Risk and Heterogeneity in Students' Wage Expectations

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Abstract

There is an increasing literature showing that higher wage risk for occupational and educational groups is associated with higher mean wages, while positive skewness is associated with a lower mean wage. This can be explained by workers' risk aversion. We replicate these findings for Switzerland. The approach of risk augmented Mincer earnings equations has, however, been criticized for using ex-post wage realizations to construct a proxy for ex-ante risk. Therefore, we use a unique data set about the future wage distribution students expect for themselves ex-ante, for different education-age-scenarios. We confirm the results found for actual wage data which supports the view that workers expect compensation for wage risk. Our findings are robust to different specifications of risk and skewness and to different estimation models. We finally test the hypothesis that students have private information about where they will end up in the wage distribution. If this is the case, cross-section variances of labour market wages contain worker heterogeneity in addition to individual risk. We find that students have very limited private information about their future wage prospects. This might explain why our direct wage risk measure leads to the same results as found in the literature using ex-post wage variances as proxy for individual ex-ante wage risk.

1. Introduction

Standard human capital theory assumes that students take into account the expected (discounted) life time income of different educational pathways when deciding about their education. If students are risk averse, the decision will not only be based on the expected value of life time income, but also on the earnings risk that is associated with each pathway. Although this has been acknowledged at least since the early seventies (see Weiss 1972 and Levhari and Weiss 1974), the empirical literature dealing with wage risk is still scant.[1]

If workers are risk averse, they should be compensated for wage risk and a higher risk should lead to a higher mean wage. Thus, one way to assess the importance of wage risk is to estimate Mincer earnings equations including a measure of wage risk. Risk can be measured as the variance around the mean wage in the particular group to which the individual belongs, i.e. education or occupation. The argument is that individuals build wage expectations for alternative educations and occupations by just looking at the average wages they observe on the labour market for the particular groups. The variance around the mean, within schooling-education groups, is a measure of ignorance, of the unpredictability of wages and hence, of risk. This risk is included in a second-stage wage regression to see whether wages are related to the risk in the individual's chosen alternative. Typically, the second stage regression also contains a measure for the skewness of the wage distribution within the occupation/education group: just as expected wages for some education should increase with the variance because individuals dislike risk, the expected wages may be lowered for positive asymmetry in the distribution: risk averse individuals appreciate a long upper tail of the distribution as it gives them chances of large gains, and they are willing to pay for it by accepting lower wages (Tsiang 1972). Different authors (see King 1974, McGoldrick 1995, McGoldrick and Robst 1996, Hartog and Vijverberg 2004 for the US and Hartog et al. 2003, Diaz-Serrano et al. 2003 for Europe) have chosen this approach and have found that mean income in an occupation or education is positively related to the variance and negatively to the skewness.

The main criticism applying to this approach is that ex-post wage realizations are not a valid proxy for the ex-ante wage risk faced by the agents (Cunha, Heckman and Navarro 2005). Only part of the variance that can be found in actual wage data is due to risk, another part is due to worker heterogeneity. Heterogeneity means that individuals have superior knowledge compared to the researcher who looks at ex-post data. Individuals would then not just look at the average wages they observe on the labour market for different groups. If individuals have

[1] For a survey over the literature and the different approaches used, see Hartog (2007).

information about their own ability and other productivity-related variables, they form more informed expectations about where they will end up in the wage distribution. Researchers who do not have this information would then overestimate individuals' wage risk when looking at the variance of ex-post realizations of wages. Cunha et al. (2005) promote this argument and present an econometric solution for the problem. They develop and apply a method for decomposing cross section variability of earnings into components that are forecastable at the time students decide to go to college (heterogeneity) and components that are unforecastable (risk).

We will use a different, more direct approach: Instead of recovering the unforecastable wage risk from ex-post data, we asked students about the wage distributions they expect under different age-education scenarios. The methodology used in the survey has been developed by Dominitz and Manski (1996) who applied it to US students. From our data on wage distributions expected by Swiss students, we can construct ex-ante measures of wage risk and skewness. Expectations data seems particularly suited for the question at hand, since compensation of wage risk, by definition, has to work through wage expectations on the supply side of the labour market: If wage risk compensation exists, it has to be expected by students and workers in the first place, and should thus be found in expectation data.

We will show, firstly, that the results of risk augmented Mincer earnings equations can be replicated for Switzerland using labour market survey data. Secondly, we will use wage expectation data to construct measures of wage variance and skewness. Using these individual, ex-ante variables in risk augmented Mincer equations, we find results which are compatible with risk compensation (and a skewness penalty) in expected wages. Thirdly, we will show that variables on students' background can only explain a very limited part of their wage expectations which does not point to a major role of private information and heterogeneity in wage variances on labour markets.

The paper is structured as follows: section 2 estimates risk augmented Mincer equations with actual wage data for Switzerland. Section 3 introduces the expectation data and presents basic results as well as robustness checks. Section 4 addresses the question whether students use information about themselves to build more informed expectations about their future wages. Section 5 concludes.

2. Risk augmented Mincer equation – a replication for Switzerland

In this section, we use wage data to show that variance within occupation groups is positively correlated with wage, while skewness within occupation groups shows negative correlation with wage. Thus, we replicate the typical findings of the literature mentioned in section 1 with Swiss data.

For these analyses, we use the Swiss Labour Force Survey. This rotating panel is collected every year by the Swiss Federal Statistical Office. We use the surveys 1998, 1999, 2000 and 2001 since the wage expectation data we will use in the later sections was collected in these years. Individuals were included in the sample if they fulfilled the following conditions: age 18 to 65, having a job at the moment of the survey and working as employee (i.e., not self-employed). Dropping cases with missing values in independent variables and cases with exceptionally low or high hourly wages, the sample contains roughly 20'000 cases, 10'394 men and 9'455 women.

In a first step, Mincer type wage regressions were estimated using log wage as the dependent variable and the following independent variables: years of education, hours worked (incl. square), potential experience (incl. square and cube), marital status, 6 regional dummies, year dummies, dummies for foreign nationality and birth in a foreign country.

From the residuals ε of this regression, measures of risk and skewness were generated for 44 (men) respectively 43 (women) occupation groups. Taking the antilog of the residuals, the measures were computed within each occupation group j as follows[2]:

$$R = \mu_2 = E_j\left\{e^{\varepsilon_{ij}} - E_j(e^{\varepsilon_{ij}})\right\}^2$$

$$\mu_3 = E_j\left\{e^{\varepsilon_{ij}} - E_j(e^{\varepsilon_{ij}})\right\}^3$$

$$S = \frac{\mu_3}{\mu_2^{\frac{3}{2}}}$$

μ_2 is the variance and thus our measure of risk R. Skewness can be measured as the third centered moment μ_3 or as the classical coefficient of skewness S (the third centered moment

[2] As we use a pooled sample, some individuals may be observed several times in the same occupation group, which might reduce the variance within the group. When calculating R and S, we have therefore applied weights equal to the inverse number of times a person is observed in a certain occupation group.

normalized by the cube of the standard deviation, making the skewness dimensionless). These measures can be plugged into a second step Mincer wage regression which now contains 15 industry dummies in addition to the above mentioned variables. These were excluded in the first step since the individuals do often not know in what industry they will end up when deciding about their occupation.

The resulting coefficients of the risk and skewness variables along with the coefficient for years of education are reported in table 1.

dependent variable: ln(wage)	**regression coefficients** men I	II	III	IV	women V	VI	VII	VIII
years of education	0.082**	0.081**	0.080**	0.077**	0.074**	0.074**	0.073**	0.074**
risk		0.119**	0.361**	0.752**		-0.017	0.049	0.053
skewness			-0.013**				-0.005**	
3rd moment				-0.127**				-0.009*
adj. R2	0.629	0.631	0.633	0.638	0.823	0.823	0.823	0.823
N	10’394	10’394	10’394	10’394	9’455	9’455	9’455	9’455

Significance levels: + p<0.10, * p<0.05, ** p<0.01

Table 1: Selected coefficients of risk augmented Mincer earnings estimations (OLS)

Table 1 shows that the years of education coefficient in model I is hardly affected by the inclusion of risk and skewness measures. This corresponds to the findings in the literature. Moreover, for men we find a positive and significant effect of risk which increases if measures for skewness are included. Skewness in turn shows a negative effect on wages. Thus, the same coefficient structure can be shown as in the literature. Multiplying the coefficients with the mean of the risk and skewness measures gives us elasticity measures. These can be directly compared with Hartog et al. (2003) where specifications have been used that are analogous to our models in columns II and IV. The wage elasticity of risk is 0.016 (based on model II) and 0.102 (based on model IV), the wage elasticity of skewness (measured as third moment) is –0.035. For risk, these results are lower than any result in

Table 2 in Hartog et al. (2003), but close to the results reported for men in West Germany. For skewness, the elasticity is slightly higher and comparable to the results for the US.

There are, however, three results that diverge from the literature:

Firstly, we find much weaker effects for women.

Secondly, the coefficient for risk remains clearly lower when using the skewness coefficient instead of the third moment.

Thirdly, if we correct the standard errors for clustering in occupation groups based on which risk and skewness are defined, then levels of significance drop: the risk coefficient in column II becomes insignificant; in column III, risk remains significant only at the 10 percent level, while skewness becomes insignificant. In column IV, the effects remain significant at the 5 percent level, however. For women, all significant effects for skewness vanish when occupation clusters are taken into account in calculating standard errors.

In the two latter points mentioned above, the results change when skewness is used instead of the third moment. This raises the question whether it is preferable to use skewness or the third moment as measure of asymmetry. Comparing the correlations between these measures and risk shows that risk and skewness are less correlated than risk and third moment (0.790 compared to 0.881 for men, 0.592 vs. 0.743 for women). The high correlations suggest that significances in the models including the third moment might be a result of multicollinearity and that the coefficient of skewness should be preferred.

Summing up, we can replicate the result that risk has a positive sign and skewness a negative sign in risk augmented Mincer wage equations. The significance of these results is, however, not beyond doubt for Switzerland.

3. Risk and skewness in students' wage expectations

The approach of risk augmented Mincer earnings equations as used in the last section has been criticized for using ex-post wage realizations to construct a proxy for ex-ante risk (see section 1). Deriving risk and skewness from residuals of a first step wage regression is one solution for the problem that individual ex-ante risk cannot directly be observed. We make use of another solution in this paper: we have asked students about the median wage as well as about the wage distribution they expect. From this information, wage risk and skewness measures can be computed.

The expectation data offers several advantages compared to the use of labour market survey data. With the latter, wage variance is defined on cross-sectional wage variance in certain groups. The group variance serves as proxy for individual wage risk for all members of the group. Our expectation data allows us to compute wage risk and skewness on the individual level.

Educational decisions are, obviously, shaped by ex-ante expectations. Our expectation data is ex-ante, whereas labour market data contains ex-post realizations.

Finally, we were able to ask students for a range of background variables such as parents' education, social class and secondary school grades. Labour market data often lacks this kind of information. In combination with the expectation data, this will allow us to test for private information of students about where they will end up in the wage distribution.

3.2 How to elicit wage expectations

Dominitz and Manski (1996, hereafter DM) did pioneer work in eliciting wage expectations of students. While there exists a literature using mean or median wage expectations (e.g., Betts 1996, Wolter and Zbinden 2001, Webbink and Hartog 2004, Brunello et al. 2004), DM asked students not only to state their expected median wage under different, specified age-education scenarios, but asked for additional information on the expected wage *distribution*. With this information, they were able to fit log-normal wage distributions for every student and every scenario. Their sample consisted of 110 US students who were surveyed via computer-assisted self-administered interviews.

We use the same methodology as DM, therefore we will describe it in some detail. Notable differences will be discussed.

First, students are asked to give their expected median wage for some specified age/education scenario. Then wage distribution information for this scenario is gathered by defining wage values below and above the median for each individual, depending on the median wage that the individual has stated. For these wage values above and below the median, the students have to state their perceived probability that they will earn at most this amount. Thus, one has some points of the expected wage distribution for whom the wage value and the corresponding probability, i.e. position in the probability distribution is known.
With the same method, students were then asked to give estimates for the actual current wage distribution (in the US or in Switzerland, respectively) in different age-education groups, instead of their own expected wage distribution. The computer software provides the respondents with information needed to understand the probability questions (e.g., definition of the median) and checks the answers in real-time for missing or inconsistent values. The software also offers interactive help in case of errors. Finally, a range of personal characteristics is asked, among which sex, age, parents' education, parents' social class and grades in secondary school.

DM's article mainly focuses on discussing the methodology of the survey and on providing evidence that the expectation data is sensible. This is done by considering the internal consistency of the answers to their questions, the prevalence of response patterns, and the comments made by respondents in debriefing sessions. DM are able to show that the internal consistency of answers is rather high and that there is a lot of variation of responses, i.e. little bunching of answers at round numbers, which would indicate careless answering. The respondents said they liked to work with the computer, and they found the interactive features of the software helpful. DM conclude that "*respondents are willing and able to respond meaningfully to questions eliciting their earnings expectations in probabilistic form*" (DM 1996, 1).
Using the information on the individual wage distributions, DM fit log-normal wage distributions for every student and every scenario which provides them with a risk measure, namely the inter quartile range of the distribution. They come to the following main results: The respondents exhibit a common belief that returns to a college education are positive and that earnings rise between ages 30 and 40. They also believe that one's own future earnings are uncertain, they even tend to overestimate the true earnings dispersion. Wolter (2000) replicated the study for Switzerland. Using 137 students, he confirms the results found by

DM. In contrast to the US, however, Swiss students seem to underestimate rather than to overestimate the true earnings dispersion.

As mentioned above, we use the same methodology as DM and Wolter, i.e. a computer-assisted survey to elicit students' expectations about their wage distribution under different scenarios.[3] The survey was administered to four successive cohorts, 1998 to 2001, of students in the Economics Department of the University of Applied Sciences in Berne. 252 students were surveyed in their first semester, descriptive statistics on their characteristics can be found in Appendix A.

Our sample has two drawbacks: First, the sample size is limited (though double the size of the mentioned precursory studies); second, it is restricted to the population of economics students at a specific university. These drawbacks are balanced by two important advantages. First, we do not have to deal with selectivity of participation: within the classes we chose, all students have participated in the survey. Thus, there is no non-participation that could have introduced selection bias issues. Second, the data is of high quality. Item non-response or implausible answers are almost inexistent, thanks to the real-time plausibility checks of the software. Thus, hardly any observations drop out of the estimations. This rules out another important potential source for selection bias. While we are aware of the exploratory nature of our analysis due to the limited external validity of the results, we believe that the data offers new insights about risk compensation as well as heterogeneity components in wage distributions.

3.3 Operationalization of risk and skewness

In 3.2 we have described how students were asked to give probabilities for certain wage values which were in turn determined based on the expected median that a student had stated. While DM used a series of fix threshold values of whom the ones closest to the median were used to elicit the corresponding probabilities, our survey used relative wage values: The students were asked to give a probability for the values 80% of the median and 120% of the median. To give "reasonable" values, these values were rounded off to the nearest 500 CHF. Thus, the probabilities associated with the median and the (rounded) values 80% and 120% of the median are known. We asked this information for six scenarios in total; for age 30 and age 40, we specified three scenarios each: (1) "expectation conditional on having secondary

[3] Wolter 2000 describes the software used for the survey in more detail (including the exact phrasing of questions etc.).

education as highest education", i.e., leaving the University of Applied Sciences now, (2) "expectation conditional on finishing tertiary education", and (3) "unconditional expectation". The unconditional expectations are, however, very close to the expectations conditional on finishing tertiary education. This finding is logical since the vast majority of students will indeed finish tertiary education. Therefore, we will only use the data on scenarios asking for conditional expectations.

The information we got from the students does not allow to calculate variance or skewness measures of the underlying wage distributions without additional assumptions. Assuming a specific distribution function allows to calculate any moment of the distribution; it comes, however, at a cost: Every distribution has its own features which limit the way students' expectations can be represented. Fitting a log-normal distribution, as DM and Wolter do, imposes a heavy restriction on the set of possible student expectations. The two-parameter log-normal distribution, apart from satisfying the standard characteristics of a distribution function, is characterized as follows: it has a support from zero to infinity; it is uni-modal with a strictly increasing part left to the mode and a strictly decreasing part right to the mode; the distribution is positively skewed.

It seems highly unlikely that all students should have such a distribution function in mind for all the scenarios. This can easily be shown by looking at the share of distributions that are positively skewed, as log-normal distributions should be. Only 62 percent of the 1008 distributions elicited is positively skewed.[4] For 38 percent of the distributions, assuming a log-normal distribution is not correct.

There is another reason why the assumption of log-normality seems too restrictive. As mentioned above, one can show that risk averse individuals appreciate positive skew. The log-normal distribution does, however, not allow to separate mean, variance and skewness: it is fully described by the parameters mean and variance, so skewness cannot vary independently from these parameters. Assuming log-normal distributions, we implicitly assume that students do not distinguish between variance and skewness when building expectations. Thus, we cannot test whether positive skew is associated with a lower expected mean wage.

[4] These distributions are either negatively skewed, symmetric or "indeterminate". The latter category results from the rounding off of the values that had to be evaluated by the students. If these values are not entirely symmetric around the median, symmetry or asymmetry of the underlying distribution cannot always be established for sure. This happens in cases that are rather close to a symmetrical distribution. The category "indeterminate" makes up 7 percent of all distributions.

We will therefore not only fit log-normal distributions and use the interquartile range of these distributions as a measure of risk (see appendix B), but also specify alternative measures of variance and risk.

The three pieces of information we ask students about their expected wage distribution – the median and the probabilities associated with one value below and one value above the median – can be used to define simple variance and skewness measures. We know three points of the distribution, which divide the respective probability density function in four parts: $[0, 0.8*m], (0.8*m, m], (m, 1.2*m], (1.2*m, \infty)$. We denote the probability masses lying in the four intervals by A, B, C and D, respectively. By definition of the median we know $A+B=C+D=0.5$. Then a natural variance measure is defined by looking at the share of total probability that has been assigned to the two outer parts of the distribution: $v=2(A+D)$. This provides us with a variance coefficient (not to be confounded with *the* coefficient of variance) that lies between 0 and 1. In the same vein, a skewness coefficient can be defined by looking at the asymmetry in the probabilities assigned to the outer parts: $s=2(D-A)$. This coefficient lies between -1 and 1; a positive sign indicates positive skew and vice versa, while 0 indicates a symmetric distribution.[5]

Although these measures seem natural and are less restrictive than assuming log-normal distributions and deriving variance measures from them, they have a drawback. In order to compare the measures between persons, the definition of the intervals containing probabilities A to D has to be the same across persons. Because the values 0.8 times median and 1.2 times median had been rounded off to the nearest 500, the interval defined by these values does not have a width of exactly 40 percent of the median. Moreover, the interval becomes asymmetric depending on the median (e.g., a median of 6'100 results in a lower value of 5'000 (instead of 4'880) and in an upper value of 7'500 (7'320)). We defined new endpoints of the interval that are exactly 0.8 times median and 1.2 times median. Then, the probability mass lying between the old and the new endpoint had to be moved (from A to B and from C to D in the example above). This requires assuming a distribution function. We have used the log-normal distribution again. After these adaptations, the variance and skewness coefficients presented above have been computed.

[5] Of course, the limited information available about the density functions does not allow to identify higher or lower variance and skewness unambiguously. Implicitly, we are still making distributional assumptions.

Finally, it is not clear whether the interval width around the median should be determined by the median at all or whether one should use a fixed interval width for all scenarios and persons. This depends on the type of risk aversion of students' utility functions. If students exhibit absolute risk aversion, the risk premium they expect for wage risk depends only on the variance, not on the expected value of the wage distribution. Therefore, a fixed interval width independent of the median seems the best choice as basis for the calculation of a variance coefficient. By contrast, if students exhibit relative risk aversion, then the risk premium becomes the smaller the higher the expected value of the wage distribution. Risk is then perceived by students as variance given a certain median. Defining the variance coefficient based on a variable interval width growing and shrinking proportionally to the median seems more adequate in this case. We will use both specifications and compare the results. The fixed interval width specification implies again that the interval endpoints and the probabilities A to D have to be adapted for each observation, as described above.

Although the proposed variance and skewness coefficients do in principle not require the strong assumption of log-normality, their computation had to make use of this assumption to a certain extent. We are still able to assess skewness independently from variance and compare different variance measures, but we were not able to do completely without assuming log-normality in one step of the calculations.

3.3 Results for risk and skewness measures

Before estimating risk augmented Mincer earnings equations, we have a look at the distributions of variance and skewness coefficients. The distributions presented in figure 1 and 2 are defined on a fixed interval width for the four "conditional" scenarios and based on 252 cases each.

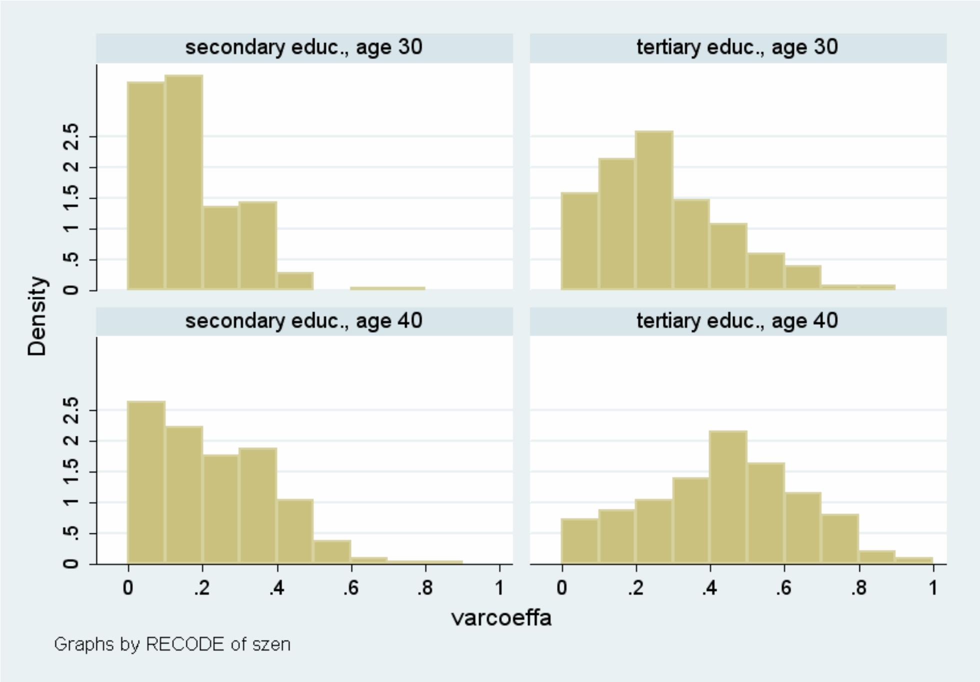

Figure 1: distribution of variance coefficients of students’ expected wage distributions

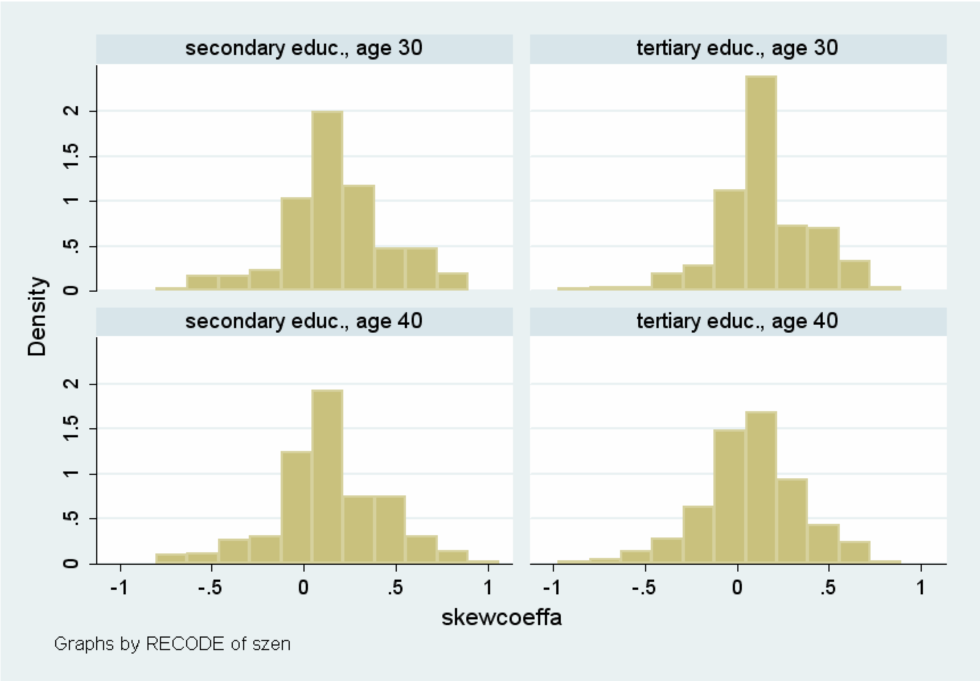

Figure 2: distribution of skewness coefficients of students’ expected wage distributions

As figure 1 shows, variances of the wage distributions are quite different for the different scenarios. Variances are clearly higher for the scenarios at age 40 and for the tertiary education scenarios. While the distribution of the variance coefficient is strongly skewed for the scenario age 30/secondary education, with hardly any values above 0.5, the distribution for scenario 40/tertiary education appears almost symmetric around 0.5. It is obvious that students assign much more wage risk to the latter scenario than to the former.

For skewness, the picture is less clear. The distributions of the skewness coefficients seem a bit broader for the scenarios with age 40. To compare the scenarios in more detail one needs to consult the descriptive statistics in Appendix C. The most interesting message of figure 2 is that expected skewness varies considerably between individuals. An important share of the expected wage distributions is negatively skewed. Furthermore, skewness is only loosely correlated with variance: Conditional on scenario dummies, skewness has a marginally significant positive correlation with variance. The partial correlation is, however, very small (regression coefficient 0.04). Most of the variance in skewness is not driven by the variance (risk) of the underlying wage distribution. These findings confirm that log normality is not a good approximation for all individual wage distributions.

With the variance and skewness coefficients at hand, the risk augmented Mincer earnings equations can be estimated. We will start with pooled results, i.e., the data for 4 scenarios for each of 252 individuals has been pooled, giving 1008 cases.

Dep. var.: ln expected median wage	I	II	III	IV	V	VI
interquartile range (divided by 1000)		0.040**				
variance coeff. (fixed interv. width)			0.425**	0.433**	0.429**	
skewness coeff. (fixed interv. width)				-0.082**	-0.082**	
variance coeff. (relative interv. width)						0.124**
skewness coeff. (relative interv. width)						-0.067**
scenario age 40/secondary education	0.219**	0.202**	0.188**	0.185**	0.185**	0.213**
scenario age 30/tertiary education	0.327**	0.298**	0.277**	0.274**	0.275**	0.320**
scenario age 40/tertiary education	0.612**	0.543**	0.499**	0.489**	0.490**	0.596**
year 1999	0.049*	0.038	0.032	0.025	0.032	0.044+
year 2000	0.104**	0.090**	0.070**	0.069**	0.079**	0.101**
year 2001	0.146**	0.140**	0.131**	0.131**	0.143**	0.156**
age	-0.003	-0.002	-0.002	-0.002	-0.002	-0.002
male	0.061**	0.041*	0.025	0.025	0.025	0.049*
part time study	0.035	0.051	0.076*	0.063*	0.063+	0.043
father's education high					0.013	0.025
father's education low					-0.009	0.010
mother's education high					0.015	-0.000
mother's education low					0.005	0.003
upper class					0.109*	0.125+
upper middle class					0.035*	0.047*
lower class					-0.050	-0.057
Second. school grade French					0.016	0.004
Second. school grade German					0.051*	0.054*
Second. school grade Math					0.014	0.011
Coefficient	8.500**	8.471**	8.448**	8.480**	8.038**	8.113**
F-Test	449.61	489.47	523.46	454.01	232.43	189.79
Adj. R-squared	0.654	0.692	0.714	0.720	0.733	0.677
N	1008	1008	1008	1008	1008	1008

Significance levels: + p<0.10, * p<0.05, ** p<0.01; Reference group: scenario age 30/secondary education, year 1998, female, father middle education, mother middle education, middle class

Table 2: Risk augmented earnings equations with student expectation data (OLS)

Table 2 shows OLS regression results for the dependent variable log median wage. Column I shows a wage regression without risk and skewness measures. According to the scenario dummies, students expect to earn 22 percent more with age 40 than with 30 if they went to work immediately. Completing tertiary education, they think to earn a good 30 percent more with age 30 than without tertiary education. With 40, they expect another 30 percent on top of that when finishing tertiary education. Year dummies reflect the boom in 2000/2001[6]. Men expect somewhat higher wages than women.

Different risk and skewness measures are the variables of interest in the models II to VI. In column II, this is the interquartile range derived from the fitted log-normal wage distributions (for descriptives see Appendix C). We find a significant positive effect on median wage, which mirrors the findings with data from actual, ex-post wage realizations. In contrast to these findings, the inclusion of a risk measure increases the goodness of fit of the estimation and has an effect on other coefficients. The scenario dummy coefficients are reduced, meaning that also the expected return on tertiary education becomes lower (while the education variable remained unaffected in table 1 of section 2).

Column III presents the results for the variance coefficient described in section 3.2 which is used in place of the interquartile range in column II. Again, we find a significant and positive effect on the median wage. This effect does hardly change when the skewness coefficient and controls for individual background are added (columns III and IV). An increase in the variance coefficient from 0 (which means that all probability mass has been assigned to the interval plus/minus 1’530 CHF around the median) to 1 (the full probability mass is assigned to the lower and upper end of the distribution[7]) is associated with a more than 40 percent higher median wage. Although based on the maximum possible difference in variance, this coefficient size shows that the effect is substantial even for smaller variance differences.

Column V shows the results with the variance (and skewness) coefficient defined on an interval width proportional to the median. The result is qualitatively the same, although coefficient size as well as goodness of fit are reduced.

The skewness coefficient shows a negative sign and is significant in all models, though its effect is clearly weaker than the one of risk. A higher skew is associated with a lower median. As discussed in the introduction, this can be explained by students’ risk aversion which implies skewness affection.

[6] On the dependence of expectations on the business cycle see also Wolter and Weber 2003.
[7] This case is theoretical and means an infinite variance.

We can thus fully replicate the results of the literature on risk augmented Mincer earnings equations which uses actual wage data: Risk variables show a positive effect, skewness variables a negative effect on median wage when analyzing students' wage expectations.

3.4 Robustness checks

Different objections might be raised against our interpretation of the results in table 2. We will discuss the following four possible shortcomings in turn: the wage expectation data might be unreliable, pooling across scenarios might hide heterogeneous results across the scenarios, there might exist unobserved heterogeneity across students, the results are not externally valid and therefore not relevant.

Unreliable wage expectation data?

As pointed out in section 3.2, the expectation data is of high quality due to the computer assisted interactive survey. Our software did, however, not only point out inconsistencies and errors to respondents, it did also trace these errors. We can therefore include variables for the number and type of errors respondents have committed. These refer to misunderstandings of the concept of probability and the median, i.e. stating probabilities higher than 100 percent or stating probabilities higher than 50 percent for the parts of the distribution above or below the median. Including this information on errors in the regressions of table 2 does not influence the results; neither does the exclusion of the (small) share of people who committed several errors. Given the plausible descriptive results of the survey, similar findings of other authors working with expectation data, and the stability of results with different specifications in table 2, we are very confident that our results are not an artefact caused by unreliable data.

Does pooling blur heterogeneity in scenarios?

Pooling the observations for four different scenarios per person might blur heterogeneous results for regressions run within scenarios. This is not the case: Running four separate regressions gives always the same signs for our variables of interest (positive sign for the variance coefficient, negative for the skewness coefficient) and with one exception, they are all significant at least at the 5 percent level in all scenarios.

Unobserved heterogeneity across students?

Although we control for different individual characteristics in the regressions of table 2, there might still exist student fixed effects, i.e. unobserved characteristics that are correlated with expected median as well as with expected risk and skewness. Therefore, we estimated a fixed effect model where the students' means over the four scenarios have been subtracted from each variable. All variables that are fix for a student drop out of the estimation. Table 3 does therefore only include scenario dummies in addition to the variance and skewness coefficients.

The results are in line with the results of the comparable models IV and VI in table 2, although the coefficients for variance and skewness are slightly reduced.

Dep. var.: ln median wage		
variance coeff. (fixed interv. width)	0.356**	
skewness coeff. (fixed interv. width)	-0.054**	
variance coeff. (relative interv. width)		0.120**
skewness coeff. (relative interv. width)		-0.045**
scenario age 40/secondary education	0.191**	0.214**
scenario age 30/tertiary education	0.284**	0.321**
scenario age 40/tertiary education	0.512**	0.598**
Adj. R2	0.836	0.808
N	1008	1008

Significance levels: + p<0.10, * p<0.05, ** p<0.01; Reference group: scenario age 30/secondary education

Table 3: fixed effects estimation

Limited external validity?

It has already been acknowledged in section 3.2 that we use a sample of economics students that might not be representative for other students. There are, however, two reasons that make us believe that our results will hold for a broader population. Firstly, the results are in line with the results of studies using ex-post wage realizations with much broader samples. Secondly, we have also surveyed students in Gymnasium (high school), Berufsschule (business school) and university. The students of the two former schools where at the end of their secondary education, while students at the university where starting their tertiary education. We surveyed the students of one class or lecture in each school to have a comparison with our sample of students in the university of applied sciences. Including these 88 additional students does not change the estimation results in a significant way.

4. Do students have private information?

The literature on risk augmented Mincer equations has sometimes been criticised for using ex-post wage variance as a risk measure. Since wage variance in occupational or educational groups might also reflect worker heterogeneity, it should not be equalised with risk. Our results have, however, been derived with ex-ante wage data, where risk is measured at the individual level and cannot be confounded with heterogeneity. At least in a qualitative sense the use of variance and skewness as observed in realized wages seems to give the "right" results. We can finally go one step further and directly address the question of private information. We will test whether students have private information about themselves that helps them forecasting their future wage. Students would then not only use the variance they observe in the labour market as a risk measure, they would also use their private information about their ability, social background etc. to assess their own wage risk. In this case, cross-sectional variance in realized wages reflects not only risk, but also worker heterogeneity.

A first test has already been included in table 2. Model IV and model V differ in the inclusion of additional independent variables describing students' background, i.e. parents' education, social class and grades in secondary school. In labour market surveys, these variables are often not collected. The SAKE data used in section 2, for example, does not provide information on any of these variables. Do these variables have an effect on the expected median wage? Two social class dummies and school grade in German[8] have an effect that is significant. All background variables together are jointly significant at the 5 percent level. The adjusted R-squared does, however, only increase by 1.3 percentage points. Students seem to have some private information that does account for a small fraction of the variance in expected median wages.

It could also be that some students face less risk than others. Students from better economic backgrounds may face less risk in general, or they might have more information about the labour market. Therefore, we regress the variance coefficient on the background variables mentioned above. Table 4 shows the results.

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[8] The university of applied sciences in Berne where the data has been collected is German speaking.

Dep. var.: variance coefficient		
scenario age 40/secondary education	0.073**	0.073**
scenario age 30/tertiary education	0.116**	0.116**
scenario age 40/tertiary education	0.265**	0.265**
year 1999	0.040	0.035
year 2000	0.083**	0.064**
year 2001	0.060**	0.047**
age	0.002	0.001
male	0.082**	0.069**
part time study	-0.092**	-0.079**
father's education high		-0.064*
father's education low		-0.007
mother's education high		0.039
mother's education low		0.059+
upper class		0.038
upper middle class		0.031+
lower class		-0.009
Second. school grade French		-0.039+
Second. school grade German		-0.000
Second. school grade Math		-0.011
Coefficient	0.044	0.294+
F-Test	62.43	33.08
Adj. R-squared	0.306	0.328
N	1008	1008

table 4: OLS regression of variance coefficient

A high father's education reduces perceived risk, while low mother's education increases risk. Good grades in French reduce wage risk. While these results suggest that a more favourable background reduces risk, a higher social class seems to increase risk. This result is slightly irritating – maybe a high social class means that one has a chance to get a very high wage, but it does not guarantee it, conditional on ability as measured by parents' education an own school grades. The background variables are jointly significant, although the R-squared increases by only 2.2 percentage points.

Until now, we used the expectation data collected in the survey. In addition to expectations, we also asked for estimates for actual wages as they can be observed in the real world. Thus, we can compare what students expect for themselves and what they perceive to be valid for the average person.[9]

Table 5 shows the wage differences between expectations and estimates for each scenario.

wage differences in CHF	1st quartile	median	3rd quartile
scenario age 30/secondary education	200	500	1000
scenario age 40/secondary education	350	1000	1500
scenario age 30/tertiary education	0	0	1000
scenario age 40/tertiary education	0	50	1000

Table 5: quartiles of the distribution of the variable “differences between expected median wages and estimated actual median wages” for different scenarios

On average, students expect a higher wage than what they perceive to be a current median wage. This holds for all scenarios. The median of the differences is, however, only significantly different from zero for the scenarios assuming secondary education. This suggests that students do have private information on their labour market value with their current education (they have all finished secondary education). Most of them thinks to have superior chances on the labour market compared to average people with secondary education. For tertiary education, they do not expect to earn more on average. On average, students think to earn an average wage. That does not mean that they do not have private information, since the difference between expected and estimated wage varies between students. Table 6 shows the results when the wage difference variable is regressed on all available independent variables for each scenario.

[9] For a comparison with actual wages from a labour market survey, see Wolter and Weber 2003.

Dep. var.: (ln expected median wage - ln estimated current median wage)	scenario age 30/secondary education	scenario age 40/secondary education	scenario age 30/tertiary education	scenario age 40/tertiary education
year 1999	-0.017	-0.005	-0.042*	-0.049*
year 2000	-0.011	-0.041	-0.034	-0.017
year 2001	0.022	-0.003	-0.022	-0.009
age	-0.006	-0.007	-0.002	-0.000
male	-0.013	-0.018	0.026+	0.016
part time study	0.087*	0.122*	-0.010	0.047
father's education high	-0.041	-0.032	-0.002	0.010
father's education low	-0.032	0.038	0.020	-0.004
mother's education high	0.053	0.044	-0.042	-0.010
mother's education low	0.017	0.016	-0.020	-0.038+
upper class	0.087+	0.088+	0.076*	0.056
upper middle class	-0.004	-0.003	0.021	0.035+
lower class	0.004	-0.016	-0.019	-0.033
Second. school grade French	-0.005	0.028	-0.023	-0.039
Second. school grade German	0.020	-0.012	0.043*	0.048
Second. school grade Math	0.005	-0.016	-0.012	-0.010
Coefficient	0.169	0.325	0.057	0.084
F-Test	1.31	1.33	1.44	1.01
Adj. R-squared	0.025	0.029	0.026	0.011
N	252	252	252	252

table 6: OLS regression of wage difference expectations - estimates

The regressions in table 6 do hardly explain anything. All variables together are jointly insignificant in every model (see F-Test results), the background variables are jointly insignificant in all models as well. Only belonging to the upper class (which holds for 2.8 percent of the sample) seems to have a fairly robust effect.

Overall, students do not seem to have private information to predict their wage more accurately than using actual wage data (as they perceive it).

5. Conclusions

If workers are in their majority risk averse, one should find compensation for wage risk in the labour market. An increasing literature on risk augmented Mincer earnings equations has established for many countries that wage variance in occupational or educational groups is positively correlated with the mean, while the skewness of the wage distribution is negatively correlated with the mean. This can be explained with risk compensation and skewness affection. We have replicated these results for Switzerland.

One important argument put forward against this approach is that the wage risk measure might not be suitable: ex-post realizations of wage variance in occupational or educational groups are composed of true individual ex-ante risk on the one hand and variance due to worker heterogeneity on the other hand. The latter is no part of individual wage risk if workers have private information about where they will end up in the wage distribution and do therefore not simply look at wage variances that can be observed in the market. If private information plays an important role, then ex-post wage variance is a bad proxy for individual ex-ante risk.

Using data containing wage expectations of students, we dispose of a measure of perceived wage risk, which has been asked for on the individual level and ex-ante. Running risk augmented Mincer earnings equations with the expectation data, we find the same results as the literature using ex-post wage data does. Students that expect to face a higher variance (risk) for a certain age-education scenario, do also expect a higher median wage. Conversely, they expect a lower median for wage distributions with a higher positive skew. These results are quite robust, among others they hold also in a fixed effects estimation where the variance between different scenarios within the same student has been exploited. These partial correlations of median, variance and skewness of the elicited wage distributions can be explained with workers' risk aversion which leads to risk compensation and a skewness discount. Having used a more direct and maybe more convincing risk measure than the existing literature, we still arrive at the same main results.

Finally, we have been looking for direct evidence that students have private information about where they will end up in the wage distribution depending on their educational decision. We found that background variables typically unavailable in labour market surveys have some influence on the expected median wage as well as on the expected variance in different scenarios. Their explanatory power, however, remains low.

Furthermore, they cannot explain the difference in expected and estimated wages. The students were not only asked for their own expectations, but also for estimates of the true wages on the labour market for the different scenarios. The most convincing sign for private information would be that background variables are able to explain differences between a student's expected wage and the average wage she estimates. Parents' education, social class and school grades are, however, not able to explain these differences.

All in all, the evidence for superior information of students in forecasting their wages is limited. Heterogeneity could therefore be the lesser part in observed wage variance which would then be dominated by wage risk. This would also explain why our main result using wage expectation data is identical with the literature that uses labour market data: higher wage variance is associated with a higher median wage, while positive skewness is associated with a lower median wage. Our confirmation of the results in the literature also lends support to the hypothesis of risk compensation on the labour market.

Appendix A

Appendix B

Appendix C

N = 252 in all tables 6 and 7

person fixed variables (no variance between scenarios)

variable	**mean**	**standard deviation**
year 1998	.274	.447
year 1999	.198	.400
year 2000	.187	.390
year 2001	.341	.475
age	23.6	2.49
male	.706	.456
part time study	.099	.300
father's education high	.071	.258
father's education middle	.830	
father's education low	.099	.300
mother's education high	.032	.176
mother's education middle	.357	
mother's education low	.611	.488
upper class	.028	.165
upper middle class	.369	.484
middle class	.540	
lower class	.063	.244
Second. school grade French[10]	4.88	.435
Second. school grade German	4.97	.368
Second. school grade Math	4.80	.639

variables varying with scenarios

variable \ scenario	age 30/secondary education		age 40/secondary education		age 30/tertiary education		age 40/tertiary education	
	mean	std. dev.	mean	std. dev.	mean	std. dev.	mean	std. dev.
expected median	5294	842	6619	1228	7346	1220	9852	2209
interquartile range (LN)	1085	657	1532	905	1826	1131	2810	2316
variance coefficient	.172	.124	.245	.166	.288	.175	.437	.200

[10] Maximum grade is 6, minimal passing grade is 4.

(fixed interv. width)								
skewness coefficient (fixed interv. width)	.176	.283	.137	.291	.152	.254	.083	.279
variance coefficient (relative interv. width)	.263	.159	.289	.163	.301	.166	.342	.171
skewness coefficient (relative interv. width)	.189	.289	.141	.296	.154	.254	.099	.282
wage difference expectation – estimation	709	759	1035	1041	363	847	675	1579

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