DISCUSSION PAPER SERIES

IZA DP No. 3026

Starting Wages Respond to Employer's Risk

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September 2007

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zur Zukunft der Arbeit
Institute for the Study
of Labor

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ABSTRACT

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Firms hiring fresh graduates face uncertainty on the future productivity of workers. Intuitively, one expects starting wages to reflect this. Formal analysis supports the intuition. We use the dispersion of exam grades within a field of education as an indicator of the heterogeneity that employers face. We find solid evidence that starting wages are lower if the variance of exam grades is higher and that starting wages are lower if the skew is higher: employers shift quality risk to new hires, but pay for the opportunity to catch the really good workers.

JEL Classification: J31

Keywords: wages, risk, ability

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1. Hypothesis

An employer hiring a new employee fresh from university has no more than imperfect information on the worker's qualities. The diploma itself, some information on school grades, extracurricular activities, a job interview and perhaps a test cannot fully resolve the uncertainty about future productivity. Firms may be expected to bill the workers for the cost of dealing with this uncertainty. Workers fresh from school have no successes yet to support a bargaining position and will have to accept that employers put a discount on starting wages in accordance with the risk they face. Thus, we predict that starting wages will be lower in fields where employers face more uncertainty on any individual's productivity. However, we also predict that starting wages will be higher if employers perceive more skewness in the productivity distribution: they appreciate the chance to catch an individual with very high productivity. We find clear support for these predictions.

We use the distribution of exam grades within a field to measure uncertainty. If the variance of exam grades across graduates in economics is larger than across graduates in physics, employers can make less accurate predictions on the productivity of an individual economist than on the productivity of an individual physicist. Our core hypothesis is that wages will reflect these differences in risk. More specifically, we predict that wages will respond negatively to the variance of exam grades in a field (workers pay a risk premium) and positively to the skew of the exam grades in a field (firms appreciate the upside risk of hitting upon a very good worker). This hypothesis is supported by a large sample of starting salaries for graduates from tertiary education in The Netherlands.

To back up our intuitive argument, we refer to the literature and we present two simple models. It is commonly assumed that workers are risk averse and firms are risk neutral. This is probably pushing the case too far. It is quite likely that on average workers are more risk averse than firms, but no doubt firms are also risk averse. Small firms may have every reason to behave as risk averters, as they often lack the resources to survive bad draws. But large firms are also observed to engage in buying all kinds of insurances, for failing debtors, worker safety hazards, currency fluctuations, etc[1]. There is sufficient evidence to assume that firms are risk averse. We formalise our core hypothesis both for the case of risk neutral and of risk averse firms.

In the next section, we derive our predictions formally. In section 3 we present the data, in section 4 we show the results. Section 5 concludes.

[1] To witness: Dutch electronics multinational Philips sells its chips division because sales and profits vary too much over the business cycle (NRC, August 2006).

2. Formal arguments

Earlier literature has produced two models where imperfect information on worker abilities leads to a negative relationship between wages and the variance in the distribution of unobserved worker quality. Rothschild and Stiglitz (1982) assume that productivity reacts negatively to mismatch, measured as deviation between imperfectly observable individual ability and the optimal ability level for a given job. Workers are assigned on the basis of expected ability, conditional on observed characteristics related to ability. Risk neutral employers pay wages equal to expected output. With a quadratic loss function, expected output conditional on observable characteristics is negative in the variance of ability conditional on observables.

Aigner and Cain (1977) assume that a skill indicator y measures true skill or productivity with error: q = y + e. Employers maximize expected utility from profits, using a utility function with constant absolute risk aversion. This is equivalent to maximizing expected productivity conditional on y minus the variance of q conditional on y. Adding the assumption of competition predicts wages to be positive in expected productivity and negative in productivity variance (both conditional on the indicator y):

(6) $w = (1-\gamma)\overline{q} + \gamma y_i - (U^{''}/U^{'})(1-\gamma)\sigma_q^2$

where γ is the squared correlation coefficient between y and q and where absolute risk aversion U”/U’ is a constant. Hence, the wage reacts negatively to the variance of the indicator.

Below, we give two arguments why the third moment of the ability distribution may also be relevant for wage determination. While indeed the variance may have a negative effect on wages, skewness may have a positive effect. The underlying models are different but generate similar predictions. In the first of two models, we simply assume that risk averse firms maximize expected utility when setting wages for their new hires. In the second model, we assume risk neutral firms that hire workers for an initial period, after which uncertainty is resolved and firms can react. The latter model brings out a distinction between upside risk and downside risk that is not visible in the first model.

2.1 Risk aversion

Suppose firms are risk averse and seek to maximise the expected utility of profits on hiring a recent graduate from a given field. The productivity of worker i is given by q_i and the starting wage paid to graduates in this field is w. Quality q has a continuous distribution across workers, with expectation $\overline{q}$ = E(q). The firm evaluates the benefits from hiring a worker by E[U(q_i – w)], with U( ) a well behaved utility function. Applying a Taylor expansion around $\overline{q}$ – w, it is straightforward to derive

(1) $$E[U(q_i - w)] = U(\overline{q} - w) + \frac{1}{2}U''(\overline{q} - w)\sigma^2 + \frac{1}{6}U'''(\overline{q} - w)\kappa^3$$

where U"(x) is the second derivative evaluated at x and U"'(x) the third derivative, σ is the variance of q and κ is the skewness (third moment). Assume firms can be started and closed down at zero cost and hire only one type of worker. Competition will establish that the expected utility of hiring workers from different fields will be equalized; for convenience we set this value equal to zero. With $\bar{q}$ sufficiently close to w to allow approximating U($\bar{q}$ – w) by U(0) + ($\bar{q}$ -w)U'(0) we can write

$$(2)\ w = \frac{U(\bar{q})}{U'(0)} + \frac{1}{2}\frac{U''(\bar{q}-w)}{U'(0)}\sigma^2 + \frac{1}{6}\frac{U'''(\bar{q}-w)}{U'(0)}\kappa^3$$

The standard utility function has U' > 0, U" < 0 and U"' > 0. The latter assumption is implied by the requirement of decreasing absolute risk aversion (Tsiang, 1972). Decreasing absolute risk aversion can hardly be disputed for individuals (as otherwise wealthier individuals would be less inclined to take risks). For firms one might hesitate, as larger, wealthier firms might become more risk averse; but as this might relate to relative risk aversion rather than to absolute risk aversion we will assume a positive U"'.

The predictions are immediate: wages across fields will decline in the variance of individual productivity within fields and will increase in skewness. The reaction coefficients can be recognised as relative risk aversion and, by analogy, relative skewness affection (Hartog and Vijverberg, 2002), with a slight twist in the points where the derivatives are evaluated.

2.2 Upside risk and downside risk

Suppose, firms do not have to set wages once and for all, but can adjust as more information becomes available. Let a firm hire a worker for a year and then react on what has been observed[2]. Worker productivity, as before, is a continuous variable, with variance σ^2 and third moment (skewness) κ^3. The firm has threshold levels for adjustment: in the low segment, workers are fired, in the intermediate segment they are retained and in the top segment they are assigned to high-value positions open only for top-quality workers (see Figure 1). The normal, acceptable segment has probability P_N, with average productivity q_N. With probability P_L the worker is in the low segment, with value q_N – R: productivity is considered substandard, the worker will be fired and replaced by a new worker. The total cost of productivity shortfall and replacement cost equals R. With probability P_H the worker is in the top segment, with a value to the firm of q_N + B. Let firms set wages equal to expected value to the firm:

$$(3)\ w = P_L\,(q_N - R) + P_N q_N + P_H\,(q_N + B)$$

[2] This reminds of models where upward sloping wage-experience profiles are explained from improved allocation as better information on worker abilities becomes available. The effect of uncertainty on wages has not been pursued in this literature, however. See Jovanovic (1979).

$$= q_N - P_L R + P_H B$$

Taking derivatives:

$$(4)\quad \frac{\partial w}{\partial \sigma^2} = -R \frac{\partial P_L}{\partial \sigma^2} + B \frac{\partial P_H}{\partial \sigma^2}$$

$$(5)\quad \frac{\partial w}{\partial \kappa^3} = -R \frac{\partial P_L}{\partial \kappa^3} + B \frac{\partial P_H}{\partial \kappa^3}$$

Let's first make the assumption that thresholds do not vary across fields. Then, the effects of variance and skew are both determined by two opposing effects. It's probably quite reasonable to assume that the distribution is such that an increase in the variance increases probability mass both in the upper tail and in the lower tail. Then, increasing variance will increase both downside and upside risk and the effect on wages will depend on the balance of the two effects. The wage will fall if downside risk dominates, and increase if upside risk dominates. We will also assume that the productivity distribution is such that if skewness increases (and the distribution will become more asymmetric to the right), the lower segment will hold less probability and the upper segment will hold more. Then, with increasing skewness reducing the downside risk and increasing the upside risk, according to (5) the wage will increase.

The assumption of equal thresholds across fields seems a strong one. One argument in its favour is simplicity: it's a good rule to start out from the simplest possible model. A second argument is based on an implicit requirement that is far less restrictive. For the positive effect of variance on the probabilities in the extreme segments we require that the effect on the threshold is not large enough to reverse the sign of the derivative. With a larger variance there will be more probability below a given threshold. The increase in the variance should not trigger a reduction in the threshold large enough to reduce the probability in the low segment. The same implicit condition holds for the effect of skewness: if skewness increases, the lower segment should not be enlarged by a more than proportional adjustment of the threshold (and similarly for the upper segment). These implicit conditions seem not overly restrictive.

3. Data

We use data from 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 fields. The survey is restricted to these 100 degree fields (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; salaries are self-reported, and will contain the associated noise. The data are characterised in the Appendix. We pool 8 cohorts, from 1996 until 2006, 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. All correlations between explanatory variables are low, and we need not worry about multicolinearity.

To estimate our model and test the predictions, we need observations on expected productivity, variance and skew of productivity. In the Elsevier/SEO data individuals were asked for their average exam grade, across courses, in tertiary education (grading uses a standard 0-10 scale; passing requires a minimum of 5.5, though not necessarily for all courses, as compensation is sometimes allowed). 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. Exam grades will depend on ability, effort, motivation, ambition, etc: typically the things employers are interested in. Assume that the distribution indeed reflects the distribution of true skills that employers care about. The distribution then indicates the employer’s risk when hiring a young graduate. The interpretation will only be valid if at the individual level the exam grade does not sufficiently reveal the individual’s true skill. The assumption may very well hold. Dutch employers do not pay much attention to individual student grades.

The dataset allows us to use many variables, to control for the situation in the labour market (region, unemployment/vacancy ratio, time in the labour market since graduation), personal characteristics (age, gender, parents education, individual grades) and job characteristics (job level, industry, type of contract). These variables should be sufficient to predict expected productivity. We also control for the workers’ risk when selecting an education, by including variance and skewness of the earnings residual in the chosen education. The argument here is that potential students will only select an education if they are compensated for the earnings risk of that education. Risk is measured as the variance of the residuals from a Mincer earnings function within that education; mirroring the consideration of employers discussed above, they are willing to take a pay reduction for a better chance of very high incomes and hence accept lower wages for higher skewness[3].

Mean wages are plotted against mean, variance and skewness of exam grades in Figure 2. The plots indicate weak correlations (positive, negative, positive, respectively); there are no clear outliers in the data. The data indicate no obvious patterns of structural relations between the variables that might be reason for suspicion. Some of the studies that are intellectually more demanding indeed have higher variance, but among the high variance fields we also find less demanding fields, like sociology and languages. A field with restrictive entry like medicine has grade variance in the higher end of the distribution but a similar field like dentistry has low variance.

4. Basic results

Tables 1, 2 and 3 give the basic result. We include the results on worker risk, as they give a strong background to the compensation for employer risk. An individual deciding on a field of study has a choice when entering university or a higher vocational institution. Thus supply behaviour can impose a compensation for the risk that potential students face, measured by the residual earnings variance from a Mincer equation: a positive effect for the variance as workers do not like risk, a negative effect for skew, as workers like positive asymmetry (with some extra probability of a very high outcome). Details of these results are given in Berkhout et al (2006); the results are similar to results in many other datasets, Hartog and Bajdechi (2007) and Hartog (2006). With education completed, workers have no alternative and employers can shift the risk from the heterogeneity they cannot observe to workers, as we argued in section 2. The results we report here on employer's risk are independent of employee's risk: regression coefficients vary only marginally and significance levels are unaffected when employee risk is excluded or included. We also include the mean of the grade distribution in a field of education, to control for differences in grading practices.

We start, in Table 1, with an OLS estimate at the level of studies, with the mean earnings in a field of study as the dependent variable. Our basic prediction is strongly supported: in studies with higher variance in grades, starting salaries are lower, with higher skewness in grades they are higher. The negative effect of grade variance implies that the downside risk (of higher risk of workers with low productivity) dominates the outcome. The results are not sensitive to including compensation for worker risk[4].

In Table 2 we present estimates with individual earnings as the dependent variable and standard errors adjusted for clustering (there may be correlation for errors within fields of education, the so-called Moulton problem). Again, the basic prediction is supported,

[3] For a discussion and survey of results on the risk augmented Mincer equation see Hartog (2006) and Hartog and Bajdechi (2007). Full analysis of worker risk compensation in the present dataset, with formal modelling and references is given in Berkhout, Hartog and Webbink (2006).
[4] They are also insensitive to how we measure worker's financial risk (from the log residuals, from hourly wages, monthly wages or their logs).

although some coefficients change in magnitude. The advantage of the estimation on micro data is the possibility to include additional controls for other variables that influence earnings. As Table 2 shows, the coefficients are sensitive to the additional controls, but statistical significance is maintained in all specifications. In Table 3, we present estimates for a random coefficients model. The random coefficients at the level of the studies are included to control for unobserved variables that explain differences in earnings and that may bias the estimates of our risk coefficients; we cannot apply a fixed effects model for this purpose, as the risk variables do not vary within the field of study. With the random effects model, our basic conclusion is unchanged.

5. Checking robustness

As a check on the robustness of our results, we have considered some alternative explanations for our results. One explanation is based on differences in intellectual requirements between fields of study: some studies can only be completed for students with high analytical ability. This will generate self-selection at entry[5] and selective drop-out based on those requirements. In the end, the population of graduates may be rather homogenous. As these high ability graduates may also be expected to obtain high earnings, we would see a negative correlation between earnings and grade variance. With truncation at the low end of the ability distribution, a positive correlation between earnings and grade skew would also result. The problem is of course to measure the differences in intellectual requirements (or “difficulty”) of studies. We considered applying a distinction based on our own perceptions but discarded this as too subjective. Instead we based the distinction on the grade points. We selected students in the middle of the ability distribution as indexed by grades for the final exam of secondary school: only students close to the overall mean exam grade are selected (we used the middle third of the distribution, symmetrically about the median). In addition, we required the variance in the individual’s exam grades across subjects to be small (we used the middle third of the distribution). Thus, we have a fairly homogeneous group of students, about 9% of the sample. We then calculated the differences between their mean exam grades and the mean exam grade in their tertiary study. Based on these differences we split studies between “difficult” and “ easy”, as two roughly equally large groups. The difficult studies have the larger average gap between tertiary grade and secondary grade. Although the resulting distinction does not always match our own perceptions, we used this distinction to add a dummy for difficult studies to our estimation equation. As Tables 2 and 3 (second panel) show, the coefficient is not statistically significant and inclusion has no effect on any of the other coefficients.

Another potential explanation is based on the organisation of the studies and on labour market structure. Some studies are rather strictly organized, with attendance requirements (eg in laboratories), regular assignments and active student monitoring. This may increase the homogeneity of the population of graduates, with low grade variance as a result. The effect on grade skewness is less clear. If these happen to be the studies leading

[5] Dutch universities do not select at entry, anyone with the proper secondary school diploma must be admitted. In higher vocational education, schools may restrict entry.

to high paid jobs, there would be a negative correlation between earnings and grade variance. Medicine would be an example. In some occupational fields government regulations lead to a monopolistic market structure. In such occupations, earnings are high. If such a monopoly coincides with strict organization and student monitoring, as in medicine, this would also generate the negative correlation between earnings level and grade variance. To check this argument, we added a dummy for 7 studies preparing for a job in a highly regulated market: physiotherapy, medical techniques and radiotherapy, dental hygiene, pharmacy, notary, medicine, dentistry. All the medical studies are strictly organised and regulated, notary is regulated but the study is not strictly organised. The dummy has a significant effect on earnings, but inclusion has no effect on any other coefficient (Tables 2 and 3, second panel).

We also considered, in Table 4, the effects within subpopulations, with variance and skewness calculated for the relevant sub-populations. With just a few exceptions, the results on employer risk have the proper sign for all sub-populations. Of these exceptions, only sign reversal is significant for grade variance and also just one for grade skew[6]. If we distinguish between university and higher vocational education, the results within these subgroups are no longer statistically significant. Separate estimation for men and women does not affect the results. Estimation within ability quartiles generates only one significant exception; ability quartiles are created on the basis of averages grade in the secondary school final exam. This means that our results are not driven by some spurious ability effect. Separate estimation for 6 employment sectors produces only one significant exception (the coefficient on grade variance for "care"). Distinction by time between graduation and time of survey (work experience longer or shorter than the mean) does not affect the results. Distinction between difficult and easy studies again produces no violation of the basic predictions.

6. How large are the effects?

We can express the magnitude of the effects in elasticities, by multiplying the coefficients by the mean of the independent variable. Table 5 collects results. It's immediately clear that all elasticities are small and not very sensitive to specification (except one large value for grade mean). The wage elasticity for grade variance is between 0.05 and 0.10, the wage elasticity for grade skew is between 0.01 and 0.02. The wage differential between the education with maximum and minimum grade variance is 1.3 % (the variances are 0.38 and 0.13), between education with maximum and minimum grade skew is 2.2% (the skew is 1.66 and -.03). Hence, truly small effects in the total of wage variation. The variance of these elasticities within subgroups is modest. Mean values of grade variance and grade skew vary remarkably little between the subgroups, and hence the estimated regression coefficients give a good indication of the variation.

[6] For employee risk compensation, there is not a single rejection (a reverse sign that is statistically significant.

7. Conclusion

We argued intuitively that firms would pay lower starting wages if they face larger variance in individual productivity and higher wages if they have more favourable odds of hiring individuals with very high productivity. Assuming firms maximize expected utility from the profit on a worker supports this intuition with a formal argument. If risk neutral firms distinguish between upside risk and downside risk that is revealed after an initial period of work, they will still value skewness, but whether they appreciate variance positively or negatively depends on the balance between two opposing effects: both downside and upside risk increase.

We postulate that the dispersion in exam grades within a field indicates the amount of heterogeneity that employers cannot observe. We find that starting wages are lower if the variance of individual qualities increases and that the starting increases if the skew in individual qualities increases. These results are robust within sub-populations and also survive some test against alternative interpretations. Actually, we find it hard to come up with a convincing alternative explanation for our results. Quantitatively, however, the effects are quite small.

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Figure 1. Upside and downside risk of worker quality

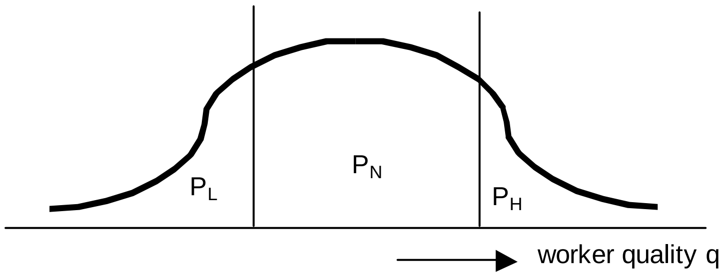

Figure 2A. Mean hourly wage and exam grade average, by education

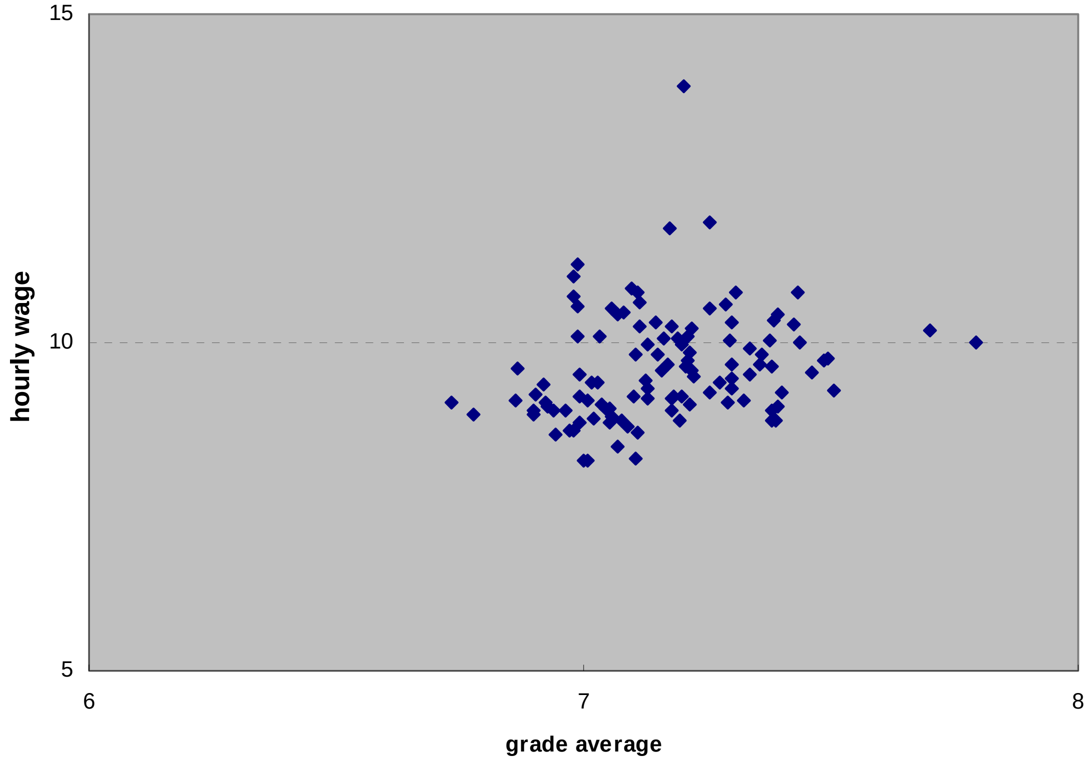

Figure 2B Mean hourly wage and exam grade variance, by education

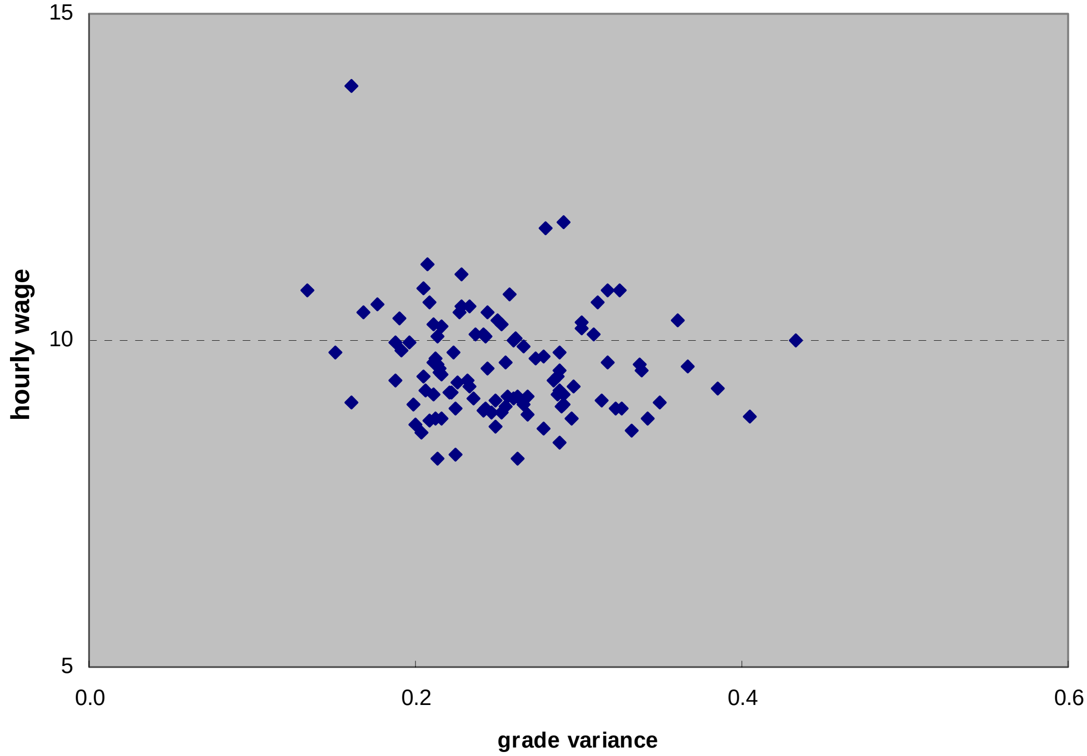

Figure 2C. Mean hourly wage and exam grade skewness, by education

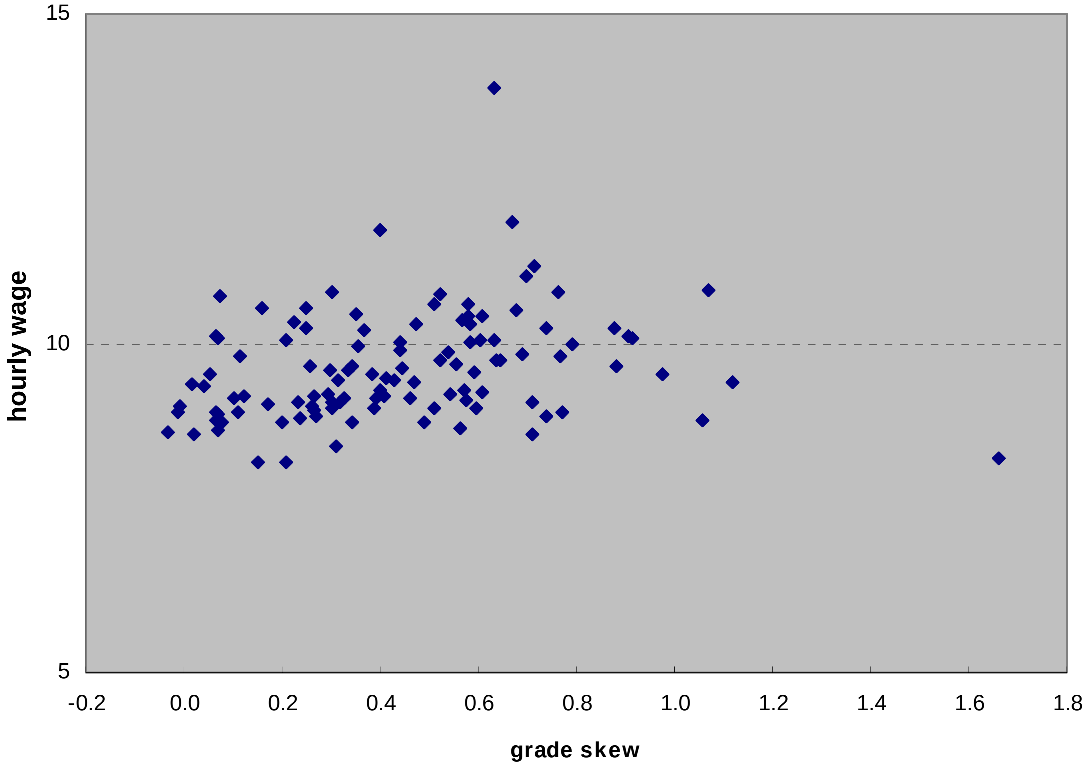

Table 1. OLS on aggregate data (111 studies)

Ln hourly wage	Coef.	Std. Err.	tval
Intercept	1,869	0,263	7,120
Grade mean	0,073	0,038	1,890
Grade var	-0,336	0,125	-2,700
Grade skew	0,048	0,023	2,090
Erisk	1,229	0,562	2,190
Eskew	-0,116	0,021	-5,500

N =111 R^2 =.0.377

Table 2 OLS on microdata

					With dummies for difficult and regulated studies			
	1	2	3	4	1	2	3	4
LN hourly wage								
erisk	0,972	0,759	0,259	1,005	1,039	0,824	0,372	1,052
t-value	(1,378)	(1,077)	(0,337)	(2,437)	(1,502)	(1,177)	(0,483)	(2,935)
eskew	-0,170	-0,168	-0,146	-0,089	-0,109	-0,112	-0,101	-0,066
t-value	(4,860)	(5,270)	(6,676)	(6,433)	(5,653)	(6,056)	(5,654)	(5,459)
grademean	0,051	0,047	0,036	0,003	0,111	0,105	0,070	0,040
t-value	(1,383)	(1,295)	(0,972)	(0,144)	(2,819)	(2,692)	(1,727)	(1,635)
gradevar	-0,471	-0,437	-0,372	-0,199	-0,597	-0,553	-0,477	-0,264
t-value	(3,187)	(3,136)	(2,943)	(2,597)	(4,687)	(4,485)	(3,969)	(3,688)
gradeskew	0,114	0,105	0,076	0,028	0,103	0,094	0,073	0,023
t-value	(4,846)	(4,713)	(3,620)	(2,096)	(4,044)	(3,946)	(3,234)	(1,666)
individual grades	0,005	0,004	0,010	0,012	0,005	0,004	0,010	0,012
t-value	(1,392)	(1,116)	(2,640)	(3,292)	(1,353)	(1,092)	(2,497)	(3,268)
Dummy D					0,016	0,016	0,006	0,009
t-value					(1,229)	(1,251)	(0,483)	(1,197)
Dummy R					0,096	0,089	0,076	0,044
t-value					(3,355)	(3,246)	(3,122)	(2,417)
R2	0,084	0,116	0,140	0,253	0,093	0,124	0,145	0,255
N	40996	40996	40996	40996	40996	40996	40996	40996

t-values based on standard errors clustered by field of education

1 = intercept only
2 = as 1, plus labour market (year dummies, regions, time since graduation)
3 = as 2, plus personal characteristics (age, gender, parental education, individual exam grades)
4 = as 3, plus job characteristics (job level, industry, contract type)

D = dummy for difficult studies (see text)
R = dummy for regulated studies (see text)

Table 3 Estimation with random effects on micro data

					With dummies for difficult and regulated studies			
	1	2	3	4	1	2	3	4
LN hourly wage								
erisk	1,253	1,049	0,891	0,662	1,338	1,122	0,989	0,692
t-value	(2,283)	(2,171)	(1,986)	(3,212)	(2,534)	(2,405)	(2,352)	(3,301)
eskew	-0,116	-0,118	-0,110	-0,072	-0,089	-0,090	-0,083	-0,055
t-value	(5,732)	(6,591)	(6,655)	(9,815)	(4,179)	(4,801)	(4,920)	(6,724)
grademean	0,076	0,077	0,050	-0,001	0,095	0,100	0,066	0,022
t-value	(2,030)	(2,350)	(1,634)	(0,091)	(2,336)	(2,797)	(2,048)	(1,381)
gradevar	-0,361	-0,351	-0,314	-0,209	-0,393	-0,384	-0,349	-0,236
t-value	(2,986)	(3,308)	(3,196)	(4,746)	(3,399)	(3,762)	(3,797)	(5,263)
gradeskew	0,051	0,046	0,035	0,031	0,041	0,036	0,026	0,023
t-value	(2,284)	(2,374)	(1,957)	(3,767)	(1,871)	(1,862)	(1,514)	(2,673)
indiv grades	0,001	0,000	0,006	0,010	0,001	0,000	0,006	0,010
t-value	(0,537)	(0,034)	(2,974)	(5,912)	(0,538)	(0,032)	(2,987)	(5,932)
DumD					0,002	0,005	0,000	0,007
t-value					(0,136)	(0,414)	(0,003)	(1,442)
DumR					0,085	0,084	0,085	0,051
t-value					(3,330)	(3,719)	(4,177)	(5,068)
sigmaU	0,060	0,053	0,049	0,019	0,058	0,050	0,045	0,019
sigmaE	0,192	0,189	0,187	0,170	0,192	0,189	0,187	0,170
R2-within	0,000	0,031	0,048	0,212	0,000	0,031	0,048	0,212
R2-between	0,418	0,467	0,545	0,708	0,474	0,522	0,603	0,726
R2-overall	0,073	0,103	0,128	0,284	0,079	0,109	0,131	0,287
N	40996	40996	40996	40996	40996	40996	40996	40996

See Table 2 for explanation of specifications and dummies R and D.

Table 4 OLS on microdata, subpopulations (clustered standard errors)

Log hourly wage

		Erisk	eskew	grade mean	grade var	grade skew	grade indiv	N
All		1,005	-0,089	0,003	-0,199	0,028	0,012	40.996
	t-value	(2,437)	(6,433)	(0,144)	(2,597)	(2,096)	(3,292)	
university		0,715	-0,080	-0,079	-0,034	-0,008	0,014	21.771
	t-value	(1,111)	((4,280)	(1,976)	(0,292)	(0,465)	(2,438)	
higher vocational		1,258	-0,073	-0,029	-0,039	0,006	0,011	19.225
	t-value	(3,431)	(4,065)	(1,056)	(0,461)	(0,322)	(3,312)	
men		1,314	-0,079	0,017	-0,363	0,030	0,023	18.180
	t-value	(3,002)	(6,339)	(0,701)	(4,681)	(1,805)	(5,485)	
women		0,907	-0,098	-0,020	-0,047	0,024	0,004	22.816
	t-value	(2,271)	(6,125)	(0,801)	(0,563)	(1,746)	(0,995)	
ability 1		1,138	-0,101	-0,095	0,179	0,063	0,006	9.456
	t-value	(1,609)	(3,604)	(1,904)	(1,038)	(4,520)	(1,567)	
ability 2		2,009	-0,060	-0,009	-0,190	-0,034	0,014	10.631
	t-value	(3,794)	(3,735)	(0,274)	(1,721)	(2,036)	(3,826)	
ability 3		2,615	-0,070	-0,195	-0,411	0,063	0,022	9.565
	t-value	(3,652)	(2,913)	(3,095)	(2,821)	(3,281)	(4,783)	
ability 4		0,562	-0,097	0,023	-0,146	-0,014	0,008	11.344
	t-value	(0,682)	(4,096)	(0,851)	(0,924)	(0,525)	(0,788)	
government		1,447	-0,044	-0,030	-0,374	0,005	0,010	4.116
	t-value	(2,195)	(1,231)	(0,894)	(2,816)	(0,343)	(2,248)	
education		1,594	-0,070	0,035	-0,080	0,011	0,001	5.927
	t-value	(5,231)	(4,132)	(0,838)	(0,721)	(0,441)	(0,344)	
services		0,828	-0,034	-0,032	-0,305	0,062	0,026	11.176
	t-value	(1,284)	(1,655)	(1,182)	(2,469)	(3,865)	(5,674)	
care		1,643	-0,128	-0,073	-0,020	0,015	0,004	7.056
	t-value	(3,737)	(10,090)	(1,429)	(0,146)	(0,517)	(0,596)	
manufacturing		1,032	-0,039	-0,027	-0,434	0,048	0,018	4.081
	t-value	(1,412)	(1,558)	(0,748)	(3,441)	(1,931)	(2,664)	
other		1,251	-0,083	0,025	-0,281	0,026	0,016	8.640
	t-value	(2,423)	(4,333)	(0,818)	(3,475)	(1,363)	(2,714)	
experience below mean		0,980	-0,088	-0,002	-0,120	0,031	0,012	24.066
	t-value	(2,615)	(7,025)	(0,090)	(1,810)	(2,400)	(2,902)	
experience above mean		0,896	-0,091	0,007	-0,282	0,015	0,012	16.930
	t-value	(1,888)	(5,785)	(0,292)	(3,061)	(0,961)	(2,892)	
difficult (D =1)		2,158	0,093	-0,027	-0,338	0,043	0,016	22.669
	t-value	(-4,929)	(-7,964)	(-1,007)	(-0,338)	(2,712)	(2,946)	
easy (D = 0))		0,842	-0,053	0,062	-0,251	0,012	0,008	18.327
	t-value	(-2.299)	(-2.137)	(-1.222)	(-2,159)	(0,488)	(2,909)	

Table 5 Elasticities

	Table 1 Aggregate	Table 2 OLS	Table 3 RE
grade mean	0.520	0.021	0.007
grade variance	0.085	0.050	0.052
grade skew	0.019	0.011	0.013
erisk	0.048	0.039	0.026
Eskew	0.135	0.103	0.083

The elasticities are based on specification 4, without dummies R and D.

Appendix. Data description

Key variables

Grademean	Mean of individuals’ average exam grade, by field of study
Gradevar	Variance of individuals’ average exam grade, by field of study
Gradeskew	Skew (third moment) of individuals’ average exam grade, by field of study
Erisk	Residual earnings variance, by field of study
Eskew	Residual earnings skew (third moment), by field of study
Residuals from earnings function: ln wage on dummies for education, cohort and region	

Correlations

	Hourly wage	Lnhourly wage	Grade mean	gradevar	gradeskw	erisk	eskew
Hourly wage	1,000						
Lnhourly wage	0,994	1,000					
Grademean	0,225	0,235	1,000				
gradevar	-0,152	-0,154	0,363	1,000			
gradeskew	0,220	0,226	0,355	0,200	1,000		
erisk	0,367	0,305	0,265	0,150	0,006	1,000	
eskew	-0,569	-0,544	-0,096	0,118	-0,091	-0,262	1,000

N=111

Descriptives.

Appendix

	grademean	gradevar	gradeskew					DumD	eindgem
VOCATIONAL									
Business Economics/Business Sciences	6.78	0.24	0.07	0.03	1.07	8.91	517	1	6.78
Commerce	6.93	0.27	0.59	0.04	1.50	9.03	476	1	6.76
Business Informatics	6.99	0.21	0.05	0.05	1.29	9.52	552	1	6.77
Communication	7.04	0.20	0.30	0.04	1.20	9.00	444	1	6.76
Accountancy	6.73	0.26	0.30	0.04	1.11	9.09	389	1	6.83
International Business and Languages	6.98	0.25	0.07	0.03	1.27	8.67	336	1	6.83
Tourism & Leisure	7.00	0.21	0.21	0.03	1.12	8.20	374	0	6.77
Hotel Management	7.02	0.27	0.24	0.04	1.56	8.85	361	1	6.76
Small Business and Retail Management	6.99	0.29	0.10	0.05	1.14	9.17	201	1	6.66
Management, Economics & Law	6.90	0.25	0.27	0.04	1.25	8.98	419	1	6.72
Logistics & Economics	6.90	0.25	0.27	0.03	1.50	8.89	472	1	6.75
Facility Services	6.99	0.21	0.20	0.04	1.38	8.79	503	1	6.70
Journalism	7.13	0.30	0.57	0.04	0.97	9.29	423	1	6.87
Business Management	7.09	0.20	0.57	0.02	0.71	8.72	90	1	6.88
Fiscal Economics	6.86	0.37	0.30	0.05	0.85	9.60	207	1	6.81
European professions	7.05	0.25	0.74	0.05	1.23	8.88	131	1	6.87
Leisure Management	7.01	0.26	0.15	0.04	1.48	8.19	120	1	6.68
Personnel & Labour	7.20	0.22	0.41	0.04	1.05	9.19	471	0	6.76
Socio-Cultural Studies	7.20	0.21	0.08	0.04	0.93	8.80	378	0	6.71
Social Work & Services	7.30	0.20	0.43	0.03	0.96	9.45	504	0	6.74
Social Pedagogy	7.18	0.22	0.07	0.03	1.19	8.95	696	0	6.70
Socio-Legal Services	7.18	0.21	0.27	0.03	1.23	9.19	362	0	6.74
Information Management	6.96	0.24	0.11	0.04	1.15	8.95	315	1	6.71
Creative Therapy	7.36	0.21	0.26	0.06	1.19	9.66	69	1	6.98

Medical Laboratory Technician	7.07	0.29	0.31	0.03	1.87	8.43	430	1	6.85
Nursing	7.18	0.26	0.33	0.02	1.34	9.15	621	0	6.69
Physiotherapry	6.98	0.26	0.07	0.05	0.73	10.71	441	1	6.67
Speech Therapy	7.25	0.29	0.54	0.04	1.34	9.23	362	0	6.71
Nutrition & Dietetics	7.01	0.26	0.23	0.04	1.35	9.12	419	1	6.72
Ergotherapy	7.16	0.24	0.34	0.03	1.14	9.58	464	0	6.72
Medical Imaging & Radiotherapy	7.43	0.32	0.52	0.02	1.54	10.76	47	1	6.62
Oral Hygiene	7.11	0.33	0.71	0.02	1.84	8.62	136	0	6.78
Environmental Management/Science/Technology	7.22	0.22	0.74	0.03	0.73	10.21	85	1	6.66
Agri-Business	6.92	0.25	0.17	0.04	0.98	9.07	360	1	6.80
Animal Husbandry	6.90	0.22	0.12	0.04	1.31	9.20	286	1	6.71
Food Technology	6.94	0.20	0.02	0.05	1.46	8.60	268	1	6.73
Primary School Teacher	6.86	0.27	0.58	0.03	0.74	9.13	100	1	6.77
Physical Education Teacher, Grade 1	7.34	0.29	0.38	0.02	1.26	9.53	603	0	6.74
Dutch Teacher	6.99	0.18	0.16	0.06	0.66	10.54	332	1	6.64
Economics Teacher (general & business)	7.21	0.19	0.54	0.05	1.07	9.85	240	0	6.71
Special Needs Teacher	7.02	0.23	0.02	0.05	1.28	9.38	300	1	6.69
Social Studies Teacher	7.49	0.28	0.52	0.02	1.68	9.75	241	0	6.71
Education Teacher	7.04	0.16	-0.01	0.04	1.43	9.05	87	1	6.65
Math/Physics Teacher	7.40	0.21	0.30	0.03	0.66	9.23	153	0	6.70
Geography/History Teacher	7.15	0.36	0.23	0.04	0.90	10.31	319	0	6.83
Arts & Crafts Teacher	7.03	0.24	0.07	0.06	0.74	10.11	409	1	6.78
English/French/German Teacher	7.33	0.24	0.32	0.07	1.18	9.12	61	1	6.74
Visual Arts & Design Teacher	7.29	0.31	0.51	0.07	0.61	10.58	442	0	6.83
Music	7.38	0.41	1.06	0.06	1.64	8.83	250	0	6.86
Chemcial Technician	7.79	0.43	0.59	0.07	0.70	10.00	140	1	7.10
Structural Engineering	6.97	0.28	-0.03	0.04	1.49	8.65	227	1	6.79
Electrical Engineering	7.05	0.22	0.34	0.03	1.32	8.79	395	1	6.80
Civil Engineering	7.13	0.26	0.46	0.03	1.00	9.15	332	1	7.00
Chemical Engineering	7.08	0.30	0.06	0.03	1.45	8.82	382	0	6.77
Applied Informatics	7.10	0.29	0.39	0.03	1.22	9.17	459	0	6.95

Mechanical Engineering	7.13	0.29	0.31	0.04	1.01	9.44	479	1	6.90
Maritime Officer	7.05	0.29	0.51	0.04	1.22	9.00	348	1	6.87
Applied Physics	7.22	0.35	0.26	0.02	1.05	9.05	69	1	7.14
Fashion Management and Technology	7.10	0.22	1.66	0.03	0.91	8.24	82	1	6.85
Car mechanics	6.94	0.33	-0.01	0.04	1.14	8.96	46	1	7.04
UNIVERSITY									
Dutch	7.33	0.27	0.44	0.05	1.13	9.90	424	0	6.98
English	7.38	0.34	0.34	0.06	1.18	9.64	313	0	7.07
Other languages	7.30	0.32	0.88	0.06	1.49	9.66	268	0	7.06
Philosophy/Theology	7.70	0.30	0.37	0.06	0.62	10.18	145	1	7.31
History	7.36	0.29	0.69	0.06	1.16	9.83	442	1	7.11
Language & Culture (general)	7.17	0.26	0.55	0.06	1.34	9.67	336	0	6.95
Art History & Archaeology	7.39	0.29	0.39	0.05	1.27	9.03	206	0	6.94
Corporate Communications	7.03	0.19	0.47	0.04	1.23	9.40	263	1	6.89
European Studies	6.92	0.23	0.04	0.03	1.49	9.36	70	1	6.86
Film, Television & Theatre Studies	7.30	0.23	0.40	0.06	0.74	9.29	84	1	6.96
Information science	7.28	0.28	1.12	0.03	0.95	9.40	142	0	7.00
Chemistry	7.38	0.32	0.77	0.06	1.77	8.95	396	0	7.44
Computer Science	7.46	0.34	0.98	0.04	1.14	9.53	191	0	7.32
Biology	7.39	0.34	0.49	0.04	1.32	8.80	569	0	7.11
Pharmacy	7.25	0.29	0.67	0.04	0.46	11.82	422	0	7.18
Pure Mathematics/Physics	7.51	0.38	0.61	0.06	1.36	9.27	393	0	7.84
Agricultural Science	7.22	0.21	0.59	0.04	1.60	9.56	267	1	7.03
Chemical/Technological Agri-sciences	7.21	0.21	0.44	0.05	1.35	9.62	576	1	7.08
Architecture	7.21	0.21	0.64	0.04	1.53	9.73	618	1	7.01
Mechanical Engineering	7.39	0.24	0.58	0.04	1.13	10.42	540	0	7.37
Electrical Engineering	7.43	0.30	0.47	0.05	1.28	10.28	346	0	7.59
Chemical Engineering	7.38	0.26	0.63	0.04	1.01	10.04	443	0	7.55
Civil Engineering	7.20	0.19	0.79	0.03	1.31	9.98	571	1	7.28
Technology & Management	7.11	0.13	0.30	0.04	1.12	10.77	559	1	7.20
Industrial Design	7.15	0.15	0.12	0.04	1.21	9.82	311	1	7.11
Aerospace Engineering	7.39	0.19	0.57	0.03	0.88	10.33	83	1	7.60

Applied Computer Science	7.44	0.26	0.44	0.03	1.00	10.01	224	0	7.44
Applied Mathematics/Physics	7.49	0.27	0.63	0.05	1.06	9.73	489	0	7.87
Economics	7.07	0.23	0.61	0.04	0.98	10.42	1,199	1	7.07
Business Science	7.06	0.23	0.68	0.04	1.23	10.52	578	1	6.86
Econometrics	7.31	0.32	0.76	0.05	0.98	10.77	417	1	7.59
Fiscal Economics	6.98	0.23	0.70	0.03	1.30	11.01	145	1	7.02
Applied Business Science	7.08	0.17	0.35	0.05	1.16	10.44	506	0	6.99
Dutch Law	7.11	0.25	0.88	0.04	1.24	10.24	861	1	6.91
Notarial Law	6.99	0.24	0.91	0.04	0.82	10.08	391	1	6.86
Fiscal Law	6.99	0.21	0.72	0.04	1.02	11.18	442	1	6.94
Healthcare	7.19	0.24	0.07	0.05	1.08	10.07	552	0	6.77
Medicine	7.17	0.28	0.40	0.04	0.38	11.72	849	1	7.15
Dentistry	7.20	0.16	0.63	0.09	-0.14	13.89	69	1	6.91
Biomedical Sciences	7.29	0.31	0.71	0.05	1.60	9.09	414	0	7.11
Veterinary Science	7.10	0.21	1.07	0.03	0.85	10.81	293	1	7.10
Sociology	7.21	0.31	0.91	0.05	0.86	10.09	372	0	6.87
Psychology	7.30	0.26	0.60	0.05	0.92	10.04	841	0	6.85
Politics	7.26	0.23	0.25	0.05	1.19	10.52	369	0	7.06
Education Science	7.18	0.21	0.25	0.05	1.04	10.24	512	0	6.77
(Applied) Education	7.30	0.25	0.58	0.05	1.08	10.30	319	0	6.86
Cultural Anthropology	7.22	0.22	0.41	0.05	1.33	9.48	301	0	7.00
Communication	7.13	0.20	0.35	0.05	1.39	9.96	495	1	6.80
Socio-Cultural Science	7.16	0.21	0.21	0.04	1.05	10.06	587	0	6.81
Public Administration	7.11	0.21	0.58	0.05	1.24	10.60	746	1	6.97
Human Geography & Planning	7.11	0.22	0.77	0.04	1.10	9.81	822	1	6.89
TOTAL VOCATIONAL (weighted)	**7.099**	**0.255**	**0.308**	**0.036**	**1.199**	**9.203**	**19225**		**6.77**
TOTAL UNIVERSITY (weighted)	**7.192**	**0.246**	**0.590**	**0.044**	**1.090**	**10.257**	**21771**		**7.09**
TOTAL TERTIARY	**7.131**	**0.252**	**0.408**	**0.039**	**1.161**	**9.605**	**40996**		**6.94**

Sub populations	**grademean**	**gradevar**	**gradeskew**	**erisk**	**eskew**	**wage**
totaal	7.13	0.252	0.408	0.039	1.161	9.605
University	7.19	0.246	0.590	0.044	1.089	10.260
Vocational	7.10	0.255	0.308	0.036	1.200	9.249
Man	7.09	0.253	0.420	0.040	1.160	9.708
Woman	7.16	0.251	0.399	0.038	1.161	9.528
Ability quartile 1 (lowest)	7.14	0.248	0.297	0.033	1.224	9.327
Ability quartile 2	7.06	0.249	0.309	0.041	1.175	9.316
Ability quartile 3	7.12	0.249	0.608	0.039	1.159	9.890
Ability quartile 4 (highest)	7.26	0.267	0.559	0.044	1.009	10.300
Government	7.12	0.243	0.473	0.040	1.172	10.000
education	7.28	0.276	0.423	0.035	1.179	9.685
Services	7.05	0.244	0.440	0.040	1.170	9.581
Care	7.18	0.247	0.308	0.036	1.033	9.913
Manufacturing	7.10	0.256	0.433	0.040	1.203	9.555
Other industries	7.10	0.250	0.410	0.040	1.235	9.127
Experience below mean	7.13	0.251	0.385	0.038	1.170	9.395
Experience above mean	7.14	0.252	0.444	0.039	1.145	9.945
Difficult	7.04	0.249	0.413	0.040	1.144	9.655
easy	7.25	0.255	0.401	0.036	1.182	9.541

N = 111