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ABSTRACT

Compensation for Earnings Risk under Worker Heterogeneity*

We use two large Dutch datasets to estimate the Risk Augmented Mincer equation and test for risk compensation in expected earnings. We replicate earlier findings of a positive premium for risk and a negative premium for skew and add confirmation of the key results if we control for individual ability. We find that immigrants have graduated in more risky educations but obtain identical risk compensation. Among recent graduates, women receive higher risk compensation than men, consistent with their higher risk aversion, while for a labour force cross-section, lower average compensation for women is consistent with their presence in less risky educations. Lower average compensation for vocational graduates than for university graduates is consistent with presumed higher risk aversion and lower observed risk.

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Introduction

In the standard Mincer earnings equation, the rate of return to education is estimated as the regression coefficient of log earnings on years of schooling. Under strict conditions, it is the compensation for postponing earnings by going to school. Much recent research seeks to refine or even question this model, by focussing on econometric issues (endogeneity biases) or on the theoretical basis of the simple model itself (heterogeneity and self-selection). The basic model underlying the equation assumes a world without risk: future earnings for any length of schooling are known for sure. Yet, the prevalence of risk surrounding the choice of education and occupation barely needs elaboration. An individual considering an education does not anticipate some *level* of post-school earnings, but an entire *distribution* of earnings. And generally, the individual will not know for sure where in that distribution she will end up. She cannot fully anticipate her abilities to benefit from the education, she does not know her future proficiency in the occupations that follow after school, she cannot predict with perfection the future market value of the skills learnt in school: uncertainties abound. The uncertainties will not be identical for every potential education, and hence, they will affect the individuals' choices. And with individuals generally shying away from risk, a properly functioning labour market will generate compensation for such risk.

In a series of recent papers, compensation for earnings risk has been established for several countries (Hartog, Plug, Diaz Serrano and Vieira, 2003; Hartog and Vijverberg, 2002; Diaz Serrano, Hartog and Nielsen, 2003; Diaz Serrano and Hartog, 2004; Christiansen, Joensen and Nielsen, 2004; for a summary see Hartog 2005). Expected earnings are indeed higher for occupations and educations with higher earnings variance. Most interestingly, they are lower for occupations and educations that are more skewed. The relevance of skew was first pointed out (and established) by McGoldrick (1995). Intuitively, positive skew points to the small probability of obtaining large gain, something people appreciate and are willing to pay for. Appreciation for skew (or skew affection) can also be shown to be required for declining absolute risk aversion, a condition one can hardly dispute. Skew affection has been confirmed empirically in betting behaviour and lottery participation (see Hartog and Vijverberg, 2002, for references).

In several analyses, compensation for risk aversion and skew affection has been established at the level of occupations, sometimes in combination with a few education types. Risk and skew are measured as variance and third moment of residuals from a Mincer earnings equation, after grouping residuals by occupation (without selectivity correction, as discussed below). But occupational attachments are not universally fixed for life, and potentially, workers may move out after receiving a bad earnings draw. The problem of selective mobility is absent at the level of education, as individuals cannot undo their accomplished education. In Diaz Serrano, Hartog and Nielsen (2003) we used observations by education for Denmark (using 75 types), and found the usual positive compensation for risk and negative compensation for skew. We also confirmed the basic results with panel data and even more relevant, we found confirmation when we used alternative risk measures based on individuals' movement through the earnings distribution over time. In Hartog and Vijverberg (2002) we have tested many different econometric specifications and estimated implied utility functions. Thus, the basic relation, which we may call the *Risk Augmented Mincer equation*, has already found substantial empirical support. We may also note that the relation is by no means trivial or a statistical artefact. Consider, for example, a model where higher education levels are chosen by individuals with higher levels of initial ability (such as childhood IQ). Then, the observed earnings distributions by schooling levels emerge as the segments of the initial ability distribution (presumably normal) transformed by the production of human capital at each of these schooling levels. Individual choice guarantees that longer educations have higher mean earnings, but the variance can not be predicted: it can just as well increase or decrease with level of education (see the model in Hartog and Diaz Serrano, 2004), as indeed is confirmed in cross-national comparison of earnings dispersion by education level (Hartog, Van Ophem and Bajdechi, 2004). In other words, a reasonable model of educational choice and selection does not predict an inevitably positive relationship between means and variances of earnings.

The Mincer earnings function, with log wages linear in schooling years and quadratic in potential experience, is a standard specification in empirical work. As noted above, research in the last decade has emphasised the endogeneity of schooling, heterogeneity and self-selection (see Card, 1999). The models that have been developed and estimated have painted a richer picture of the returns to education than the OLS Mincer equation suggests. Still, in this paper we will start out from the basic homogenous model underlying the Mincer equation. This is simply a matter of research strategy, as we consider the canonical earnings equation a natural starting point for empirical work.

Residual earnings variance as observed in the labour market is only a proper measure of risk if individuals are not better informed and if they cannot insure or otherwise evade the earnings uncertainty. The issue of information and selectivity bias will be discussed in Section 1. Like many authors (Blanchard and Fisher, 1989: 283; Shaw, 1996), we do not believe that individuals can insure themselves against the financial risk of investing in schooling. As Shaw (1996:626) 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.” Recent work on the possibilities to reduce the risk of education by financial investments supports this view. For example, Davis and Willen (2000) show that an optimal portfolio of financial and human capital requires totally unrealistic stock holdings. Palacios-Huerta (2003) finds that at the aggregate level, the mean-variance frontier, tracing maximum compensation for given risks, does not improve if returns from financial assets are added to returns from human capital, whereas in the converse case (adding human capital to financial assets) the frontier does improve (for separate demographic groups, the results vary by level of education.) We will thus stick to using earnings variance as our measure of risk.

We will use observations by education for The Netherlands, as in our Danish (and Spanish) data and replicate the standard results. Our main contribution is a test for the effect of worker heterogeneity by ability and an investigation of heterogeneous risk attitudes. In Jacobs, Hartog and Vijverberg (2005), we show that unobserved ability differences will give a downward bias in the estimated risk coefficient if risk and ability are independent, but that the bias cannot be determined if they are correlated. We will show that ability bias is not responsible for our core results. We interpret different outcomes for different groups of workers by referring to differences in risk attitudes and in the distributions of risk. We can give consistent explanations for our findings, but are unable to perform the necessary test for non-linearity. We will briefly outline the underlying model in section 2, introduce the data in section 3, present the basic results in section 4 and then compare results for subgroups in section 5. Section 6 concludes.

1. The Risk Augmented Mincer equation

In Hartog and Vijverberg (2002) we formally derive the Risk Augmented Mincer equation. Here, we just present the main argument. Assume, 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 after school earn a stochastic income Y_s for the rest of their working life, with realisation of Y_s revealed after completing schooling. We assume individuals have an uninhibited choice between alternatives, just as in the seminal Mincer framework. In equilibrium, lifetime utility should be equal. We write the stochastic post school earnings option as mark-ups on the safe no-schooling alternative, one for risk, one for postponing earnings:

$$Y_s = \mu_s = \left(1 - \Pi_s\right)^{-1} \left(1 - M_s\right)^{-1} Y_0 \exp(\varepsilon) \tag{1}$$

With a standard utility function *U(Y)* and using Taylor series expansion up to the third order we can write

$$M_s = \left(1 - e^{-\delta s}\right) \frac{U(Y_s)}{U'(Y_s)} \frac{1}{Y_s} \tag{2}$$

$$\Pi = \frac{1}{2} V_r \frac{m_{2s}}{\mu^2{}_s} - \frac{1}{6} V_r F_r \frac{m_{3s}}{\mu_s{}^3} \tag{3}$$

$$V_r = V_a \mu_s = -\frac{U''(\mu_s)}{U'(\mu_s)} \mu_s > 0 \tag{4}$$

$$F_r = F_a \mu_s = -\frac{U'''(\mu_s)}{U''(\mu_s)} \mu_s > 0 \tag{5}$$

$$\frac{m_{2s}}{\mu_s^2} = \frac{E\left[\left(Y_s - \mu_s\right)^2\right]}{\mu_s^2} = E\left[\left(\frac{Y_s - \mu_s}{\mu_s}\right)^2\right] \tag{6}$$

$$\frac{m_{3s}}{\mu_s^3} = \frac{E\left[\left(Y_s - \mu_s\right)^3\right]}{\mu_s^3} = E\left[\left(\frac{Y_s - \mu_s}{\mu_s}\right)^3\right] \tag{7}$$

M_s is the compensation for postponing earnings (with discounting at rate δ), reduced to the standard Mincer compensation under earnings maximisation (when U(Y) = Y). π is the compensation for earnings uncertainty, separately for variance and skew, with coefficient V_r reflecting relative risk aversion and coefficient F_r reflecting relative skew affection. We use the latter phrase as both casual observation and analytical analysis suggest individuals like positive skew: they appreciate a small probability of a large gain (some fat in the upper tail) and the inevitable assumption of decreasing absolute risk aversion implies a negative third derivative of the utility function and hence, positive F_r. Thus, individuals are willing to pay for positive skew. With a CRRA utility function (Constant Relative Risk Aversion, at rate ρ), the earnings function reduces to

$$E(\ln Y_s) = \ln Y_o + \frac{\delta}{1-\rho} s + \frac{1}{2} \rho \frac{m_{2s}}{\mu_s^2} - \frac{1}{6} \rho(\rho+1) \frac{m_{3s}}{\mu_s^3} \tag{8}$$

a simple equation in schooling years, variance (6) and skew (7). Hence with observations on relative variance and relative skew we could estimate a Mincer earnings equation augmented with risk compensation. If we don't assume CRRA, the parameters of (8) will not be constant but depend on income levels. However, as a linearization, it would still be a good starting point for empirical work.

Admittedly, our basic model is very simple, with just two periods and all uncertainty eliminated at the start of the second period. But this is not unusual, and in fact similar to the seminal model presented in Levhari and Weiss (1974) and more recently, the real option approach presented by Hogan and Walker (2002). We think it is a useful approach to analyse the choice facing a student about to embark on education and hence, at the beginning of the first period. From that perspective, lifetime uncertainty may very well be compressed to uncertainty in the period beyond education.

For estimation, we apply a straightforward two-step procedure. Imagine an individual considering whether to engage in extended education. How would this individual assess the financial risk? We believe that the individual will simply look around and assess earnings risk by observing the variance of earnings in the education under consideration, allowing for the effects of schooling length and experience. That is, she will consider the distribution of residuals from a Mincer earnings function. One might conjecture that the residuals should be purged from selection effects. In some recent literature, schooling choices are modeled and conditional on this modeling and estimation, observed ex post variance in earnings is distinguished from ex ante uncertainty (Chen, 2005; Cunha, Heckman and Navarro, 2005). Selectivity correction is indeed imperative if one wants to measure true risk, but in our case one can forcefully argue that it is not needed. It will only be necessary if individuals themselves use selectivity corrected estimates to assess their risk. The risk compensation we claim should be established by supply reactions to perceived risk (supply is withheld at insufficient compensation). Thus we need to measure the risk perceived by individuals when they make their schooling decisions. Cunha et al. conclude that a large share of ex post variability in earnings is ex ante forecastable by students, and hence presents no risk. But this is an interpretation of ex post observed choices and realised earnings based on an elaborate structural model, not on direct observation of individuals' information set. Dominitz and Manski (1996) have set a standard for measuring the uncertainty in student expectations, by intelligent interviewing. The dispersion that students on average perceive is substantially larger than the actual dispersion. Wolter (2000) applies the same method to students in Switzerland; whereas American students overestimate the inter-quartile range, Swiss students underestimate the ranges relative to their actual values. Webbink and Hartog (2004) compare an individual's stated expected earnings with realised earnings and find that freshmen are unable to predict their position within the actual distribution of starting salaries after graduation, only four years later: the correlation between prediction and realisation is 0.06. The literature generally indicates that individuals certainly have a fairly good perception of differences in mean earnings between types of education (Botelho and Pinto, 2004; Webbink and Hartog, 2004), but clearly cannot accurately predict their position within each distribution. We firmly believe that this line of research, on direct observation of student perceptions should be extended. We think that our hypothesis that student perceptions of earnings risk can be measured by residual dispersion is part of a sound research strategy.

As our assumptions may not convince everyone, we have investigated the possible impact of self-selection on estimated coefficients. We conclude that if ability and risk are independent, ignoring selectivity from individuals' superior information will bias the estimated risk compensation coefficient downwards: if the residual will also reflect ability heterogeneity, risk will be overestimated, and the coefficient underestimated (Jacobs, Hartog and Vijverberg, 2005). With ability and risk correlated, we can no longer draw unequivocal conclusions. However, empirically we know next to nothing on this correlation; all we have is mere speculation

2. Baseline results.

In our present empirical procedure, we first estimate for each year separately the following cross-section log-earnings equation

$$\ln Y_{ij} = X_i \beta + \sum_j \alpha_j d_j + \varepsilon_{ij} \tag{9}$$

where the subscripts *i* and *j* denote individuals and the education cell the individual belongs to respectively. *Y* is hourly earnings and the d_j are dummy variables for education cells. The variables included in *X* are years of education, age and age squared and, depending on specification, dummies for gender and ethnicity. We use age instead of experience because it is exogenous. The education fixed-effects α_j are included in order to control for the effect of omitted variables that may bias our measures of risk and skew within an education cell. We use the estimated residuals to compute measures of R and K, as in McGoldrick (1995), and Hartog, Plug, Diaz-Serrano, and Vieira (2003)

$$R_j^{(1)} = \frac{1}{N_j} \sum_i \left(e_{ij} - \overline{e}_j \right)^2 \qquad\qquad K_j^{(1)} = \frac{1}{N_j} \sum_i \left(e_{ij} - \overline{e}_j \right)^3 \tag{10}$$

where e_{ij} is the exponential of the estimated residuals ε_{ij} in equation (9). In (10), R and K are simply estimated as the second and third moment of the distribution of $exp(\varepsilon_j)$.[1] In the second step we include estimated values for R and K in the following wage equation

$$\ln Y_{ij} = X_i \beta + \gamma_R R_j + \gamma_K K_j + \varepsilon_{ij} \tag{11}$$

where we expect that $\gamma_R > 0$ and $\gamma_K < 0$. Contrary to equation (9), in equation (11) we do not include dummies for education cells since R and K are already fixed in a given education cell. In (10), we do not include any other explanatory variables in X, as the common variables that may be available (such as industry, firm and job characteristics) are all unknown to the individual at the time of deciding on education, and hence, should not be controlled for. However, in the second stage regression we want an unbiased estimate of the risk compensation and hence such controls should be included. In Diaz Serrano and Hartog (forthcoming), we corrected for the fact that R and K are generated regressors and that conventionally estimated standard errors in (11) may be biased; using Spanish data, we found correction to be immaterial. Hence, we will not apply that correction here.

[1] Of course, we could also use the empirical counterpart of (6) and (7), but this would make no difference. In our Danish analysis (Diaz-Serrano, Hartog and Nielsen, 2003) the measures correlate better than 0.99 in each of 17 years.

For our analyses, we use two Dutch datasets. The first, called LSO 1997, is a large nationwide survey on labour earnings. The data are from the Wage Structure Survey (*Loon Structuur Onderzoek (LSO)*) held by Statistics Netherlands (CBS). Data on gross hourly wages are taken from administrative sources (firms or administrations on insured people). The dataset also contains information on gender, age and job characteristics. We use the survey of 1997, covering approximately 120,000 employees. The advantages of the dataset are the large number of observations, many education types (66) and very reliable earnings observations. The data are characterised in Appendix A.

Table 1a gives basic estimation results. We find (but do not report) common results for returns to education at 4 to 5%, the usual concave age-earnings profiles, and earnings disadvantages for women and immigrants. Acknowledging heteroscedasticity as a central feature of our model, we estimate robust standard errors in all the regressions reported in this paper. Computed standard errors are also adjusted for cluster sampling by education (allowing for correlated errors for individuals with the same education); allowing for clustering substantially increases estimated standard errors[2]. The regression for the entire sample solidly confirms the key theoretical predictions of positive compensation for risk and negative compensation for skew[3]. The coefficient for R in the total sample is 1.24. Appendix A gives typical values of R around 0.15; an increase by 0.15 points (which is well within the interval of observed values) would increase earnings by 18.6 %. At a typical value of K, the elasticity for K is 0.1. The wage elasticity for R, at about 0.2, is within the range of earlier estimates (Hartog, 2005), the elasticity for K is relatively high. We also estimate risk compensation for some subgroups. The results for immigrants and natives are identical. The results for men are markedly "stronger" than the results for women, in the sense of larger coefficients and smaller standard errors. In fact, the results for women are not significant. We also distinguish between the public and the private sector, although this is not quite proper: the choice between public and private sector is endogenous, and may be governed by differences in risk attitude. As estimated, the public sector pays much less compensation for risk, and has higher rebate for skew; the risk compensation is not significantly different from zero. In section 5 of this paper we will discuss the differences between groups of workers.

Table 1a. Replication results, LSO data

	R	t	K	t	N
All	1.24	3.69	-0.0471	2.57	119 456
Men	1.80	5.39	-0.0515	3.85	73 991
Women	0.14	0.34	-0.0251	0.77	45 465
Immigrants	1.27	3.72	-0.0487	2.43	8 489
Natives	1.24	3.67	-0.0471	2.56	110 957
Public	0.32	1.07	-0.0542	2.30	31 809
Private	1.90	5.27	-0.0399	2.59	87 647

Regression includes years of schooling, age and age squared; t-values from standard errors clustered by education type.

[2] The equations in Table 2 have also been estimated with aggregate values by education. The main conclusions are very similar to those from estimates with individual observations acknowledging clustering.
[3] If we drop K from the regression, the coefficients for R barely change, but standard errors increase a little.

The second dataset is called the Elsevier/SEO survey, held among graduates from tertiary education. A new cohort of graduates has been interviewed every year since 1996, with focus on outcomes in the first 20 months in the labour market. Dutch tertiary education is basically divided into two levels: higher vocational education (in Dutch abbreviated as HBO) and academic education (WO). HBO-education prepares students for specific (categories of) professions. It is taught at about 60 special institutes evenly spread over the Netherlands. On average, 50,000 students graduate each year from HBO. WO-education is considered to be of a somewhat higher intellectual level and has a more general academic character. It is taught at 14 universities. Approximately 23,000 students graduate every year. At HBO-level students can choose between 250 different courses of study, while at WO-level they may choose between 260 different specializations. Most of them, however, produce only small numbers of graduates, making statistical analysis unreliable. About 80 percent of the student population is concentrated in the 100 largest degree subjects. The survey is restricted to these 100 degree subjects (studies) which divide evenly over HBO and WO. This means the survey is representative of 80 percent of the yearly outflow of graduates at HBO- and WO-level. Every year a sample of on average 7,500 observations is drawn. The special feature of the survey is the large number of studies within tertiary education and the focus on starting salaries; as salaries are self-reported, they will contain more noise than the LSO measurements. The data are described in Appendix B. We pool 7 cohorts with a time dummy to distinguish them. Earnings are defined as net hourly wages at the time of the survey, i.e. on average 20 months after graduation (reported earnings are divided by reported hours). For our empirical purposes, we excluded all respondents who are self-employed, part time employed (less than 32 hours a week) and all those for whom data on control variables are unavailable. To eliminate outliers, we discarded both the highest and the lowest 1% of the sample (the measure of K is rather sensitive to outliers).

In the Elsevier/SEO data individuals were asked for their average exam grade in tertiary education. We use this information to control for compensation for employer risk. We take the dispersion of exam grades, for all students with a given type of tertiary education, as an indication of individual heterogeneity within a given education, by assuming that the distribution reflects the distribution of true skills that employers are interested in. It indicates the employer's risk when hiring a young graduate. The interpretation requires the assumption that at the individual level the exam grade does not sufficiently reveal the individual's true skill. The assumption may very well hold in the Dutch context, as Dutch employers do not pay much attention to students' grades. We indeed find a negative coefficient on the variance of exam grades when included in a wage regression. By analogy to the case of worker risk, we include the third moment of the grade distribution within an education, and find a positive sign: employers are willing to pay for positive skew, the possibility of catching a worker on the high end of the distribution.[4] The results suggest that starting salaries are affected simultaneously by the risk for employees associated with choosing an education and the risk for employers when hiring a worker. As we are here only interested in the effects of uncertainty associated with students' schooling choices, we will leave further analysis of the latter for a separate paper.

Basic regression results for this dataset are given in Table 1b. As before (and throughout this paper), standard errors have been adjusted for clustering. In the first stage regression, we only include a dummy for education (and cohort dummies), as this sample is homogenous by experience and years of education. In the second stage, we use all the relevant variables that are

[4] The results are significant for all tertiary educated, weakly significant for university educated and not significant for HBO graduates. We also included the mean grade in a given education.

available in the dataset: highest education level of the parents, time elapsed since graduation, time spent unemployed, time worked while still in school, region, job level, labour market tension (unemployment/vacancy ratio), dummies to distinguish seven industries. Results on those variables contain no surprises. For starting salaries in tertiary education, our basic conclusion on risk compensation is confirmed: a positive premium for earnings risk, earnings reduction for skew. The magnitude of the estimated risk compensation coefficients in the Elsevier/SEO data is somewhat smaller than for the LSO data. If we double R from its mean value of 0.0414 for university graduates, their earnings would increase by 9%. An increase in K by 10% would reduce their earnings by 0.24%. In the subgroup estimations, we find no significant effect of skew for men, neither in the total sample nor in the sub-samples. If we split the sample by education, we find essentially the standard results for the university educated. For HBO graduates, we find the proper signs, but no coefficient is statistically significant. The effect of decomposition by education is similar for men and for women. Risk compensation for women is larger than for men. Below, we will return to differences between groups.

Table 1b. Replication results, Elsevier/SEO data

	R	t	K	t	N
All tertiary					
Total	1.69	4.53	-0.0218	3.25	31 893
Men	0.84	2.45	-0.0007	0.10	14 865
Women	1.53	3.35	-0.0289	3.41	17 027
Vocational					
Total	0.90	1.61	-0.0038	0.51	14 955
Men	0.41	0.66	0.0065	0.61	6.619
Women	0.59	1.20	-0.0032	0.33	8 355
University					
Total	2.18	6.67	-0.0256	2.69	16 938
Men	0.98	2.52	0.0015	0.14	8 246
Women	2.60	4.52	-0.0459	4.48	8 692

Second stage regression includes parental education, time worked, unemployed/work/unemployment after graduation, region, job level, labour market tension, industry dummies; t values based on standard errors clustered by education type.

4. Controlling for ability

An important point of concern in interpreting the results that have been obtained so far is the possible confusion of risk with heterogeneity. The residual will reflect both the returns to unobserved individual quality differences and true unpredictable earnings fluctuation. To the extent that individuals know the qualities that we do not observe (and their earnings impact), we overestimate risk. We may test the argument by purging the residual as much as possible from the effects of quality differences between individuals. We should then look deliberately for indicators that individuals indeed will know when they have to make their decisions. In the Elsevier/SEO survey, individuals were asked to report their average exam grade in secondary school. They may condition their perception of earnings risk with tertiary education on their secondary school exam grade, as a measure of ability. To mimic this, we split the sample in quartiles of average grade in the final exam of secondary education and then apply the standard analysis. Thus, we assume that the labour market is segmented by ability quartiles, with individual ability indexed by the individual's average exam grade. Every segment will then have its own risk and may generate compensation, based on supply reactions by individuals who measure risk (and skew) from the residuals for their own ability quartile. We use quartiles (rather than, say, deciles) to retain a sufficient number of observations. Results are given in Table 2. We estimate a single equation based on quartile specific distribution measures, hence with identical risk compensation coefficient for each quartile. We now even find stronger results than before, as all coefficients are significant at 10% or better (if we include control for employer risk). We have also estimated regressions in which the coefficients on R and K are allowed to vary by school grade quartile (while restricting coefficients on other variables to be identical). However, equality of the coefficients could not be rejected at conventional significance levels.

We conclude that the results we have obtained so far are not due to confusing ability heterogeneity and risk. If we control for ability information from school grades that we share with individuals themselves, we still get clear support for our key finding of risk compensation. The magnitude of risk compensation for vocational education is marginally higher if we control for school grade quartile, which is in line with underestimation predicted in Jacobs, Hartog and Vijverberg (2005) under independence of ability and risk. For university graduates the school grade control substantially reduces the estimated risk coefficient, which may be related to covariance between ability and risk. In the absence of solid information on correlation between ability and risk we cannot test the consistency of this interpretation, however.

Table 2. Risk compensation: controlling for worker heterogeneity (Elsevier/SEO)

	R	t	K	t	N
All tertiary					
	1.20	4.22	-0.013	2.79	31 893
Vocational					
	0.99	3.28	-0.007	1.74	14 955
University					
	1.24	3.14	-0.013	1.83	16 938

t values based on standard errors clustered by education type.

5. Heterogeneity

5.1 Differences between groups

Both casual observation and empirical research (Hartog, Ferrer-i-Carbonell and Jonker, 2002; Harrison, Lau and Rutstrom, 2004) indicate that attitudes towards risk differ among individuals and groups of individuals. As we have results on some sub-samples, we can check our results for consistency with such known or assumed differences.

Higher measured risk aversion for women as compared to men is well documented. One would therefore predict that estimated risk compensation for women is higher. This is not what we find in the LSO data: Table 1a reports substantially lower risk compensation (we focus on compensation for the variance R). Alternatively, women might find refuge in less risky educations, and therefore claim lower compensation. The distribution function of risk for men and women in the LSO data is given in Figure 1 (the frequency of risk level is the number of respondents with education at that level of risk). Interestingly, both distribution functions seem closer to a uniform risk distribution than to a normal distribution. Women indeed have a risk distribution that has shifted to the left, relative to men's, although with less probability mass in the second quartile of the distribution. Thus, there is a consistent story: women are more risk averse than men, and accommodate this by seeking less risky educations rather than by requiring higher risk compensation in wages (the explanation requires that the reservation price for risk for a given group is not a constant, as we will discuss below).

In the Elsevier/SEO data (Table 1b), we found risk compensation clearly higher for women than for men, which is directly consistent with higher risk aversion. In Figure 2 we present the risk distribution functions; they are closer to the normal distribution than those from the LSO data. Now, the distribution functions only cross once, with women in less risky educations in the first quartile of the distribution, but thereafter in more risky educations. The difference between LSO results and Elsevier/SEO results is not due to the latter's restriction to tertiary education: if we restrict LSO observations to tertiary education only, we find the same results. It may reflect different education choices by the most recent entry cohorts, in comparison to the cross-section of cohorts in the LSO sample. With recent cohorts of women much more focussing on labour market careers, their educational choices (and associated risk properties) may indeed be different from those of older cohorts. Apparently, they no longer seek the less risky educations, but even take up more risky schooling than men, and demand good compensation for it.

In the Elsevier/SEO data, without conditioning risk on school performance (ability) quartile, risk compensation for university graduates is much larger than for vocational graduates. Conditioned on performance quartile, the differences are smaller but in the same direction[5]. To a large extent this is compatible with the difference in the risk distribution functions presented in Figure 3. Up until about the 70th percentile, percentile positions for vocational graduates are at less risky educations than those for university graduates. Beyond that, vocational graduates have higher densities over some range of high-risk educations. We have no information on differences in risk attitude between WO and HBO graduates. One might, perhaps, presume vocational students to be more risk averse than university students: they may prefer the vocational education precisely because it is less risky, with its more structured and guided programme and its lower reliance on student independence and initiative. Then, again, there is a consistent interpretation. University graduates are less risk averse than graduates from higher vocational education, but they obtain higher risk compensation because they are in more risky educations.

Figure 4 shows that for equal percentile positions, immigrants face higher earnings risk than natives, up to about two thirds of the distributions. Table 1a shows that their risk compensation is equal to that of natives, which suggests identical risk attitudes. These results are jointly

[5] In the LSO data, we only have 8 types of university education and 10 types of vocational education. In separate estimations for these two groups, risk compensation for university graduates is larger than for vocational graduates (the effect of skew is not significant).

consistent. One might perhaps conjecture that immigrants are less risk averse than people from their home country who do not migrate, but of course this gives no information on their risk attitude relative to workers in the destination country. A recent study by Bonin et al. (2006b) indeed finds that immigrants are more risk averse rather than less, while their descendants born in Germany have the same risk attitude as native Germans.

Figure 5 gives the distribution of risk for civil servants and for private sector workers. As anticipated, the public sector has substantially lower earnings risk than the private sector. Lower risk for public servants is compatible with the notion that the more risk averse workers opt for the public sector precisely for this reason. The risk in the public sector is so much lower than in the private sector that higher risk compensation for civil servant is not necessary. Note however, that the public-private sector decomposition is different from the other decompositions, as it does not reflect disjoint categories in the labour market: at any moment every individual always can switch between the public and the private sector.

5.2 A reflection on heterogeneous risk attitudes

We have estimated compensation for earnings risk in a linear specification and we have interpreted different compensation coefficients among population groups. However, proper analysis reveals that things are more complicated. Risk attitudes may vary in two ways. First, for a given individual, the required risk compensation may depend on the situation (such as wealth or income) or vary with the level of risk[6]. If it varies with the level of risk, a linear specification is inappropriate. Second, the appreciation of risk may differ between individuals. This also calls for a non-linear specification. A linear specification is only warranted if all individuals have identical risk attitudes, and if all demand the same constant compensation per unit of risk. In that case, a regression of wages on risk R should yield the same coefficient for any sample of individuals and for all risk levels. Now suppose that all individuals have identical risk attitudes, but the reservation price of risk varies with the level of risk. We could test for such variable individual reservation price with a non-linear regression on R. As declining disutility of risk is not very likely, we would expect the price of risk to increase with its level and predict a convex function in risk R.

The situation is more complicated if the appreciation of risk differs across individuals. Now, the allocation of individuals to different positions is no longer immaterial. We expect individuals with low levels of risk aversion to occupy the more risky positions, as this will generate the cheaper allocation. Assigning the typically highly risk averse civil servant to commission-based real estate sales work would be too costly. A competitive market will establish such an efficient arrangement. Clearly, this implies a declining reservation price of risk with increasing risk, as we find less risk averse individuals at the more risky positions: a concave function in risk R.

With differences in individual risk attitudes, the estimated coefficients in a linear regression are less informative and in fact, linearity is a misspecification. Also, our reconciliation of higher risk aversion with lower estimated compensation coefficient by considering the distribution of risk requires heterogenous risk attitudes, as otherwise lower risk aversion can only lead to lower risk compensation. Thus, to maintain our consistent interpretations above, we should test for linearity of the compensation function. The case is quite interesting, as the two hypotheses yield exactly opposing predictions on the nature of the risk compensation function: convex for increasing

[6] Indeed, Saks and Shore (2003) find that students from wealthier backgrounds choose more risky occupations.

individual risk aversion, concave for heterogeneity. Indeed we have attempted to test by estimating a general non-linear compensation function in the second stage regression:

$$C(R,K)=r_1 R+r_2 R^2+k_1 K+k_2 K^2+qRK \tag{20}$$

Unfortunately, in all our samples the correlation between R and R^2 and between K and K^2 is above 0.92. This precludes any meaningful testing for non-linearity and we shall have to look for other datasets to attempt this.[7]

6. Conclusion

Our empirical work started out from estimating Risk Augmented Mincer equations on two new datasets, one for a labour force cross-section and one for recent graduates from tertiary educations. Replication generally confirms the basic result of positive compensation for earnings variance and a negative effect for skew. Precision of the estimates varies between subgroups. While for subgroups some coefficients are not significantly different from zero, we never find an opposite sign that is statistically significant. We found (but did not report comparisons) that allowing for correlation of errors within educations (clustering) had a substantial effect on estimated standard errors and hence, on significance levels. The paper adds two contributions to the existing evidence.

First, our basic results are upheld if we allow for ability differences as reflected by exam grades in secondary school. This is important, as the residuals that we use to assess risk will also include unobserved heterogeneity. If ability and risk are uncorrelated, this will lead to an underestimate of the risk compensation coefficient (as risk is overestimated), but empirically we are very poorly informed on this correlation. For vocational graduates we find that controlling for exam grades marginally increases the estimated risk compensation coefficient, while for university graduates the coefficients are substantially reduced.

Second, we analyse differences between sub-samples. We find that natives and immigrants have identical risk compensation coefficients. Immigrants face higher earnings risk by education than natives. For decomposition by gender, in the Elsevier/SEO sample of starting salaries, we find substantially higher risk compensation coefficients for women than for men, in line with their higher risk aversion. In the LSO cross-section, compensation for women is substantially lower, but they find refuge in less risky educations (in the recent cohorts surveyed by Elsevier/SEO, women have moved into riskier educations). In the Elsevier/SEO sample, we find something similar for vocational graduates compared to university graduates. One might conjecture that students who opted for vocational education are more risk averse. This is not reflected in a higher risk compensation coefficient, but in concentration in less risky earnings distributions.

Our interpretation of the results requires that the price of risk is not a constant. However, we could not test for non-linearity of risk compensation, because of strong multicolinearity. This calls for new datasets that exhibit more variation in this respect.

Obviously, there is much more other work to be done as well. Probably we should dig deeper in the process of assigning workers with heterogeneous risk attitudes to positions with different degrees of earnings risk. Recent work by Bonin et al (2006a) clearly indicates a negative

[7] Correlations between R and K are low in all samples.

correlation between earnings risk and degree of risk aversion.

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Appendix A. LSO data

The data are taken from the so-called Wage Structure Survey (*Loon Structuur Onderzoek (LSO)*) held by Statistics Netherlands (CBS). Data on wages are obtained through the annual survey on employment and wages among firms (*Enquête naar Werkgelegenheid en Lonen*) and partly through administrations on insured people (*Verzekerden Administratie (VZA)*). This means that all information, on gross hourly wages, comes from administrative sources (firms or administrations on insured people). The dataset also contains information on gender, age and job characteristics. Data on education are obtained from the annual labour force survey (*Enquête Beroepsbevolking (EBB)*) and matched with the wage data. The matched dataset is called the Wage Structure Survey. We use data from the survey of 1997. This survey consists of approximately 120,000 employees.

Statistics

Column 1: education in SOI code:
- 1000 less than basic
- 2000 basic
- 3000 lower secondary (*lbo/mavo*)
- 4000 upper secondary (*havo/vwo/mbo*)
- 5000 tertiary: higher vocational
- 6000 tertiary: university
- 7000 post-graduate

Column 2: mean log wage
Column 3: mean exp(e), e = Mincer residual
Column 4: variance exp(e)
Column 5: skew exp (e)
Column 6: mean length of education (decimals because of institutional changes in length)
Column 7: number of observations

Table A1 Statistics by type of education, LSO 1997

(1)		(2)	(3)	(4)	(5)	(6)	(7)
		Log wage		Risk			
Education		Mean	mean	variance	skew	duration	N
1000	Less than primary education	3,07	1,05	0,13	2,18	5	517
Primary education							
2000	Primary education	3,16	1,05	0,13	2,39	6	8695
Lower vocational/ general secondary education							
3000	General	3,19	1,06	0,16	3,35	9,9	1449
3013	3 years of general secondary education	3,31	1,07	0,18	2,17	9	129
3014	General secondary education	3,23	1,05	0,12	2,57	10	5653
3100	Language/ cultural	3,11	1,07	0,18	2,81	10	122
3200	Agricultural	3,25	1,04	0,12	3,15	10	854
3360	Technical general	3,26	1,04	0,11	3,50	9,9	2519
3361	Technical construction	3,31	1,04	0,08	2,06	9,4	2780
3363	Technical Metal	3,30	1,04	0,09	2,17	9,4	2590
3365	Technical electro technics	3,30	1,04	0,11	4,86	10	1094
3400	Transport	3,34	1,04	0,10	1,79	10	869
3500	Medical	3,21	1,02	0,05	0,62	10	93
3610	Economic/ administrative	3,14	1,05	0,11	1,45	9,6	1894
3700	Social cultural	3,16	1,10	0,49	5,99	10	79
3800	Personal/ social care	3,10	1,07	0,17	1,27	9,4	82
3810	Personal/ social care	3,00	1,06	0,12	0,19	9,4	3560
3900	Public order/ safety	3,23	1,04	0,10	2,25	10	348
Higher general secondary, pre-university, intermediate vocational							
4000	General intermediate vocational	3,28	1,05	0,11	1,87	14	673
4015	Higher general secondary	3,27	1,05	0,14	2,47	11	3206
4016	Pre-university (4-6 years)	3,71	1,10	0,26	1,78	11,6	400
4017	Gymnasium	3,35	1,07	0,17	1,73	12	1351
4200	Agricultural intermediate vocational	3,26	1,04	0,10	2,32	14	1502
4300	Technical	3,37	1,05	0,13	2,21	14	2203
4361	Construction	3,37	1,04	0,10	3,58	14	2765
4362	Construction, roads and water	3,47	1,04	0,10	3,33	14	523
4363	Metal	3,35	1,03	0,08	1,77	14	1455
4364	Machinery	3,38	1,04	0,11	3,48	14	2766
4365	Electro techniques	3,38	1,04	0,09	2,65	14	3249
4366	Graphical techniques	3,38	1,05	0,11	1,40	14	553
4367	Process techniques	3,44	1,04	0,10	0,90	14	1250
4368	Other techniques	3,15	1,06	0,13	1,34	14	417
4369	Other	3,35	1,05	0,11	1,23	14	386
4400	Transport, communication, traffic	3,44	1,05	0,13	2,67	14	953
4500	Medical	3,30	1,03	0,07	1,89	14	6174
4600	Economic, administrative general	3,51	1,04	0,08	1,43	14	1227
4610	Economic	3,45	1,06	0,16	2,93	14	1395

4613	Administrative	3,33	1,05	0,14	2,90	14	6560
4614	Commercial	3,39	1,06	0,15	2,88	14	2178
4615	Trade	3,24	1,05	0,14	2,56	14	3657
4700	Social cultural	3,29	1,04	0,09	1,87	14	1298
4800	Personal/ social care	3,15	1,05	0,11	1,70	14	5015
4900	Public order/ safety	,48	1,04	0,08	1,03	14	2273
Higher vocational education							
5000	Teacher/ education	3,53	1,03	0,06	1,75	15	6119
5100	Language/ cultural	3,39	1,06	0,13	0,55	15	163
5200	Agricultural	3,49	1,06	0,13	1,15	15	483
5300	Technical/ nature	3,67	1,05	0,14	2,20	15	3489
5400	Transport	3,80	1,12	0,37	2,27	15	437
5500	Medical	3,44	1,03	0,06	1,32	15	2562
5600	Economic/ administrative	3,59	1,06	0,16	2,34	15	5500
5700	Social cultural	3,48	1,05	0,11	1,86	15	2899
5800	Personal/ social care	3,45	1,08	0,20	2,07	15	761
5900	Public order / safety	3,87	1,05	0,13	1,20	15	265
University education							
6000	Education	3,71	1,03	0,06	0,51	17	544
6100	Language/ cultural	3,58	1,06	0,12	1,39	17	990
6200	Agricultural	3,68	1,06	0,15	1,74	17	279
6300	Technical/ nature	3,81	1,08	0,20	1,81	17	1935
6500	Medical	3,66	1,07	0,15	1,14	17	595
6600	Economic/ administrative/ juridical	3,81	1,08	0,20	1,55	17	2525
6700	Social cultural	3,67	1,05	0,12	1,15	17	1904
6800	Personal/ social care	3,48	1,07	0,14	0,59	17	134
Post graduate education							
7000	Education	3,63	1,04	0,11	2,85	18	100
7300	Technical/ nature	3,98	1,06	0,13	1,57	18	222
7500	Medical	4,04	1,06	0,14	1,16	18	554
7600	Economic/ administrative/ juridical	4,05	1,07	0,18	1,68	18	188
7700	Social cultural	3,84	1,08	0,18	0,93	18	52

Appendix B: Elsevier / SEO data

This survey of graduates with a tertiary education has been conducted on a yearly basis since 1996. Every year a new cohort of graduates is examined. The survey focuses on outcomes in the first 20 months in the labour market. Dutch tertiary education is basically divided into two levels: higher vocational education (in Dutch abbreviated as HBO) and academic education (WO). HBO-education prepares students for specific (categories of) professions. It is taught at about 60 special institutes evenly spread over the Netherlands. On average, 50,000 students graduate each year from HBO. WO-education is considered to be of a somewhat higher intellectual level and has a more general academic character. It is taught at 14 universities. The yearly output amounts to approximately 23,000 graduates per year. At HBO-level students can choose between 250 different courses of study, while at WO-level they may choose between 260 different specializations. Most of them, however, produce only small numbers of graduates, making statistical analysis cumbersome. About 80 percent of the student population is concentrated in the 100 largest degree subjects. The survey is restricted to these 100 degree subjects (studies) which divide evenly over HBO and WO. This means the survey is representative of 80 percent of the yearly outflow of graduates at HBO- and WO-level. Every year a sample of on average 7,500 is drawn. Basic data are given in Appendix Table B1. We pool the 6 cohorts with a time dummy to distinguish them. Earnings are defined as net hourly wages at the moment the survey was held, i.e. on average 20 months after graduation. For our empirical purposes, we excluded all respondents who are self- employed, part time employed (less than 32 hours a week) and all those for whom data on control variables are unavailable.

Statistics

Column 1: Education
Column 2: mean log wage
Column 3: mean exp(e), e = Mincer residual
Column 4: R = variance exp(e)
Column 5: K = skew exp (e)
Column 6: N = number of observations

Table B 1 a. HBO (Higher vocational education)

education	Sample means				
	Lnwage	Exp(e)	R	K	N
VOCATIONAL					
Business Economics/Business Sciences	2,159	1,013	0,041	1,513	537
Commerce	2,179	1,018	0,057	1,999	445
Business Informatics	2,208	1,015	0,051	1,623	566
Communication	2,154	1,021	0,047	1,280	410
Accountancy	2,174	1,023	0,057	1,481	378
International Business and Languages	2,135	1,024	0,040	1,927	339
Tourism & Leisure	2,067	1,032	0,040	1,099	377
Hotel Management	2,154	1,025	0,067	2,888	388
Small Business en Retail Management	2,179	1,044	0,066	2,412	211
Management, Economics & Law	2,163	1,021	0,057	2,714	397
Logistics & Economics	2,171	1,012	0,048	2,064	434
Facility Services	2,150	1,023	0,068	3,343	507
Journalism	2,197	1,028	0,054	1,329	411
Business Management	2,128	1,007	0,044	1,159	256
Fiscal Economics	2,221	1,025	0,053	1,135	197
European professions	2,150	1,032	0,079	2,069	107
Leisure Management	2,069	1,035	0,042	1,565	100
Personnel & Labour	2,181	1,016	0,040	0,952	435
Socio-Cultural Studies	2,144	1,024	0,051	1,512	365
Social Work and Services	2,218	1,015	0,042	1,521	462
Social Pedagogy	2,160	1,012	0,034	1,225	640
Socio-Legal Services	2,189	1,015	0,035	1,736	348
Information Management	2,169	1,030	0,065	2,718	329
Medical Laboratory Technician	2,101	1,009	0,042	2,902	421
Nursing	2,191	1,016	0,037	2,896	599
Physiotherapy	2,365	1,035	0,108	1,726	440
Speech Therapy	2,208	1,034	0,098	2,882	381
Nutrition & Dietetics	2,176	1,026	0,071	2,564	443
Ergotherapy	2,240	1,018	0,054	2,105	469
Medical Imaging & Radiotherapy	2,126	1,010	0,022	1,619	93
Oral Hygiene	2,337	1,041	0,105	2,508	62
Environmental Management?Science/Technology	2,177	1,036	0,056	2,686	357
Agri-Business	2,188	1,019	0,045	1,764	275
Animal Husbandry	2,133	1,054	0,071	1,858	247
Food Technology	2,175	1,018	0,031	0,755	100
Primary School Teacher	2,237	1,015	0,037	3,312	577
Physical Education Teacher, Grade 1	2,331	1,042	0,093	1,228	333
Dutch Teacher	2,253	1,030	0,078	1,928	254
Economics Teacher (general & business)	2,220	1,036	0,069	2,143	315
Special Needs Teacher	2,264	0,996	0,037	3,240	253
Social Studies Teacher	2,144	1,020	0,043	1,231	96
Education	2,211	1,025	0,076	3,198	111
Science Teacher	2,310	1,032	0,081	1,816	295
Geography/History Teacher	2,276	1,042	0,089	1,133	407

Arts & Crafts Teacher	2,137	1,043	0,106	1,378	76
English/French/German Teacher	2,332	1,049	0,100	0,916	458
Visual Arts & Design	2,124	1,047	0,093	1,821	257
Music	2,299	1,044	0,113	1,233	149
Chemical Technician	2,124	1,027	0,040	1,340	247
Structural Engineering	2,141	1,023	0,039	1,563	345
Electrical Engineering	2,196	1,009	0,034	1,286	344
Civiel Engineering	2,148	1,022	0,044	1,811	360
Chemical Engineering	2,186	1,020	0,032	0,983	414
Applied Informatics	2,221	1,025	0,052	1,755	471
Mechanical Engineering	2,171	1,023	0,054	2,722	339
Maritime Officer	2,064	1,047	0,091	1,365	89
Fashion Management and Technology	2,081	1,019	0,029	0,806	57
TOTAL	**2,191**	**1,021**	**0,051**	**2,000**	**18,854**

Table B 1 b University

UNIVERSITY					
Dutch	2,259	1,026	0,068	2,245	389
English	2,229	1,029	0,084	1,705	298
Other languages	2,245	1,036	0,101	2,543	273
Philosophy/Teology	2,250	1,035	0,075	1,617	98
History	2,251	1,028	0,067	1,272	395
Language & Culture (general)	2,230	1,031	0,084	2,892	308
Art History & Archeology	2,156	1,024	0,068	3,120	180
Corporate Communications	2,217	1,018	0,057	2,408	278
European Studies	2,235	1,032	0,094	2,881	70
Film, Television & Theatre Studies	2,162	1,026	0,056	0,457	52
Chemistry	2,132	1,030	0,083	3,046	383
Computer Science	2,223	1,023	0,065	2,720	210
Biology	2,135	1,036	0,097	3,836	525
Pharmacy	2,440	1,026	0,058	0,801	331
Pure Mathematics/Physics	2,168	1,024	0,073	1,604	371
Agricultural Science	2,233	1,028	0,071	3,142	243
Chemical/Technological Agri-sciences	2,220	1,024	0,058	1,566	580
Architecture	2,247	1,024	0,040	1,816	541
Mechanical Engineering	2,313	1,023	0,051	1,596	478
Electrical Engineering	2,311	1,025	0,063	2,328	318
Chemical Engineering	2,276	1,026	0,067	2,532	411
Civil Engineering	2,277	1,019	0,051	3,163	481
Techology & Management	2,352	1,015	0,051	1,733	504
Industrial Design	2,259	1,018	0,044	1,561	283
Aerospace Engineering	2,290	1,008	0,032	0,665	60
Applied Computer Science	2,288	1,012	0,043	2,144	219
Applied Mathematics/Physics	2,239	1,021	0,068	2,230	456
Economics	2,310	1,034	0,056	2,185	1,100
Business Science	2,316	1,016	0,057	1,710	935
Econometrics	2,334	1,023	0,060	1,633	414
Fiscal Economy	2,361	1,012	0,030	1,369	128
Dutch Law	2,293	1,015	0,045	1,602	733
Notarial Law	2,278	1,019	0,040	1,582	355

Fiscal Law	2,384	1,019	0,055	2,396	376
Healthcare	2,270	1,025	0,064	1,510	513
Medicine	2,380	1,024	0,061	1,609	708
Dentristy	2,808	1,065	0,148	0,123	108
Biomedical Sciences	2,162	1,020	0,059	1,773	401
Veterinary Science	2,302	1,029	0,040	0,669	180
Sociology	2,271	1,024	0,054	1,227	328
Psychology	2,270	1,031	0,072	1,747	753
Politis	2,312	1,030	0,078	2,811	323
Education Science	2,298	1,023	0,059	1,626	466
(Applied) Education	2,300	1,023	0,060	2,058	327
Cultural Anthropology	2,219	1,033	0,104	2,941	258
Communication	2,258	1,026	0,065	2,114	503
Socio-Cultural Science	2,281	1,024	0,054	1,928	517
Punlic Administration	2,318	1,015	0,050	1,693	648
Human Geography & Planning	2,251	1,019	0,050	2,237	751
TOTAL	**2,289**	**1,025**	**0,060**	**1,935**	**19,560**

Figure 1. Distribution function of risk, men and women, LSO

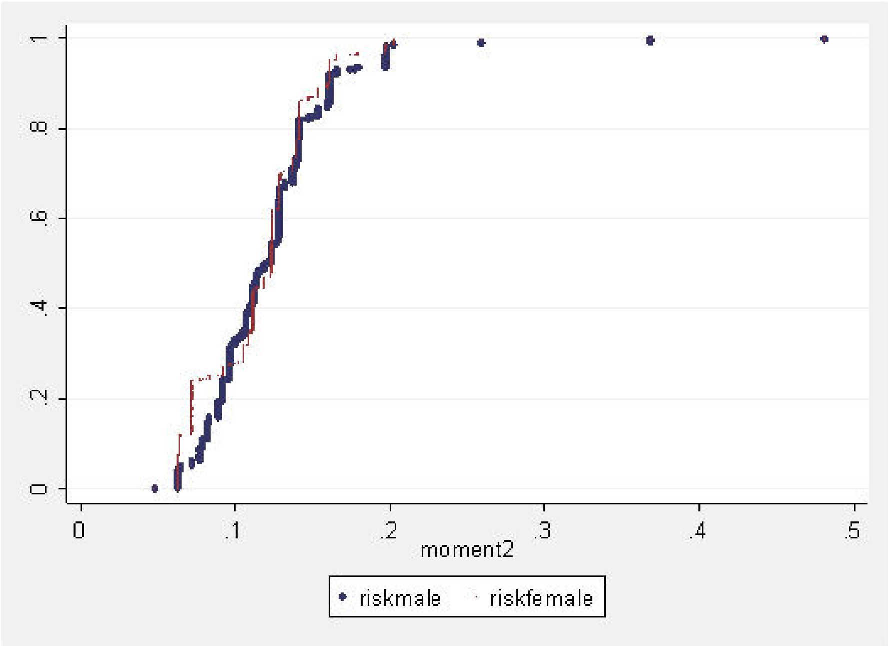

Figure 2. Distribution function of risk, men and women, Elsevier/SEO

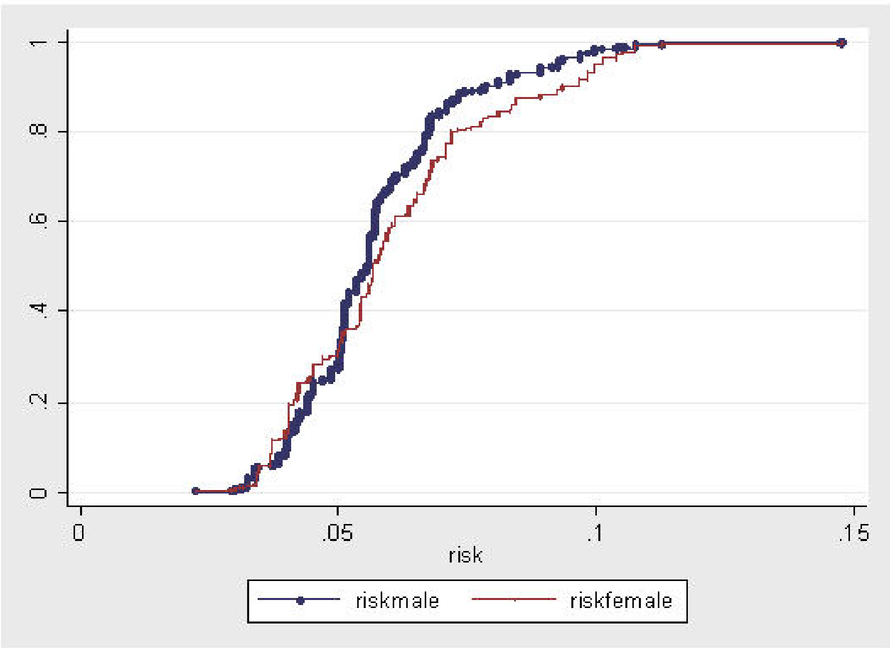

Figure 3. Distribution function for risk, university and higher vocational education, Elsevier/SEO

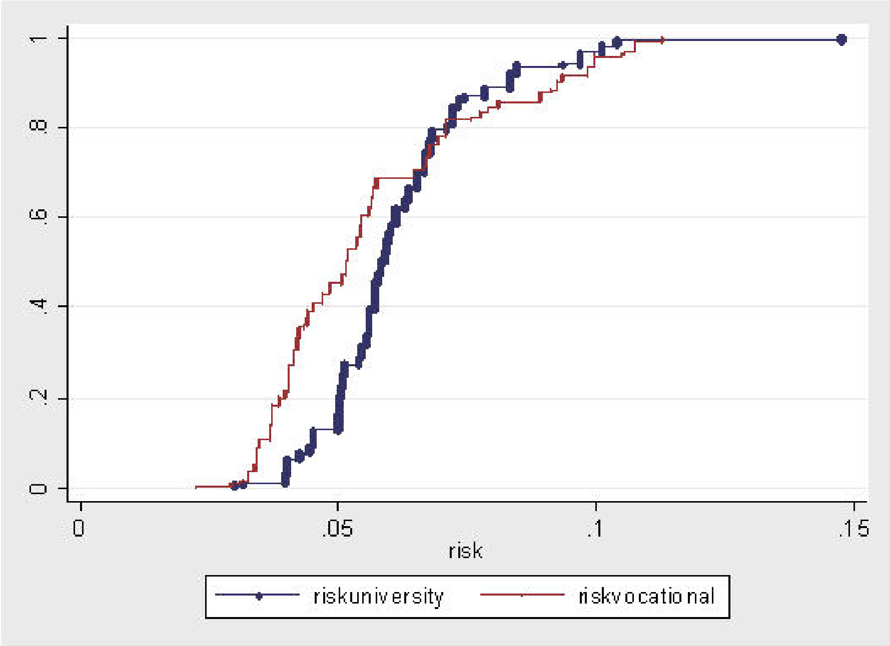

Figure 4. Distribution function of risk, natives and immigrants, LSO

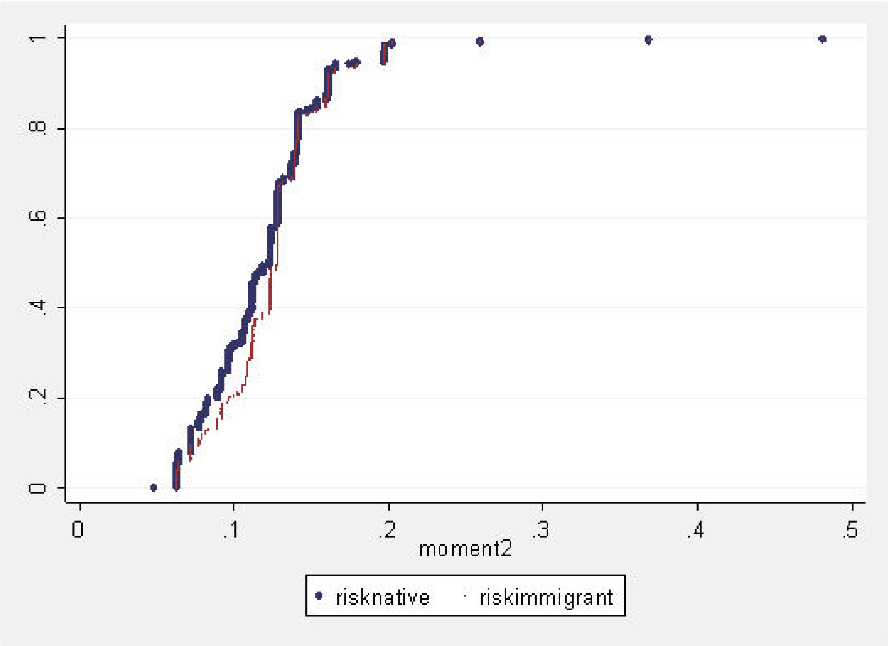

Figure 5. Distribution function of risk, public and private sector, LSO