (13) as an equation for the relative risk premium $\Pi = \Theta / m$ (and hence, $Y^* = (1-\Pi)\, m$). Dividing (13) by m and slightly rewriting yields

$$\Pi = \frac{\Theta}{m} = \frac{1}{2}V_r \frac{m_2}{m^2} - \frac{1}{6}V_r F_r \frac{m_3}{m^3} \tag{15}$$

where relative risk aversion is given by

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

and relative skewness affection by

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

Note that without further assumptions, V_r and F_r depend on m. But under constant relative risk aversion as in equation (6), we would have V_r = ? and F_r = ?+1; thus the relative risk premium would be constant. In the literature on lifetime wealth accumulation, relative skewness affection is called relative prudence (see, e.g., Dynan, 1993).

2.3 Towards an Empirical Model

Now, let us apply the risk compensation argument in the Mincer framework. Suppose, after s years of schooling the individual can choose between two occupations. One offers a stochastic income Y_s, with expectation $E[Y_s] = m_s$ and second and third moments around the mean m_{2s} and m_{3s}. The other occupation provides a non-stochastic income $(1-\Pi_s)m_s$ where, as before, Π_s is the risk premium, belonging to the occupational choice set after s years of schooling. Lifetime equal utility requires

$$\int_s^{\infty} U\left((1-\Pi_s)m_s\right)e^{-dt}dt = E\left[\int_s^{\infty} U\left(Y_s\right)e^{-dt}dt\right] \tag{16}$$

Clearly, the discounting factors drop out as income is as yet time-independent. Expanding the left hand side around m_s in first-order, and the right hand side around m_s up to the third order, the earlier result simply re-appears, and we can write

$$\Pi_s = \frac{1}{2}\frac{m_{2s}}{m_s^2}V_r - \frac{1}{6}\frac{m_{3s}}{m_s^3}V_r F_r \tag{17}$$

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

$$E\left[Y_s\right] = m_s = \left(1-\Pi_s\right)^{-1}\left(1-M_s\right)^{-1} Y_0 \tag{18}$$

where Y_0 is the riskless income of those without any schooling (as in equation (1)). If we introduce disturbance terms 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 (18) yields an expression that is close to the familiar empirical model:

$$\ln Y_s = Xb - \ln\left(1-\Pi_s\right) - \ln\left(1-M_s\right) + e_s \tag{19}$$

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.

Suppose, we apply the CRRA simplification

$$M_s = \frac{1-e^{-ds}}{1-r} \tag{20}$$

$$\Pi_s = \frac{1}{2}\frac{m_{2s}}{m_s^2}\,?-\frac{1}{6}?(?+1)\frac{m_{3s}}{m_s^3} \tag{21}$$

and we take Taylor expansions

$$-\ln(1-M_s) = -\ln\left(1-\frac{1-e^{-ds}}{1-r}\right) \approx -\ln\left(1-\frac{ds}{1-r}\right) \approx \frac{ds}{1-r} \tag{22}$$

$$-\ln(1-\Pi_s) \approx \Pi_s \tag{23}$$

Furthermore, rewrite the second and third-order terms in equation (17):

$$\frac{m_{2s}}{m_s^2} = \frac{E\left[\left(Y_s - m_s\right)^2\right]}{m_s^2} = E\left[\left(\frac{Y_s - m_s}{m_s}\right)^2\right] \tag{24}$$

$$\frac{m_{3s}}{m_s^3} = \frac{E\left[\left(Y_s - m_s\right)^3\right]}{m_s^3} = E\left[\left(\frac{Y_s - m_s}{m_s}\right)^3\right] \tag{25}$$

Then, the earnings function would read

$$E(\ln Y_s) = \ln Y_o + \frac{d}{1-r}s + \frac{1}{2}?\frac{m_{2s}}{m_s^2} - \frac{1}{6}?(?+1)\frac{m_{3s}}{m_s^3} \qquad (26)$$

a simple equation in schooling years, variance term (24) and skewness term (25). Hence with observations on relative variance and relative skewness we could estimate a Mincer earnings equation augmented with risk compensation. If we don't assume CRRA, the parameters of (26) 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 (26) 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 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 has to be solved from

$$\int_o^\infty U(a_t m_{00})\ e^{-dt}\ \ dt\ =\ \int_s^\infty U\{a_t(1-M)^{-1}m_{00}\}e^{-dt}\ \ dt \qquad (27)$$

This does not easily simplify, and in general requires numerical methods to solve for M at given d and specified utility functions. In our empirical specification we have defined the profile on age rather than potential experience (see below). If the profile would be defined on experience the RHS of (27) would have a_{t-s} instead of a_t, and a shift of the integration interval (from (s,a) to $(o,\infty-s)$ would then lead to equation (7) for M under the assumption of a CRRA utility function.

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

$$\int_s^\infty U\left((1-\Pi_s)m_{st}\right)e^{-dt}dt = E\left[\int_s^\infty U\left(Y_{st}\right)e^{-dt}dt\right] \qquad (28)$$

The same Taylor expansions as before yield the following equation for Π_{rs}:

$$-\Pi_s\int_s^\infty a_t U'(a_t m_{s0})e^{-dt}dt = \frac{m_{2s0}}{2m_{s0}^2}\int_s^\infty a_t^2 U''(a_t m_{s0})e^{-dt}dt + \frac{m_{3s0}}{6m_{s0}^3}\int_s^\infty a_t^3 U'''(a_t m_{s0})e^{-dt}dt \qquad (29)$$

a_t cannot be separated from m_{s0} and joined to e^{-dt}, so the integrals cannot be simplified. These, and other complications will be discussed later. We will now first turn to estimation of (26) as a linearized, reduced form equation.

3 Estimation

In this section, we add measures of variance and skewness of earnings within an occupation to an earnings function and test whether wages indeed are increased to compensate for risk aversion and decreased to compensate for skewness affection. We develop several alternative specifications to test the robustness of our findings. In the next section, we specify a structural model and try to estimate the key parameters, namely the discount rate and the degree of risk aversion.

A foremost problem to solve is the measure of risk (and skewness). Individuals face uncertainty in the rewards to their education-occupation alternatives. They have imperfect information on their own abilities, they do not know where in the wage distribution they will end up, they don't know what the market fortune or misfortune of their chosen line of business will be. Market theory assumes that individuals have perceptions on these vaguaries when they decide on education and occupation and that supply responses will enforce the market compensation. We assume that, basically, individuals gather their information from the observable wage distributions for the education-occupation alternatives they consider. A proper dynamic specification would use the individuals' information at the time they make their decisions. If perceived earnings variability is not constant over time, each cohort would command a premium for cohort-specific variability: we should relate a cohort's wages to that cohort's anticipated earnings variability. This obviously would lead to a complicated estimation strategy: we would need information on perceived earnings variability up to thirty or forty years back in time. On top of that, we would have to consider the potential effect of competition between successive cohorts on their premium for earnings variability. Things are much simpler if we assume that perceived earnings variability is stable over time: the same measure of variability applies to all cohorts. We can then measure earnings variability from the same dataset we use to estimate the wage premium: a single cross-section provides all the information we need. This is exactly how we proceed. We start out from a single-year cross-section and derive the measures of risk and skewness from the same dataset that gives us the individuals' wages for estimating the earnings function. But we will experiment with different measures of *R* and *K*, including measures that span a longer period than just one year. We are also aware of the selectivity problem that exists if we only use measures of *R* and *K* in individuals' observed occupation, without allowing for selective exits. Neither do we allow for superior information that individuals may use for predicting their relative position in the earnings. We believe it is a perfectly acceptable research strategy to leave a serious treatment of these issues for a later stage, not only because of its modelling complications, but also because it implies many additional data requirements. We will further discuss the issues in the concluding section.

Our primary data source is the U.S. Current Population Survey of March 1998, supplemented with information from other years and from the One-Percent Public Use Sample of the 1990 U.S.

Census. We focus the analyses on full-time employees and so we restricted the sample to individuals working between 30 and 70 hours a week, while also requiring at least 4 weeks of work during the year. We excluded individuals under 16 and over 65. Hourly earnings were obtained from dividing annual earnings by regular hours worked. Relative variance and skewness are calculated for each occupation/education cell; to make these measures meaningful, we delete all cells with less than 6 observations. For most of the analysis, the detailed 3-digit CPS occupational codes with its 500 listings are aggregated into one with 25 categories. The CPS educational measure is categorical and is transferred into year equivalents. This yields 7 groups: = 10, 11, 12, 14, 16, 18 and 20. After omission of cells with too few observations to allow measurement of risk and skewness, we are left with 129 cells for men and 104 cells for women, rather than the maximum of 7 x 25 = 175 cells.

A straightforward, intuitively appealing approach proceeds in two steps. First, estimate a standard Mincer earnings function. Then, use the estimated equation to get measures for 'unsystematic earnings risk' by education/occupation. Include these in the Mincer earnings equation and re-estimate the expanded model. This was our own starting point, and this is also what McGoldrick (1995) did. We measure risk and skewness from the first-stage regression and compensation in the second-stage regression, by including risk and skewness as measured in the individual's education occupation cell. We first present the basic estimate and then reflect on the validity of this approach.

Formally, we proceed as follows. First, estimate

$$LnW_{ji} = X_i b + e_{ji} \quad (30)$$

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. We prefer age over potential experience for three reasons. First, age is exogenous, whereas experience is not. Second, we have no measure of actual experience, which in particular for women may be a serious misrepresentation. Third, the profile shifts upward for longer education, rather than being independent from education. 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:

$$\hat{W}_{ji} = \exp\left(X_i \hat{b} + \hat{s}_j^2 / 2 \right) \quad (31)$$

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

$$R_j = \frac{1}{I_j} \sum_{i=1}^{I_j} \left(\frac{W_{ji} - \hat{W}_{ji}}{\hat{W}_{ji}} \right)^2 \quad (32)$$

$$K_j = \frac{1}{I_j} \sum_{i=1}^{I_j} \left(\frac{W_{ji} - \hat{W}_{ji}}{\hat{W}_{ji}} \right)^3 \quad (33)$$

In (31), 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 (31) would hold exactly. R and K are the sample estimates of (24) and (25) and they are added as regressors in equation (30) to test wage compensation for risk aversion and skewness affection. As Table 1 shows, there is sufficient variation in R and K to search for effects on wages. The standard deviations of R and K are large relative to the mean, especially so for K. Negative skewness is not uncommon, but most distributions are skewed to the right.

The basic results for men and women are given in Table 2. The rate of return to education is 9.7 percent for men and 11.8 percent for women, wages are concave in age[4], wages differ between regions, and they vary by race. Earnings variability is compensated as theory predicts. Wages increase with earnings risk and decrease with skewness, at high levels of significance both for men and for women. 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% higher. If the relative skewness is one unit higher, wages are depressed by some 2%. Significant effects for R and K are also reported by McGoldrick (1995) for the United States and confirmed in Hartog et al. (1999) for Germany, the Netherlands, Portugal and Spain.[5]

Table 1 around here
Table 2 around here

So, we have six estimates for five countries confirming the basic relation. How credible and robust are these results? We address a number of immediate concerns in Table 3 (where the first row just repeats the coefficients from Table 2). First, we added controls for job characteristics (in both stages) from the *Dictionary of Occupational Titles* (disamenities such as physical burdens of the worker, exposure to weather conditions, electric shocks, radiation, toxic conditions and explosive risks[6]). Clearly, as specification 2 indicates, including job characteristics has no effect. As a further test on the disturbing role of omitted variables, we include fixed effects for the schooling/occupation cells in the first-stage regression. Hence, this regression equation will contain only age–16, its square, dummies for race and region, and dummies for the schooling/occupation cells. The

[4] 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.

[5] 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 (32) and (33). 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.

[6] The data and their grouping by factor analysis are described in detail in Vijverberg and Hartog (1999).

predicted wage, $\hat{W}_{ji}$ in equation (31), includes the fixed effect associated with cell j. The estimate of s_j^2 is based on the residuals of this equation: it explicitly excludes the contribution of the fixed effects (unlike in the calculations above) and therefore better succeeds in measuring the variation of wages around the group mean. In the second-stage regression, we then explain the log-wage with the same set of explanatory variables as done so far (see Table 2).[7] For men, including fixed effects has no consequences, for women our results break down to an insignificant effect of R and a wrong sign for K (see row 3). In fact, up until our final and preferred specification the results for women are at variance with our theory. We will therefore first discuss results for men and then return to the estimates of women. Note that all estimation equations below row 3 in Table 3 use values of R and K derived from first-stage fixed effect regression models.

Our measures of risk and skewness, when inserted in the regression equation in the second stage, also employ the individual's own wage deviation. For schooling/occupations cells with many observations this has negligible effect on the estimated value, but for cells with few observations it is quite a disturbing statistical feature of the methodology. Therefore, we also calculated R_j and K_j for each individual i while omitting this individual from the subsample that makes up cell j (row 4). Again, for men, the restriction is immaterial.[8]

Table 3 around here

As discussed above, a vital issue in our tests is the proper measure of R and K. We started out, for simplicity, with R and K measured contemporaneously with the individuals' wages, acknowledging that cohort specific measures might be more relevant. As a step in that direction, we have used the U.S. Census of 1990 (One Percent Public Use Sample) to estimate R and K. A measure of earnings variability taken eight years earlier than the wage sample may be a better approximation for the variability perceived, on average, by individuals deciding on entering educations and occupations. And if perceived variability is indeed stable over cohorts, this would give a valuable check on the robustness of our results in the wage equation. A prime advantage of the Census dataset is its large number of observations, which gives more observations per cell to estimate R and K. The drawback is that the Census no doubt has larger intrinsic measurement errors in wages; the Census is based on self-reporting by individuals, whereas the CPS respondents are queried by trained interviewers (Borjas, 1980). So, what we gain on the one hand we may lose on the other.

Since the Census dataset is much larger, we are also in a position to use a much finer classification of occupations: in the CPS we would not have enough observations to estimate R and K properly. In principle, the results reported in rows 1–4 are based on 175 schooling/occupation cells, while the

[7] It may be noted that the same fixed effects cannot be entered in the second stage analysis because there would not be any within-group variation in R and K. 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.

[8] Several commentators suggested that the effects of R and K reflect a non-linearity in the returns to schooling. Although we have here one of those rare cases where theory predicts functional form (human capital theory predicts log-linearity) and hence, adding the square of years educated is an unfounded ad hoc specification, we did include it in our basic equation with the fixed effects. It had no effect whatsoever on any of the coefficients. Actually, we don't think that just adding in all kinds of interactions and higher order terms is a sound research strategy, as the specification has no basis in theory.

size of the Census sample conceptually allows 3500 cells (a good number of which are empty of course).[9] We measure risk and skewness on two levels: one with the detailed cells (labelled *fine*), and another with the aggregate groupings we use with the CPS (labelled *crude*). We have some preference for the *crude* specification, as it is less vulnerable to selective exit in case of failure. Results are summarized in rows 5 through 9. Both with fine aggregates (row 5) and crude aggregates (row 6), the effect is dramatic as the coefficients are now significant with the wrong sign.

We also replicated our entire two-step estimation procedure on just the Census data (i.e. both first and second stage regression). The impact is no less dramatic. We scrutinized our data for *R* and *K* and found some strong outliers, especially among employees who reported working only a limited number of weeks. In these cases, reporting few annual working hours blew up the hourly wage to incredible levels. Excluding these, by restricting weeks worked to be over 40 (row 9), brought the estimated cœfficients again in line with our theoretical model.

The contrast between the good performance with the CPS data and the poor performance with the Census data might be due to the larger measurement errors in the latter, from various sources. We applied different minimum cell sizes to estimate *R* and *K*. In our basic estimates, the minimum education-occupation cell size to include *R* and *K* in the dataset was put at 5. This may imply strong sensitivity to outliers. But restricting the minimum cell size to 10 or to 50 had no substantial effect on means and standard deviations of *R* and *K*, nor on the estimated regression coefficients. Cell size itself does not seem to be relevant for the difference in results between samples. Neither is there a role for possible differences in measurement error between subgroups by annual working hours. Excluding groups with low or high annual working hours and restricting estimation to employees who worked full year full time has no substantial effect on the estimation results, as shown for the CPS data in the extra row for basic specification 1 in Table 3 and by applying the same restriction to all our estimates that involve using Census data (not reproduced here).

If we maintain our hypothesis of essential stability of earnings variability by education-occupation, we should look for a more "permanent" estimate, purged as much as possible from measurement errors. For this purpose we turned to the 'Merged Outgoing Rotation Group file' that comprises CPS data files over a period of over two decades and is available from the National Bureau of Economic Research. We shall refer to these as the NBER-CPS data. Unlike the CPS and the Census datasets which yield a wage rate by dividing annual income by annual hours, both referring to the previous year, 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.

From this file, we used five years, 1995-1999. For each cell, we calculated the five annual observations on *R* and *K*. To test whether there is any stability in the wage distribution for a given cell, we applied an Analysis of Variance, allowing for separable effects of education-occupation category and time. In the case of mean wages, education-occupation and time explain over 99% of the variation, both for men and women and the effects of both variables are highly significant.[10] In

[9] In practice, the number of cells in the Census sample is 1061 for men and 742 for women.
[10] 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.

case of *R*, the two variables explain 39 and 45% of the variation for men and women, respectively and the effect of both variables is significant at 5% or better. In case of *K*, the two variables explain 21 and 23% of the variation (male/female), but the education-occupation effect is insignificant both for men and for women. However, removing *K* values greater than 5 (no more than 15 cases in some 600 observations) would already make both effects significant at conventional levels. (Of course, after removal of outliers we cannot apply the test, but the procedure 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. This picture is also supported by other research. Abowd and Card (1989), using the PSID, the NLS and some specific datasets, concluded to the presence of important measurement errors in earnings and hours and noted that "negative serial correlation between consecutive changes in log earnings is a pervasive phenomenon" (o.c., p 427). Davis and Willen (2000) studied the residuals from wage regressions in 10 occupations in CPS data for the period 1967-1994 and found that the innovations could be modelled as an MA(2) model. Carrol and Samwick (1997) used 1981-1987 observations from the PSID and found that for decompositions in 8 occupations, 6 educations and 12 industries transitory shocks in income were substantially larger than permanent shocks. All this evidence suggests that there are systematic differences in risk between educations/occupations, but that annual measures are highly variable. Thus, aiming for a more "permanent" characterisation of this risk is both meaningful and necessary. As a start we selected the median of the five annual estimates of *R* and *K* for this purpose.

The ANOVA results are also supported by the correlation between the various measures of *R* and *K* that we now have available (see Appendix D for a summary of these correlation coefficients). For *R*, correlations between CPS years are below 0.42, for *K* they are below 0.06 (except K98-K99, at 0.20) and even negative in several cases. Correlations of CPS estimates with the Census estimate are very low, both for *R* and *K*, and correlations with the median from the NBER-CPS set are relatively high, at 0.28 to 0.72 for *R* and 0.10 to 0.61 for *K*. In both cases, however, the correlation with the observations for 1998 (our base year, that we started the estimations with) stand out as unusually high: 0.72 for *R* (the next highest is 0.51) and 0.61 for *K* (the next highest is 0.16). Apparently, in our innocence, we started with a year that has relatively high correlations between *R* and *K* measured for that year and a more permanent measure of *R* and *K*.

Regression results with the five-year medians for *R* and *K* are reported in Rows 10 and 11 of Table 3, and are strongly supportive of the theory: highly significant and with the proper sign. Moreover, the magnitudes of the effects are substantial.

As the final results also hold for women, we need an explanation why the other results for women are so poor. We would point to the variability of *R* and *K*, and the disturbing impact of outliers that is more destructive for women than for men. This variability is not a simple consequence of women working part-time or having less stable labour force attachment. Both with CPS data and with Census data, if fixed effects are included, neither restricting the women sample to full-time full-year nor restricting it to young women (those under 40, presumably with more solid labour force attachment than older generations) puts the results in line with theory. Outliers affect both *R* and *K* and this is particularly devastating for the women sample in the Census. The correlation between *R* and K for this sample is 0.984, essentially precluding separating effects. In the other cases, correlations are no higher than 0.94 (and for the medians even below 0.81).

To assess the importance of a 'permanent' measure of wage variability, we constructed Table 4. For each year of the five-year selection from the NBER-CPS data set, we estimated the risk augmented Mincer earnings function, with R and K either estimated from that year's sample itself or from the five-year median. Table 4 also presents the means and the standard deviations of R and K. Both for men and women, the mean of R is fairly stable 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, the annual estimates show only modest variation. For women we only find 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.

The five year median value for R and K may still be a less than fully satisfactory measure of permanent variability because of the way very high earnings (wages) are treated in the CPS data and in the NBER processing. Both datasets 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. We decided to use percentile-based statistics to eliminate this effect; in particular for R we used the difference between the 75^{th} and the 25^{th} percentile wage and for K we used $\left(75^{th} - 50^{th}\right)/\left(50^{th} - 25^{th}\right)$ percentile wages.

Table 4 around here

Table 5 around here

Table 5 is similar to Table 4, but now based on percentiles of the distribution. Just as with the medians, taking the longer-term measures generates results supportive of theoretical predictions whereas the annual own-sample measures do not. The left-hand estimates use percentile-based R and K measures from the own sample, the right-hand estimates use the pooled five year database to estimate them. In both cases we required a minimum education-occupation cell size of 20 observations. For women in the NBER-CPS data, R and K have the right sign, and are highly significant. For men, we find the predicted negative sign for K, highly significant, while R has no significant effect. In the annual measures, the means of R and K are very stable; the correlations between R and K are quite low (less than 0.4).

We tend to conclude that there is more support for Adam Smith's theoretical argument than he believed himself. But 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. 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). There is more 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 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. Two considerations are neatly in line with the powerful role of *K*. First, the argument of Adam Smith, that supply is attracted to the "reputation of superior excellence": these are typically the high end outliers that catch the imagination. It's the exceptional success that has a strong impact, 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 Four Structural Specifications of the Empirical Model

After establishing the relevance of risk compensation in wages, we will now develop models that allow for structural estimates of parameters. We believe this to be useful exercise, as structural models provide the necessary link with related theoretical and empirical work in economics. Estimating discount rates and degrees of risk aversion permits comparison with results found elsewhere and helps to build a body of systematic research results. But we are aware that this is a hazardous venture, as the estimation exercises available in the literature have not yet generated a body of generally accepted robust results on the parameters we are interested in.

It is only natural to start estimating the empirical model with the simplest utility function possible, the CRRA function we used in section 2. At the same time, we need to be sensitive to the possibility that the individual's utility function may not exhibit CRRA. For that reason, it is necessary to specify an alternative utility function that nests CRRA as a special case.

We develop a simple extension of the CRRA utility function. Notice that if U is CRRA as in (6), $U'(Y) = Y^{-?}$, or $\ln U' = -r \ln Y$. A suitable extension is therefore a translog marginal utility (TLMU) function, written as:

$$\ln U' = r_1 \ln Y - 0.5 r_2 (\ln Y)^2 \tag{34}$$

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:

$$\Pi_s = -\left[\frac{m_{2s0}}{2m_{s0}^2}\int_s^\infty a_t U'(m_{st})\left(r_1 - r_2 \ln m_{st}\right)e^{-dt}dt + \frac{m_{3s0}}{6m_{s0}^3}\int_s^\infty a_t U'(m_{st})\left\{\left(r_1 - r_2 \ln m_{st}\right)^2 - r_1 - r_2 + r_2 \ln m_{st}\right\}e^{-dt}dt\right] / \left[\int_s^\infty a_t U'(m_{st})e^{-dt}dt\right] \tag{35}$$

Furthermore, since M_s depends on U as was shown in equation (5), we must find the utility function U that yields a translog marginal utility as in (34). As Appendix A shows, this function is:

$$U(Y) = \sqrt{\frac{2p}{r_2}} \exp\left(\frac{(r_1+1)^2}{2r_2}\right)\Phi\left[r_2^{1/2}\left(\ln Y - \frac{r_1+1}{r_2}\right)\right] \qquad (36)$$

where Φ is the standard normal cumulative distribution function. Interestingly, our generalisation of the CRRA utility function has led us to the welfare function of derived by Van Praag (1968) from basic axioms on individual choice behaviour. Indeed, the two utility functions are formally equivalent, as we demonstrate in Appendix B. Van Praag and associates have developed a survey method to measure the two parameters of the lognormal welfare function ("mean" and "standard deviation") at the individual level. In many studies, based on thousands of individual observations they have established very robust results and interesting applications (for a survey, see Van Praag and Frijters, 1997; for a review, Hartog, 1988). Thus, our generalised utility function is backed up by substantial empirical support.

To estimate the structural model, we must make a distributional assumption about its disturbance term, which was called e_s in equation (30). Before we do so, we generalize the model in one aspect. Sections 2.2 and 2.3 tracked the discussion into a hypothetical world where there is one risky and one riskless occupation and possibly several levels of education. It is not a leap of faith to broaden the model to a world where many occupations exist: they are all compared with a possibly hypothetical riskless income stream. The various occupation-cum-education tracks are indexed by j, and as such, the regression model (19) is rewritten trivially as

$$\ln Y_{ji} = X_i b - \ln\left(1-\Pi_{ji}\right) - \ln\left(1-M_{ji}\right) + e_{ji} \qquad (37)$$

with i denoting the individual. However the impact of schooling (through M_{ji}) is the same across occupational tracks.

In regard to e_{ji}, we may assume normality, as is common in the literature. Due to the nature of the model, e_{ji} is necessarily heteroskedastic: $Var(e_{ji}) = s_j^2$. Furthermore, it is straightforward to prove that, if U is CRRA,

$$-\ln\left(1-\Pi_{rs}\right) = 0.5?s_j^2 \qquad (38)$$

and, in general (e.g., when U is TLMU),

$$\frac{m_{2j0}}{m_{j0}^2} = R_j = e^{s_j^2} - 1 \qquad (39)$$

$$\frac{m_{3j0}}{m_{j0}^3} = K_j = e^{3s_j^2} - 3e^{s_j^2} + 2 \qquad (40)$$

Thus, under normality, whether U is CRRA or TLMU, the risk premium itself or the components of the risk premium are simple functions of s_j^2.

In principle, one could estimate s_j^2 for each occupation/education cell jointly with the other parameters of the wage equation. We prefer a two-stage approach parallel to the strategy adopted in section 3. Thus, s_j^2 is estimated as a five-year median of occupation/education cell variances from a first-stage fixed effects 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.[11] Furthermore, one may note that equation (34) dictates the measurement of m_{st} at all t. Thus, for each individual, we compute his/her 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.

In estimating the model, we wish to leave the possibility open that e_{ji} is not normally distributed. If this is so, R_j and K_j are not simply a function merely of s_j^2 but rather of all of the parameters of the distribution. But as this distribution is left unspecified, we employ the five-year median values of R_j and K_j, and we estimate the log wage equation by means of weighted nonlinear least squares.

To sum up, we estimate four specifications of equation (19).

1. CRRA/Normal

   CRRA implies (20) for the compensation for schooling and (38) for the compensation for risk. In fact, this is exactly the equation Yoram Weiss (1972) derived and used for risk correction on the rate of return to schooling.

2. CRRA/Nonnormal

   Again, CRRA implies (20) for M_j, while (21) applies for Π_j.

3. TLMU/Normal

   M_j is now given by (5), where utility and its derivative are taken from (36) and (34). Normality implies (39) and (40), which are substituted into (35) for Π_j

4 TLMU/Nonnormality

   Again, M_j is given by (5), with utility function (36) substituted. Π_j is given by (35), with the moments now estimated in the first stage from their definitions (32) and (33).

We will estimate the structural models for a single year, the NBER-CPS data of 1999, for reasons that these data are recent and contain more observations.

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

5. Estimates of the Structural Model

Estimation results for the four specifications on the CPS data are given in Table 6. The results for 'TLMU,unrestr' correspond to specifications 3 and 4 above. Below, we will explain what we mean by the *restricted* estimates, 'TLMU,restr.' The CRRA results are unconvincing. The coefficient of risk aversion is estimated to be negative in 3 cases; it would imply that employees are generally risk lovers. In the only case it is estimated positive (women, non-normal), the discount rate is estimated to be negative, which is even more implausible. The reasonable estimates for the discount rate in the other cases, high but not outside the range estimated by others (Lawrance, 1991; Carroll and Samwick, 1997), are not sufficient to rescue this model. Hence, while CRRA is an elegant specification, useful for analytical purposes, it is not a specification supported by empirical research. The same conclusion has been drawn from other econometric work (Dynan, 1993; Guiso and Paiella, 2000).

In the 'TLMU,unrestr' results, for normal errors, we find very high values of the discount rate, well above 1. Moreover, as test results reported in Appendix C indicates that residuals in the first-stage regressions are not normally distributed, we must also discard these results. This leaves 'TLMU,non-normal' as our preferred specification. It has an estimated discount rate of 0.20 for men and 0.89 for women. Judged against intuition, these are high values. But they cannot be judged against a body of solid empirical evidence, as it does not exist. High values are not uncommon in structural models. Lawrance (1991), using Euler equations for lifetime consumption patterns, finds .12 in the top 5 percent of the labour income distribution and .19 in the bottom fifth of the distribution. Carroll and Samwick (1997), also modelling intertemporal consumption, find a very wide interval, in one case even with a point estimate of .38 and two-standard-error band from .21 to .79. 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:

$$U'' = U'(r_1 - r_2 \ln Y)/Y \qquad (41)$$

$$V_r = r_2 \ln Y - r_1 \qquad (42)$$

$$F_r = 1 + V_r - r_2 / V_r \qquad (43)$$

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 estimates for 'TLMU, non-normal, unrestr' put these thresholds at hourly wages of \$18.10 for men and \$14.86 for women. These are fairly high values, implying 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, thus satisfying a condition that was required by Arrow (Guiso and Paiella, 2001:14) who also report increasing relative aversion in their own data). 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 $r_1 = r_2$. The estimation results for this specification are given under *restr* (restricted) in Table 6. The assumption regarding the distribution of the errors proves irrelevant for the results. The estimated discount rate of 0.05 and 0.075 is quite reasonable.

With equations (42) and (43) 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 1998). This yields the following results

	TLMU, unrestr, non-normal		TLMU restr, 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

The empirical literature on risk aversion has not led to unambiguous conclusions on magnitudes. 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. Such high aversion rates are usually not found. Analyses of individual asset holdings suggest a coefficient of relative risk aversion somewhere in the interval between 2 and 3 (Beetsma and Schotman, 2001). But exceptions occur. Dynan (1993) finds a relative risk aversion coefficient of about 10. However, she finds a very low rate of relative skewness affection, at about 0.3 and a 95 percent confidence interval from –0.12 to 0.75. In a direct survey approach, where we ask individuals for the reservation price of a specified lottery ticket, and then derive an individual measure of absolute risk aversion, we find, in three different datasets, that 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, 2001). In a similar approach, Guiso and Paiella (2000), 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 behavior in a television game and find a coefficient of relative risk aversion of about 7. Thus, the results we find for risk aversion and skewness affection are not out of step with results found elsewhere. In our preferred specification, relative risk aversion appears on the low side. This may very well be a consequence of self-selection, where highly risk averse individuals shy away from high risk occupations.

Table 6 around here

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.

6. Conclusion

In our desire to test for the risk compensation in wages that was anticipated by Adam Smith in his famous rules on wage differentials, we added the hypothesis that skewness affection gives rise to a negative compensation: individuals appreciate the small probability of a large prize. In a simple two-stage estimation procedure both hypotheses have been corroborated, elsewhere, for five countries (the US, Germany, Spain, Portugal and The Netherlands). In this paper we confirm the simple, basic results. But concern for econometric impurities drove us to further testing. Basically, we find support for the hypotheses, provided we apply "permanent," longer-term measures of income variation. Annual measures apparently are too noisy.

We also developed a structural model of schooling and occupational choice under earnings risk. We clearly have to reject the CRRA utility function. We specified a more general utility function, the Translog Marginal Utility function, which turned out to be identical to the firmly empirically supported welfare function developed by Van Praag. A key issue remaining for further empirical work is the curvature of the utility function. Without restriction, we found rather implausible values for the discount rate and increasing marginal utility of income up to fairly high income levels. Restricting the model to declining marginal utility led to quite plausible values for the discount rate. The results imply increasing relative risk aversion, a condition identified by Arrow as necessary for consistency with the theory of wealth accumulating by consumers.

We consider our results as sufficiently encouraging to propose further research along the lines initiated here. The key issue is the proper measure of earnings variability faced by individuals. In the model developed here, we need measures of risk and skewness of the options open to individuals at the time they decide on entering educations and occupations. If risk and skewness are stable over time, we can use contemporaneous estimates, derived from the same data as used for estimating the earnings functions. Our results clearly indicate that contemporaneous measurement is not adequate. But that still leaves the question whether the high variability in year-to-year measures of R and K that we have found is due to measurement errors in our samples or an indication that it is an illusion to search for stable "permanent" measures of education-occupation specific earnings variability. We believe that such permanent differences in earnings variability do 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). But of course the thorny issue of measurement error remains. Bound et al (1990), comparing survey data with company and social security records, have shown this to be a genuine reason for concern, although they give no information on possible variation in the share of measurement errors in observed variance of earnings and hours worked across occupations. Thus we share the worries of Murphy and Topel (1987) in their search for compensation for employment and earnings risk across industries. But without a source of "error free" measurement, as Bound et al exploited we see no good solution for this problem.

It is important to note that according to our model, the wage premium has to be enforced in the market from individuals' supply reactions and thus depends on the individuals' perception of the earnings variability they face. This makes it questionable whether panel data of individual earnings are of any help. With panel data we can eliminate individual fixed effects, but the real question is whether individuals know these fixed effects when they have to make their decisions. It seems much more relevant to condition perceived earnings variability on information available to the individual. For example, an individual may know, from school grades, an IQ test or otherwise, what her abilities are, and this may reduce perceived uncertainty of success. Thus, conditioning on these variables seems much more interesting to us, and is certainly not infeasible. Whether the effect will be large or not remains to be seen. Becker (1964, 204), discussing the large variation in rates of return to education across individuals, argues that most of it reflects *ex ante* risk to the investor, and that the role of known measures of ability such as IQ and grades, is small.

An obviously important step in our research should be to fully acknowledge individual heterogeneity in risk attitudes and to allow for self-selection of individuals into the various occupations. This can only be accomplished with direct estimates of the individual's risk attitudes. While such estimates are not routinely available, there is a growing interest in applying subjective, survey based measures. For example, Hartog, Ferrer-i-Carbonell and Jonker (2000) used a simple lottery evaluation question with very encouraging results.[12] Friedman and Kuznets (1945, 128) speculated that more individuals would be inclined to study medicine rather than dentistry because the greater variability in income acts as an attraction rather than a deterrent. Testing such speculations would obviously be most interesting.

As noted in the introduction, we ignore possible compensation for the risk of unemployment. But this 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 Murphy and Topel's dataset (CPS 1977-1984), the coefficient of variation is 0.24 for the hourly wage rate and 0.067 for annual hours worked (o.c., 109). Suppose, every individual faces an annual unemployment risk of 10%, and when unemployed receives 70% of his earnings and we 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, relative earnings risk is in the order of 0.6, according to Table 1, which would require a wage premium of 15%. Abowd and Ashenfelter (1981) estimate wage compensation for anticipated unemployment risk in the context of a structural model, and indeed estimate a high coefficient of hours risk aversion (the counterpart of the Arrow-Pratt measure of income risk aversion), at values around 14. But when applied to actually experienced unemployment, the compensating wage differential is in the order of 4%. Murphy and Topel (1984) find that a one standard deviation increase in the weeks worked variability would generate compensation in average annual earnings of about 0.5% (we should add that they are very worried about measurement errors invalidating their estimates). Naturally, a model including both wage and unemployment risk is preferable to a model considering only wage risk. But considering the problems still facing us, we are not inclined to give possible compensation for the differences in unemployment risk top priority on our list of further research. Rather, we would focus on the topics indicated above: good measurement of perceived earnings variability and selectivity on the basis of differences in attitudes towards risk. And the latter should certainly include selective exits, as individuals may respond to gradual unfolding of information about their possibilities of success during their career. Johnson (1978) has shown that risk neutral individuals should always try the riskiest sector first. Such patterns of course have important implications for attempts to deduce anticipated risk from observed dispersions. In our

[12] Risk attitude measured from the simple lottery reservation price significantly affects the choice for entrepreneurship. See Cramer *et al*. (2000).

view, integrating labour market mobility in the model of risk compensation should indeed have a high priority.

Appendix A: Derivation of equation (36)

The utility function $U(Y)$ is found by integrating the marginal utility:

$$U(Y) = \int_{0}^{Y} e^{r_1 \ln X - 0.5 r_2 (\ln X)^2} dX \; = \int_{-\infty}^{\ln Y} e^{(r_1+1)Z - 0.5 r_2 Z^2} dZ$$

The right hand side can be rewritten such that one recognizes the normal density function as a part of it. This allows one to state the integral as a normal cumulative distribution function, although, of course, there is no normally distributed random variable at play here:

$$\begin{aligned} U(Y) &= \int_{-\infty}^{\ln Y} \exp\left(-0.5 r_2 \left\{ Z^2 - 2\left(\frac{r_1+1}{r_2} \right) Z + \left(\frac{r_1+1}{r_2} \right)^2 \right\} + 0.5 \frac{(r_1+1)^2}{r_2} \right) dZ \\ &= \Phi\left[\frac{\ln Y - (r_1+1)/r_2}{\sqrt{1/r_2}} \right] \sqrt{\left(\frac{2p}{r_2} \right)} \exp\left(0.5 \frac{(r_1+1)^2}{r_2} \right) \end{aligned}$$

The last term results from the last expression (which is a constant) under the integral on the first line. The middle term appears because the first term under the integral inside the curly brackets resembles the normal density function with mean $(r_1+1)/r_2$ and variance $1/r_2$.

Appendix B: TLMU and Van Praag's lognormal welfare function

Corresponding with the Van Praag utility function, suppose

$$U(Y) = \Phi[\ln Y; m, q] = \int_{-\infty}^{\ln Y} \left(2pq^2\right)^{-0.5} \exp\left(-(x-m)^2 \big/ \left(2q^2\right)\right) dx$$

Then

$$U'(Y) = \left\{\exp\left(-m/q^2\right) \big/ \left(2pq^2\right)\right\} \exp\left\{-\ln Y^2 \big/ 2q^2 + \left(\left(m/q^2\right) - 1\right) \ln Y\right\}$$

The TLMU function yields a marginal utility of

$$U'(Y) = \exp\left\{ r_1 \ln Y - \left(r_2/2\right) \ln Y^2 \right\}$$

The constant term in front of the Van Praag marginal utility function is irrelevant. Thus, the two approaches are identical when the two exponential terms with *Y* are identical. This is accomplished whenever

$$-1\big/\left(2q^2\right) = -r_2/2$$
$$\left(m/q^2\right) - 1 = r_1$$

This implies a one-to-one correspondence:

$$q = 1\big/\sqrt{r_2}$$
$$m = \left(1 + r_1\right) \big/ r_2$$

Appendix C: Testing residuals for normality

We extracted the residuals from the first-stage fixed-effects model and subjected them to three tests to examine whether, within each occupation/education cell, they are normally distributed. These test statistics are; (1) a chi-square test on the third and fourth order moments; (2) the Shapiro-Wilk test; and (3) the Shapiro-Francia test. Table C.1 summarizes the outcomes of the tests at a significance level of five percent for each of the datasets used in this study.

Table C.1: Testing for Normality by the Chi-Square Moments test, the Shapiro-Wilk test, and the Shapiro-Francia test

	Outcome of the tests			Average number of observations per cell		
Data source	None of the tests rejects normality	The three tests are ambiguous	All three tests reject normality	None of the tests rejects normality	The three tests are ambiguous	All three tests reject normality
Males						
CPS 1998	56	7	66	36	70	242
Census 1990	41	11	92	51	125	512
NBER-CPS 1995	60	7	70	168	370	691
NBER-CPS 1996	61	11	69	102	248	646
NBER-CPS 1997	54	7	76	99	254	624
NBER-CPS 1998	54	14	73	79	246	643
NBER-CPS 1999	52	11	75	105	172	632
Females						
CPS 1998	45	10	49	39	42	276
Census 1990	47	8	69	42	98	545
NBER-CPS 1995	56	10	62	72	173	737
NBER-CPS 1996	48	12	57	58	172	702
NBER-CPS 1997	53	13	55	78	112	738
NBER-CPS 1998	49	13	59	42	185	703
NBER-CPS 1999	56	14	51	52	194	790

In about one half of the cells, the outcome of the three tests is unambiguous: a Null hypothesis of normality must be rejected. As one should expect, the number of observations in these cells is typically large: the power of the test increases as the sample size gets larger. But this also means that, out of the total sample of wage earners, the disturbance term should be considered nonnormally distributed for over 80 percent of workers in the sample. We must therefore give more careful consideration to models that are more distribution-free.

Appendix D: Correlations between measures of *R* and *K*

Table D.1 presents correlation coefficients of measures of *R* and *K* computed from the various samples used in the analysis of this paper. The measures indicated by R(NBER) and K(NBER) represent the median values of *R* and *K* drawn from the five years of NBER-CPS data. The subscript "p" denotes measures of *R* and *K* based on percentiles, as discussed in Section 3. The table offers correlation coefficients of men below the diagonal and of women above the diagonal.

Notable features are, first of all, the low correlation between the various measures of *R* and, similarly, of *K*. In other words, the measured risk and skewness appears quite data-dependent. Second, the correlation between *R* and *K* within a dataset is often very high, but that between *R* of one dataset and *K* of another is low. This corresponds with the first finding. Third, the median values from the NBER-CPS data capture more of the variation in other datasets. Fourth, the median values of *R* and *K* are not as highly correlated as those derived from a single data source. Fifth, the percentile-based measures do not suffer from a high correlation between *R* and *K* and, with the exception of the value of *K* for females, correlate well with the median values.

Similar correlation coefficients can be computed with respect to each individual year of the NBER-CPS data. These are summarized in Table D.2, where the subscripts "t" and "s" denote the various years. The summary reinforces the conclusions drawn above but adds that the NBER-CPS data appear to yield somewhat more stable measures of R and K than the CPS or Census data.

Table D.1: Correlations between measures of *R* and *K* (males below the diagonal, females above the diagonal)

	R(CPS)	R(Census)	R(NBER)	R_p(NBER)	K(CPS)	K(Census)	K(NBER)	K_p(NBER)
R(CPS)		0.021	0.257		0.897	0.003	0.192	
R(Census)	0.101		0.131		0.023	0.984	0.043	
R(NBER)	0.310	0.118		0.576	0.197	0.114	0.631	
R_p(NBER)			0.648					0.376
K(CPS)	0.865	0.141	0.150			0.000	0.157	
K(Census)	0.037	0.945	0.060		0.057		0.014	
K(NBER)	0.199	0.179	0.807		0.182	0.113		−0.016
K_p(NBER)				0.169			0.419	

Table D.2: Summary of correlations between *R* and *K* involving the individual years of the NBER-CPS data.

Range of correlation between	Males	Females
R(CPS) and $R(NBER)_t$	0.030 – 0.160	0.043 – 0.281
R(Census) and $R(NBER)_t$	0.016 – 0.078	0.043 – 0.129
$R(NBER)_t$ and $R(NBER)_s$	0.086 – 0.418	0.069 – 0.532
K(CPS) and $K(NBER)_t$	-0.028 – 0.047	-0.020 – 0.109
K(Census) and $K(NBER)_t$	-0.026 – 0.057	-0.029 – 0.034
$K(NBER)_t$ and $K(NBER)_s$	-0.028 – 0.204	-0.034 – 0.462
$R(NBER)_t$ and $K(NBER)_t$	0.772 – 0.957	0.461 – 0.874
$R(NBER)_t$ and $K(NBER)_s$	-0.013 – 0.347	-0.059 – 0.486

TABLE 1 VARIANCE AND SKEWNESS IN RELATIVE WAGE DEVIATION,[1] CPS 1998

	Mean	St.Dev	Percentiles		
			5^{th}	50th	95^{th}
Males					
R	0.577	0.500	0.159	0.456	1.344
K	3.017	5.657	-0.070	1.541	10.918
Females					
R	0.523	0.615	0.146	0.307	1.214
K	5.052	13.685	-0.049	1.369	18.429

Note: [1]Across occupation/education cells.

TABLE 2 BASIC REGRESSION OF LN WAGES ON R AND K, CPS 1998

	Males		Females	
	estimate	t-stat	estimate	t-stat
Years of Education	0.0967	41.00	0.1183	52.26
Age-16	0.0557	33.28	0.0426	24.83
$(Age-16)^2$	-0.0008	-23.80	-0.0007	-19.60
R	0.3338	11.64	0.5131	15.97
K	-0.0191	-7.36	-0.0187	-13.02
Mid Atlantic	0.0487	2.39	0.0141	0.69
East North Central	0.0030	0.15	-0.0599	-2.98
West North Central	-0.1133	-4.70	-0.1564	-6.48
South Atlantic	-0.0553	-2.76	-0.0958	-4.73
East South Central	-0.0971	-3.88	-0.1959	-8.15
West South Central	-0.0789	-3.60	-0.1682	-7.65
Mountain	-0.1000	-4.52	-0.1330	-5.93
Pacific	0.0375	1.79	0.0160	0.76
Black	-0.1956	-11.67	-0.0545	-3.73
Hispanic	-0.2428	-17.05	-0.1172	-8.24
Asian	-0.1722	-5.71	-0.0838	-3.20
Indian	-0.1895	-3.54	-0.1162	-2.64
Intercept	0.5186	14.05	0.1352	3.42
N	18459		15695	
R^2	0.3526		0.3149	

TABLE 3 ALTERNATIVE SPECIFICATIONS OF *R* AND *K*, CPS 1998 AND CENSUS 1990

		MEN				WOMEN			
		R		*K*		*R*		*K*	
	Estimation feature	coeff	t	coeff	T	coeff	t	coeff	t
A: Without fixed effects, using CPS 1998 data									
1	Basic specification	0.3338	11.64	-0.0191	7.36	0.5131	15.97	-0.0187	13.02
	Full-time, full-year	0.2623	7.20	-0.0166	5.39	0.4247	6.00	-0.0089	1.27
	Young women					0.3801	8.45	-0.0149	7.85
2	Include job characteristics	0.3779	10.72	-0.0239	7.79	0.4221	10.83	-0.1610	8.40
B: With fixed effects, using CPS 1998 data									
3	CPS	0.3341	10.84	-0.0273	9.77	0.0192	0.49	0.0056	2.60
4	CPS, delete own residual	0.2897	9.91	-0.0258	10.00	-0.0637	1.77	0.0093	4.66
C: With fixed effects, using CPS 1998 data, *R* and *K* from Census 1990 data									
5	Occupation codes: *fine*	-0.0801	6.35	0.0024	7.12	-0.0953	6.49	0.0030	5.86
6	Occupation codes: *crude*	-0.1895	10.24	0.0054	11.71	-0.2635	7.26	0.0082	7.23
C: With fixed effects, using Census 1990 data									
7	Occupation codes: *fine*	-0.0229	2.35	0.0008	3.39	-0.0670	6.11	0.0022	5.61
8	Occupation codes: *crude*	-0.1492	13.28	0.0043	15.57	-0.1576	7.69	0.0049	7.85
9	Occupation codes: *crude, weeks worked>40*	0.0971	2.88	-0.0111	2.05	-0.3355	7.00	-0.0001	0.02
D: With fixed effects, using median *R* and *K* in NBER-CPS 1999 data									
10	Occupation codes: *fine*	0.5716	6.79	-0.9581	14.12	0.4983	7.32	-0.4312	12.37
11	Occupation codes: *crude*	0.7585	6.85	-1.1023	17.55	0.2524	3.62	-0.4999	23.75

TABLE 4: 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	β_R	t	β_K	t	β_R	t	β_K	t
A: Males												
95	0.178	0.049	0.132	0.224	-1.122	17.72	0.051	3.53	0.464	4.32	-1.068	17.21
96	0.193	0.133	0.448	2.058	-1.170	21.28	0.061	17.28	0.612	5.47	-1.100	17.23
97	0.182	0.074	0.175	0.676	-1.316	22.99	0.094	14.51	0.479	4.39	-1.039	16.59
98	0.203	0.064	0.205	0.205	0.336	5.11	-0.280	14.11	0.873	7.65	-1.301	20.12
99	0.214	0.106	0.474	1.685	-0.204	5.17	0.002	0.99	0.759	6.85	-1.102	17.55
μ	0.178	0.041	0.114	0.075								
B: Females												
95	0.203	0.096	0.646	1.492	-0.881	16.52	0.022	6.91	-0.088	1.26	-0.483	22.17
96	0.198	0.128	0.969	3.794	-1.104	21.38	0.024	13.74	-0.030	0.42	-0.469	21.96
97	0.178	0.052	0.199	0.242	-0.627	9.10	-0.117	7.52	-0.045	0.65	-0.446	21.16
98	0.193	0.072	0.303	0.428	-0.232	4.22	-0.068	7.48	-0.074	1.08	-0.412	20.06
99	0.193	0.094	0.382	0.978	0.051	0.90	-0.028	5.19	0.252	3.62	-0.500	23.75
μ	0.179	0.050	0.190	0.168								

Note: μ denotes the median over 1995-99.

TABLE 5: 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	β_R	t	β_K	t	β_R	t	β_K	t
A: Males												
95	0.494	0.081	1.294	0.293	-0.282	6.62	-0.081	6.43	-0.048	0.87	-0.177	7.94
96	0.497	0.085	1.306	0.371	-0.327	7.14	-0.020	1.55	0.073	1.29	-0.231	9.92
97	0.496	0.085	1.285	0.369	-0.291	6.23	-0.077	6.24	0.046	0.83	-0.231	10.34
98	0.499	0.079	1.344	0.419	-0.021	0.43	-0.006	0.49	0.062	1.08	-0.194	8.52
99	0.479	0.085	1.403	0.454	0.445	9.56	-0.100	10.34	0.091	1.65	-0.141	6.29
μ	0.492	0.066	1.285	0.179								
B: Females												
95	0.465	0.106	1.396	0.420	0.628	12.33	-0.407	31.85	1.077	16.85	-0.590	32.30
96	0.472	0.104	1.422	0.436	0.641	12.12	-0.294	20.35	1.084	16.78	-0.573	30.38
97	0.471	0.096	1.389	0.398	0.374	7.14	-0.192	16.07	1.041	16.62	-0.563	31.35
98	0.473	0.092	1.515	0.680	0.369	6.80	-0.109	9.80	1.014	16.18	-0.535	30.05
99	0.462	0.101	1.339	0.419	0.719	14.30	-0.222	19.24	1.240	19.61	-0.542	30.19
μ	0.469	0.085	1.362	0.250								

Note: μ refers to values based on pooled data 1995-99.

TABLE 6 STRUCTURAL ESTIMATES

MALES

	CRRA Normal		CRRA Nonnormal		TLMU,unrestr Normal		TLMU,unrestr Nonnormal		TLMU,restr Normal		TLMU,restr Nonnormal	
parameter	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat
Intercept	1.856	134.87	2.008	150.61	1.966	135.52	2.219	165.56	1.869	173.44	1.867	173.06
(Age-16)	0.044	66.90	0.043	67.01	0.038	61.17	0.039	62.33	0.043	68.01	0.043	67.97
$(\text{Age-16})^2$ (x 100)	-0.065	-48.44	-0.065	-48.40	-0.055	-42.80	-0.057	-44.25	-0.066	-49.91	-0.066	-49.87
ρ	-0.473	-4.00	-1.873	-30.42								
ρ_1					10.019	54.89	15.008	24.16	0.402	31.49	0.392	31.21
ρ_2					3.559	57.61	5.180	23.69				
δ	0.189	11.32	0.362	45.95	1.347	18.13	0.199	13.46	0.053	26.53	0.054	26.56
Black	-0.176	-27.94	-0.173	-27.74	-0.056	-9.15	-0.048	-7.56	-0.146	-23.51	-0.146	-23.51
Indian	-0.115	-5.56	-0.107	-5.25	-0.033	-1.67	-0.029	-1.48	-0.097	-4.76	-0.097	-4.76
Asian	-0.108	-10.60	-0.112	-10.95	-0.032	-3.25	-0.038	-3.83	-0.101	-10.00	-0.101	-9.96
Hispanic	-0.191	-32.00	-0.193	-32.83	-0.041	-6.81	-0.057	-9.42	-0.202	-34.71	-0.201	-34.64
Mid Atlantic	0.016	1.59	0.019	1.93	-0.023	-2.46	-0.025	-2.63	0.009	0.88	0.009	0.90
East North Central	0.010	1.05	0.008	0.82	-0.023	-2.54	-0.025	-2.73	0.007	0.77	0.007	0.80
West North Central	-0.078	-7.15	-0.078	-7.21	-0.017	-1.60	-0.016	-1.51	-0.057	-5.27	-0.057	-5.28
South Atlantic	-0.051	-5.27	-0.048	-5.05	-0.031	-3.35	-0.031	-3.44	-0.045	-4.74	-0.045	-4.73
East South Central	-0.108	-9.32	-0.108	-9.37	-0.044	-3.97	-0.047	-4.28	-0.095	-8.35	-0.095	-8.35
West South Central	-0.074	-7.19	-0.074	-7.28	-0.033	-3.38	-0.033	-3.42	-0.063	-6.31	-0.063	-6.32
Mountain	-0.041	-3.68	-0.038	-3.45	-0.012	-1.11	-0.009	-0.85	-0.028	-2.56	-0.028	-2.56
Pacific	0.024	2.50	0.028	2.88	-0.018	-1.89	-0,018	-1.97	0.019	2.00	0,019	2.01
Number of observations	54774		54774		54774		54774		54774		54774	
log Likelihood	-32942.85		-32657.46		-30081.09		-29989.91		-32157.29		-32165.21	

(Table 6, continued)

FEMALES

	CRRA Normal		CRRA Nonnormal		TLMU,unrestr Normal		TLMU,unrestr Nonnormal		TLMU,restr Normal		TLMU,restr Nonnormal	
parameter	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat	estimate	t-stat
Intercept	1.755	121.90	1.750	149.47	1.979	144.64	1.833	150.46	1.793	158.29	1.795	160.00
(Age-16)	0.030	44.03	0.029	43.69	0.026	40.76	0.026	40.77	0.029	44.25	0.029	43.37
$(Age-16)^2$ (x100)	-0.047	-32.78	-0.045	-32.47	-0.039	-29.50	-0.039	-29.20	-0.046	-33.31	-0.046	-32.57
ρ	-0.412	-3.10	0.906	76.54								
ρ_1					11.931	54.51	7.585	82.89	0.326	30.53	0.330	36.22
ρ_2					4.375	57.18	2.810	81.17				
δ	0.194	9.95	-0.028	-5.90	1.141	20.45	0.890	27.11	0.076	41.96	0.075	47.74
Black	-0.064	-11.10	-0.062	-10.95	-0.019	-3.56	-0.023	-4.36	-0.055	-9.76	-0.055	-9.71
Indian	-0.072	-3.30	-0.082	-3.87	-0.035	-1.73	-0.033	-1.66	-0.076	-3.62	-0.076	-3.90
Asian	-0.035	-3.42	-0.033	-3.22	-0.012	-1.26	-0.005	-0.49	-0.039	-3.92	-0.040	-4.08
Hispanic	-0.117	-17.71	-0.126	-19.45	-0.044	-7.21	-0.031	-5.05	-0.128	-20.02	-0.129	-20.60
Mid Atlantic	-0.015	-1.46	-0.012	-1.19	-0.034	-3.50	-0.035	-3.65	-0.015	-1.46	-0.014	-1.50
East North Central	-0.065	-6.58	-0.062	-6.37	-0.043	-4.64	-0.044	-4.78	-0.054	-5.54	-0.054	-5.61
West North Central	-0.120	-10.74	-0.116	-10.47	-0.015	-1.43	-0.022	-2.08	-0.086	-7.80	-0.086	-8.52
South Atlantic	-0.079	-8.04	-0.079	-8.06	-0.041	-4.46	-0.042	-4.51	-0.067	-6.92	-0.067	-6.97
East South Central	-0.185	-15.66	-0.181	-15.56	-0.059	-5.34	-0.063	-5.66	-0.153	-13.17	-0.153	-13.46
West South Central	-0.141	-13.41	-0.139	-13.38	-0.042	-4.27	-0.045	-4.54	-0.116	-11.28	-0.117	-11,40
Mountain	-0.090	-7.74	-0.087	-7.57	-0.008	-0.72	-0.014	-1.24	-0.065	-5.72	-0.065	-6.01
Pacific	0.008	0.76	0.007	0.68	-0.025	-2.60	-0.027	-2.83	0.006	0.64	0.006	0.67
Number of observations	45928		45928		45928		45928		45928		45928	
log Likelihood	-24846.15		-24485.72		-21850.89		-21990.06		-24132.19		-24160.30	

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