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Do Students Expect Compensation for Wage Risk?

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Abstract

We use a unique data set about the future wage distribution that Swiss students expect for themselves ex-ante, suggesting that students use very little private information about their wage prospects. Expectations appear much more anchored to perceptions of actual contemporaneous market data. Students even anticipate that the market provides compensation for risk, as has been established with Risk Augmented Mincer earnings equations estimated on market data: higher wage risk for educational groups is associated with higher mean wages. With observations on risk as expected by students we find compensation at similar elasticities as observed in market data. The results are robust to different specifications and estimation models.

JEL classification: D8, I2, J2, J3
Keywords: wage, expectations, wage risk, risk compensation, skewness

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1. Introduction

What do potential students know when they decide on their education? Do they use private, idiosyncratic information or do they only use contemporaneous market information on workers who have completed the education they are considering? What about the uncertainty about their potential wages? Are they aware of it, is there variation between individuals? Do they expect compensation for the risk in future earnings just as the stock market is known to present a trade-off between returns and risk?

Individuals' choices on education are inevitably made under conditions of uncertainty, and thus expectations on consequences are essential input in the decision process. Yet about expectations we know very little. Only a handful of studies use information from questionnaires asking for individuals' expected mean or median wages that would ensue after some specified schooling (e.g., Kodde 1986, Betts 1996, Wolter and Zbinden 2001, Nicholson 2002, Webbink and Hartog 2004, Brunello et al. 2004,); Dominitz and Manski (1996) extended this approach with eliciting information on the uncertainty of expected incomes. It is an obvious way to start research on the nature, relevance and impact of individuals' expectations, but Friedman's methodology of instrumentalism seems to have precluded its widespread adoption (Friedman, 1953).[1]

The common approach in empirical work is to treat expectations as unobserved variables and model the way individuals are supposed to extract the relevant input from information that is available to the researcher (including the possible filtering effect of self-selection). For example, Cunha and Heckman (2007) retrieve the information set that individuals must have used ex ante by exploiting the idea that if agents know something and use that information in making their schooling decisions, it should leave its traces in the their realised schooling choices.

In this paper, we will use the direct approach and analyse data directly obtained from students on the perceived consequences of schooling choices. We agree strongly with Manski (2004) that we can reap great benefits from eliciting and analysing the actual expectations that individuals hold when they have to take their decisions and that there is no

[1] Manski (2004) assesses the status of direct measurement of individuals' expectations and discusses examples of relevant use.

convincing reason for banning such information from economic research. As one of the advantages of this approach we may note that it solves the problem of the counterfactual in a natural way: benefits from options that are not chosen are not measured indirectly by construction, but simply by asking what individuals would expect.

Standard human capital theory assumes that students take into account the expected (discounted) lifetime income of different educational and occupational pathways when deciding about their education and occupation. However, if students are risk averse, the decision will not only be based on the expected value of lifetime income profiles, but also on the risk that is associated with each pathway. While 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, although interest is growing.[2] In our analysis of expectations, we will pay particular attention to the earnings risk that is associated with schooling choices. We will also investigate to what extent individuals' expectations reflect compensation for earnings risk. A small literature, exemplified by Hartog and Vijverberg (2007), claims that wage levels for given education and occupation include a compensation for the risk emanating from imperfect predictability of wages at the time that individuals have to make their education-occupation investment choices. Wages are indeed higher in occupations-educations where wage variance is higher and lower in occupations-educations where skewness is higher: people dislike risk but appreciate favourable odds of very high wages relative to very low wages[3].

A main criticism addressed at this approach is that the variance in the distribution of wages for a given education may not be a valid proxy for the ex-ante wage risk faced by the agents. The observed distribution will also reflect heterogeneity and may be twisted and truncated by selectivity as individuals act on their private information. To deal with this criticism, we will turn directly to the individuals themselves and ask about the wage distributions they expect under different age-education scenarios. Applying the methodology developed by Dominitz and Manski (1996) to Swiss students we construct ex-ante measures of wage risk and skewness. Expectations data are particularly suited for the question at hand, since market compensation for wage risk has to be imposed by supply reactions: with insufficient compensation, students will not enter that education. For wage risk compensation to

[2] For a survey of the literature and the different approaches used, see Hartog (2007). See also the Special Issue of *Labour Economics*, December 2007, on Education and Risk.
[3] The literature is surveyed and assessed in Hartog (2007).

materialise, students should be aware of risk and evaluate wages in view of that risk; in other words, risk compensation should be found in expectation data, in much the same way as investors anticipate higher returns for more risky assets. In this paper we contribute to the small empirical literature on actually held perceptions of financial consequences of schooling alternatives, by analysing differences in perceptions among individuals and by testing awareness of compensation for earnings risk.

We find wide variation in expected benefits from educations, both in levels and dispersions. But our results do not point convincingly towards the relevance of private information in the formation of expectations. If private information were relevant, one would predict family background and indicators of ability to have a systematic relationship with expected benefits from education and we do not find this. Instead, we find support for expectations anchored directly to perceived realisations for graduates already in the labour market. We also find support for anticipated risk compensation in the labour market. In fact, with measures of wage variance and skewness constructed from individual, ex-ante variables we find results that are compatible with foreseen risk compensation (and a skewness penalty) in expected wages, at magnitudes equal to those found in market data.

The paper is structured as follows: Section 2 explains how we measure expected wage distribution parameters and presents the data. Section 3 analyses the relationship between personal expectation and perceived market results, Section 4 tests the Risk Augmented Mincer earnings equation on expectation data and Section 5 concludes.

2. Calculating risk and skewness from wage expectation data

2.1 How to elicit wage expectations?

Dominitz and Manski (1996) 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), Dominitz and Manski 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. Wolter (2000) replicated the findings of Dominitz and Manski (1996) in Switzerland with Swiss students.

Dominitz and Manski (1996) mainly focus on discussing the methodology of the survey and on providing evidence that the expectation data is informative. This is done by considering the internal consistency of the answers, the prevalence of response patterns, and the comments made by respondents in a debriefing session. Dominitz and Manski 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. Dominitz and Manski conclude that "*respondents are willing and able to respond meaningfully to questions eliciting their earnings expectations in probabilistic form*" (Dominitz and Manski 1996, 1). Wolter and Weber (2003) also find that the quality of expectation data gathered with the computer-assisted interviews is far superior to the quality of data gathered in paper and pencil surveys.

Using the information on the individual wage distributions, Dominitz and Manski fit log-normal wage distributions for every student and every scenario which provides them with a risk measure, namely the interquartile range of the distribution. The main results of their analysis are that 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) in his replication study for Switzerland confirms the results found by Dominitz and Manski. In contrast to the US, however, Swiss students seem to underestimate rather than to overestimate the true earnings dispersion.

The data used in the present study was gathered with the same computer-assisted interviews as described in Wolter (2000) but with a new sample of students. 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.[4]

[4] Wolter (2000) describes the software used for the survey in more detail. See also Wolter and Weber (2003) for some descriptive information about this data sample.

First, students were asked to give their expected median wage for a specified age/education scenario (Appendix B shows the exact phrasing of the questions). Then wage distribution information for this scenario was gathered by defining wage values 20 percent below and 20 percent above the median stated by each respondent.[5] The students had to state their perceived probability that they will earn at most 80 percent of the median and at least 120% of the median respectively. Thus, one has three points of the individual expected wage distribution for which the wage value and the position in the probability distribution are known. This procedure has been used for a total of six different age/education scenarios. With the same method, students were then asked to give estimates for the actual current wage distribution for different age-education groups, instead of their own expected wage distribution.[6] We asked for their perceived wage distribution for individuals with secondary school only (that is, for individuals with a secondary professional qualification - *Berufslehre* -, the common degree for individuals entering the University of Applied Sciences[7]) and for individuals who have graduated from the University of Applied Sciences).

The computer software provided the respondents with information needed to understand the probability questions (e.g., definition of the median) and checked the answers in real-time for missing or inconsistent values. The software also offered interactive help in case of errors. Furthermore, information about personal characteristics was gathered, such as gender, age, parents' education, parents' social class and grades in secondary school. Finally, students were asked to express their agreement with different normative statements.

Our new sample has some major advantages. First, the sample size (although limited) is more than double that of comparable studies in the past. Second, the sampling was restricted to a well defined and homogenous group of students, limiting the risk that inter-individual differences would be driven too much by institutional or individual background variables. Third, there are no problems related to selectivity of participation. All students in all classes at the University of Applied Sciences participated in the survey (during class hours). Last but not least, the data is of higher quality than the data from written surveys. Item non-response or implausible answers are almost inexistent, thanks to the real-time plausibility checks of the

[5] This is different from Dominitz and Manski (1996) who asked students about predetermined fixed threshold values, choosing those three values out of six that were closest to the median the student had stated before. They did thus ask about four data points, one of which was typically close to the median, however.
[6] See Appendix B for the phrasing of the questions.
[7] In the classes surveyed about half of the students also had a "Berufsmaturität". This is a program aimed at preparing for the Fachhochschule. It is unlikely that this degree affects wages.

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 about heterogeneity in wage distributions.

2.2 Operationalization of risk and skewness

In 2.1 we have described how students were asked to give probabilities for some wage values around their expected median wage. While Dominitz and Manski used a series of fixed threshold values of which 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 corresponding to 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 will use this information from four scenarios: (1) "wage expectation conditional on being of age 30 and having achieved secondary education as highest education", i.e., leaving the University of Applied Sciences now, (2) "expectation conditional on age 40 and having achieved secondary education as highest education", (3) "expectation conditional on age 30 and having achieved tertiary education" and (4) "expectation conditional on age 40 and having achieved tertiary education". Two scenarios for age 30 and age 40 without conditioning on education were asked, too. These are, however, very close to the expectations conditional on finishing tertiary education. This finding is logical since the vast majority of students expected to finish their study. Therefore, we will only use the data of the scenarios asking for expectations conditional on a specific education.

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 Dominitz and Manski and Wolter do, imposes a heavy restriction on the set of possible student expectations. The two-parameter log-normal distribution is, among other features, always 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: only 62 percent of the 1008 distributions elicited are positively skewed.[8] Assuming a log-normal distribution is thus not correct for roughly one third of the individual distributions.

There is another reason why the assumption of log-normality seems too restrictive. As discussed below, 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 making expectations. Thus, we cannot test whether positive skew is associated with a lower expected mean wage.

We will therefore not only fit log-normal distributions[9] and use the interquartile range of these distributions as a measure of risk (see appendix C), but also specify alternative, non-parametric 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. The three points divide the respective probability density function into four parts. We denote the probability masses lying in the four intervals by A, B, C and D respectively:

$$
\begin{aligned}
A &= P(0 \leq w < 0.8 * m) \\
B &= P(0.8 * m \leq w < m) \\
C &= P(m \leq w < 1.2m) \\
D &= P(1.2 * m \leq w < \infty)
\end{aligned}
$$

[8] 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” accounts for 7 percent of all distributions.

[9] We also fitted Beta distributions instead of log-normal distributions. The literature (see McDonald 1984) typically finds that the Beta distribution performs better than the log-normal distribution in fitting wage distributions since it entails two shape parameters (instead of one in case of the log-normal). Applying a root mean squared error criterion, our Beta distributions perform worse, however, than the log-normal in three of the four scenarios. The reason is that some students gave answers that indicate distributions that are strongly skewed to the right. The log-transformation is well suited to deal with these cases, whereas the Beta distribution parameters take on extreme values without providing a good fit. Considering the limited information available per individual wage distribution and the need for a distribution with a limited number of parameters to be estimated, the log-normal seems to be the best parametric assumption available, despite its shortcomings noted in the text.

By definition of the median (m) we know that $A+B=C+D=0.5$. 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 non-parametric *variance coefficient* (not to be confounded with the coefficient of variation) 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 two outer parts of the distribution: $s=2(D-A)$. This coefficient lies between -1 and 1; a positive sign indicates positive skewness and vice versa, while 0 indicates a symmetric distribution.[10,11]

Although these measures seem intuitively appealing and 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.[12] 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 original (rounded) and the new endpoints had to be moved.[13] 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.

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.[14] If students exhibit constant absolute risk aversion, the risk premium they expect for wage risk depends

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[10] 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.

[11] Note that these definitions do not imply correlations between the variance coefficient and skewness from the presence of the same term in both (A and D), as a change in A must always imply a change in B, C and/or D, without preset pattern. Indeed, the correlation turns out to be virtually zero (see section 3.3).

[12] For instance, a median of 6,100 results in a lower value of 5,000 (instead of 6,100*0.8=4,880) and in an upper value of 7,500 (6,100*1.2=7,320). Both values in this example have been rounded up.

[13] In the example in the previous footnote, probability mass had to be moved from A to B and from C to D in order to find the probabilities associated with the values that equal exactly 80 percent and 120 percent of the median. The actual size of probability adjustments is reported in footnote 16.

[14] For the following short section on risk aversion, we assume that students' wealth is largely determined by their life time income from work. Furthermore, we ignore that students' individual expectations do not necessarily reflect their own risk aversion, but their expectation about the risk compensation provided by the labour market.

only on the variance, not on the expected value of the wage distribution.[15] 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 constant relative risk aversion, they expect a risk premium that is constant for risk that is proportional to their wealth, independent of their wealth level. In other words, the risk premium is constant for the wage variance divided by the expected value of the wage distribution. 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.[16] We used the mean interval width which amounts to 3061.8 CHF.

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. Our alternative variance measure is still quite different from using the interquartile ranges of the fitted log-normal distributions. In addition, we are able to calculate skewness measures and to assess skewness independently from variance.

2.3 Descriptives for risk and skewness measures

Before analysing the expectations data, we have a look at the distributions of expected median wages (figure 1) as well as variance and skewness coefficients. The distributions presented in figure 2 and 3 are defined on a fixed interval width for the four "conditional" scenarios and based on 252 cases each.

[15] "They expect" has to be interpreted as: a student exhibiting constant absolute risk aversion is indifferent between receiving the expected value of the wage distribution for granted and getting a draw from the wage distribution plus the risk premium.

[16] For the specification using interval width relative to the individual median, the necessary probability adjustments were minor: in 2016 adjustments (252 students * 4 scenarios * 2 wage values around median), only 16 cases occurred where more than 5 percentage points of probability had to be moved. For fixed interval width over all individuals and scenarios, the adjustments were necessarily more important: 41.4% of all adjustments included changes of more than 5 percentage points. 7.7% even entailed changes of more than 10 percentage points.

[figures 1, 2 and 3 about here]

As figure 1 shows, the distribution of medians for secondary education at age 30 is fairly concentrated. The dispersion of expected medians across individuals increases with level of education and with age. For tertiary education, at age 40, the distribution has a remarkably long upper tail.

Figure 2 shows that distributions of the variance coefficients 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.[17]

For skewness, the picture is less clear. The distributions of the skewness coefficients seem a bit broader for the scenarios with age 40, but actually, the dispersion of skewness coefficients is remarkably stable across scenarios; locations also vary modestly, with the lowest mean for 40/tertiary. To compare the scenarios in more detail one needs to consult the descriptive statistics in Appendix A. The most interesting message of figure 3 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: Calculating the correlation of variance and skewness 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 distributions. These findings confirm that log-normality is not a fully satisfactory approximation for all individual wage distributions.

[17] Not surprisingly, the differences between the scenarios are smaller if one considers the variance coefficient based on a variable wage interval around the median (see Appendix A). The risk in scenario 30/secondary education appears higher then, whereas it appears lower in scenario 40/tertiary education. The ranking of scenarios remains the same, however, with the highest risk attached to scenario 40/tertiary education.

We conclude that individuals' anticipated wage distributions exhibit much variation, are not always symmetric (nor symmetric in logs) and exhibit variation in skewness independent from variation in the individuals' anticipated variance.

3. Explaining variation in expected wage distributions

3.1 Why would there be variation?

Why would students' expected wage distributions vary across individuals? As described in section 3, we use a sample of first-year students who all study Business Administration at the same university. Since our students have all opted for the same education, different educational pathways cannot be the source of differing risk expectations.

It is quite likely that students anchor their expectations on their perceptions on the wage distribution for working individuals who have already completed the relevant education scenario and perceptions may differ. Thus in the next section we will first analyse how strong this relationship is. We will then move on and analyse the deviations between what students perceive to be the situation for individuals with a given educational profile and the prediction for themselves. This allows us to get some idea of the effect of private information. Expectations are predictions of future outcomes on the basis of present information. The expectations will generally be conditional on perceptions to reflect known relationships, such as the dependence of wages on gender, age (or experience) and of course education. Individuals have *private information* if they can condition on variables that researchers cannot observe. This requires two conditions: the individual should indeed know the value of the conditioning variable but he should also know the relationship between that variable and the relevant outcomes. Knowing your ability does not help much if you do not know how ability will affect your benefits from education. If there is indeed private information, the "revealed knowledge" approach has to acknowledge this in its modelling (and distil the potential outcomes that determine choice from the observed outcomes as shaped by choice). In the direct approach, one may try to push back the boundary of private information as far as possible by collecting observations on variables that individuals may use to condition their expectations. One can then test if these variables have any significant and plausible effect on expectations. Thus we can test if variation in expectations can be due to the private information on the variables that we have available. We will use data on family background variables, ability (school grades) and preference indicators to test whether personal characteristics and preferences influence wage expectations.

Private information may also relate to anticipated sorting into particular market segments (e.g. occupations, industries) with differing wage distributions. The notion of anticipated sorting is well-known in the literature of directed job search where agents direct their search to the most attractive alternatives available on the market (see e.g. Decreuse and Zylberberg (2006); for an overview see Rogerson et al. 2005). Bonin et al. (2007) show that workers even sort themselves into segments (occupations) that differ in earnings risk on the basis of their risk aversion. One may then hypothesise that students foresee that differential risk across segments leaves its traces in expected wages, as claimed in the Risk Augmented Mincer earnings equation. We will elaborate on this hypothesis and test its predictions in Section 4.

3.2 Anchoring expectations on perceptions

In Table 1 we show results from regressing an individual's expectations, as relevant to his own situation, on his perceptions of actually prevailing values. The actually prevailing values are asked for individuals without specifying their specific field of studies: just a secondary or tertiary vocational education. So the comparison is within vocational tracks, but does not apply to strictly identical vocations. The regressions also contain an intercept (always highly significant), but no other regressors.

[table 1 about here]

Consider first the results for the medians. The marginal effect of perceived actual value on personal expectation is between 0.50 and 1.00, significantly different both from zero and from unity, but much closer to unity than to zero. The relationship between the two is tighter for tertiary education than for secondary: explained variance is higher and the coefficient is closer to unity. Personal expectations are anchored to perceptions of actual values, although they are far from equal to it. Variation in personal expectations cannot be fully reduced to variation in perception of actual values.

Our result on anchoring personal expectations to perceived contemporaneous market values ties in with Nicholson and Souleles (2001), who report similar coefficients for medical students in the US. For every 1000 dollars increase in the actual contemporaneous income of the specialty that the student plans to enter, the student's expectation for that specialty goes up by 590 dollars. For every 1000 dollars difference between the student's estimate of contemporaneous specialty income and actual specialty income, the student's expected income goes up by 840 dollars. Misperceptions in actual specialty income end up almost dollar for dollar in income expectations.

The slopes for the dispersion variables (interquartile range, variance, skewness) are much smaller (with the exception of iqr and variance for tertiary education) and they differ more from 1 than from 0. Thus individual dispersion variables are less tightly anchored to perceived group values than individually expected medians. For all measures, slopes and R^2 are higher for tertiary education than for secondary education. We have no immediate explanation for this result. It suggests that expectations for an actually chosen alternative are tighter anchored to perceptions on actual outcomes than expectations for the counterfactual, the alternative that is not chosen.

3.3 Private information?

Are the deviations between perceptions and individual expectations systematically related to the individual's personal situation? If so, that would suggest that expectations are related to private information. Of course, we do not have observations on all the potential sources of private information, as this is almost impossible by definition. All we can do here is find out if there are patterns that are compatible with the use of private information for the variables that we do observe: ability, social background and preferences for job security and wage levels. If private information would be relevant in explaining differences in expectations, we would expect these variables to have a systematic impact: higher median wage for higher ability, better family background and higher willingness to take risk. The direction of the effect on expected dispersion would be hard to predict however.

Table 2 shows the distribution of differences between expected own median wage, variance coefficient and skewness coefficient and perceived market values for each scenario[18].

[table 2 about here]

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 may have private information on the labour market outcome with their completed education (they have all finished secondary education). Most of them believe that their chances on the labour market compared to average people with secondary education are better. This might also explain why they go to university: they may see themselves as better than the median person who has finished secondary education[19]. For tertiary education, the median student does not expect to earn more than the average. That does of course not mean that they do not have private information on themselves, since the difference between expected and estimated wage varies between students.

The second panel in table 2 shows that students expect less wage risk for themselves than the variance they perceive on the labour market. The difference is substantial and significant for secondary education scenarios, but small (and only in one case marginally significant) for scenarios assuming tertiary education. The smaller variance seems to suggest that students feel very well informed about their prospects on the labour market for workers with secondary education, but less so about their prospects on the labour market for workers with tertiary education. As our respondents have already completed secondary education, this may indicate that information gradually becomes sharper as they advance through their education.

The third panel shows that on average, the individually expected skewness coefficient is not substantially different from what students perceive to hold for the graduates, in particular for tertiary education[20]. But there is much heterogeneity, with a substantial upper and lower tail in

[18] For a comparison of students' estimated wages with actual wages from a labour market survey, see Wolter and Weber (2003).

[19] One might take this as evidence of private information. However, after adding controls in a multiple regression, the intercept is not sigificantly different from zero. See below.

[20] The difference is statistically different from zero for the secondary scenario, not for the tertiary.

the distribution of differences. The distribution for tertiary education is not far removed from symmetry, but the distribution for secondary education is clearly positively skewed.

The next step in our analyses is to regress the wage and variance difference variables on individual characteristics: do students with different background expect different labour market outcomes? In these regressions, we include not only the background variables on individuals like social class, but also the importance they accord to a high wage and a secure job. In the survey, students were asked to express their opinion on eight different statements. We chose two[21] of them which are of direct relevance for the issue of wage risk: "How important is it to you to earn a high wage?" and "How important is it to you to have a secure job?" Importance could be expressed on a scale from 1 (not important) to 5 (very important). We defined two dummy variables equal to 1 if importance equals 4 or 5.

The hypotheses associated with these two variables are straightforward: students attaching high importance to a high wage will sort into high wage/high risk segments of the labour market, ceteris paribus, and thus expect a higher median as well as a higher risk. The opposite holds for students attaching a high importance to a secure job: they may be willing to trade wage against job security. As they are likely to be more risk averse, they will also be less inclined to bear wage risk.[22]

Table 3 shows the results when the wage difference variable is regressed on all available independent variables for each scenario.

[table 3 about here]

The regressions in table 3 exhibit very weak explanatory power. All variables together are jointly insignificant in every model (see F-Test results), in median wage difference models as well as in variance difference models; for the skewness coefficient differences there is only

[21] The remaining 6 questions related to the importance of chances for promotion, of professional challenge, of the image of the employer, of the working climate in the firm, of the possibility to work part-time and of the opportunities for continuing training. As these variables have no bearing on the risk issues we pursue here, we ignore them. Using all variables in wage regressions (alone or in combination), the two variables discussed in the text are the only ones that do not change signs in different specifications and/or scenarios.

[22] We do not have a direct market measure of wage risk in our data. The variables on the importance attached to a high wage and job security may partly substitute for this shortcoming.

one exception[23]. A few variables are significant in some of the specifications. Part-time students think they can earn more than average if they go to work with their secondary education, presumably meaning that they see themselves as a positive selection of the population of all workers with secondary education. For tertiary education, they do not seem to have expectations above average. Parents' education has no significant influence, apart from a small expected wage penalty for tertiary education at age 40. Upper class students consistently expect higher median wages in all scenarios, though the coefficient is significant in only one (and only 2.8% of the surveyed students say they belong to the upper class). School grades exhibit no clear pattern, maybe with the exception of German grades for the tertiary scenarios. While mathematical ability is one of the few (if not the only) specific abilities with significant effect in regressions of individuals' market wages (Hartog 2001: 533), math grades do not explain differences between personal expectations and market perceptions. The variables on the importance of a high wage and a secure work place show the expected signs in all scenarios: students who attach importance to high wages expect to earn more, those who find a secure job important expect to earn less. The coefficients are only significant however, for the importance of high wages in the tertiary education scenarios.

As for the variance difference regressions[24], male students expect a higher wage risk for the tertiary scenarios. This could be explained by findings in the literature that men are less risk averse than women (Jianakoplos and Bernasek 1998, Sunden and Surette 1998): it points to anticipated sorting in more risky segments. Low mother's education is, maybe surprisingly, expected to be associated with higher wage risk. Finally, a high importance of a high wage leads to a higher wage risk: this is the only variable with three significant coefficients in the variance difference regressions. The result also fits nicely with our hypothesis that students with a strong preference for high wages sort into high risk market segments with a higher median wage – partly as a premium for the risk. Students that attach a high importance to a secure job expect less wage risk for secondary scenarios, but not for tertiary scenarios. These coefficients are, however, not significant.

The skewness coefficient regressions fit in with the other results: barely any coefficient is significant. But admittedly, we have no theory to expect otherwise.

[23] The conclusions are not different if we estimate on the total (pooled) sample with dummies for the scenarios.

[24] Qualitatively, the results do not differ when the interquartile range of the fitted log-normal distributions or the variance coefficient with variable interval width is used instead of the variance coefficient with fixed interval width.

One might wonder whether the deviations between expectations and perceptions are reflections of private information: are private expectations based on superior information that individuals possess and that allows them to make better predictions than just follow the perceived actual values? Of course we cannot know without confronting expectations with realisations and that is beyond our reach with the present data[25]. But our results do not point in the direction of private information. Ability related variables as well as variables related to students' preferences show some significant coefficients. This result is in line with our explanation of foreseen sorting of students into labour market segments, causing variation in students' expected median wages and expected wage risk. At the same time, the explanatory power of all the different variables tested is weak. In none of the regressions is the intercept significantly different from zero: given our controls, expectations and perceptions are not different, neither for medians nor for dispersions. We observe little systematic effects in the differences between perception and own expectation. Whereas in particular the effect of family background on economic success is well documented and whereas one might expect abler students to believe that they will do better than average, we do not find convincing relationships of this sort. The results are similar to Nicholson and Souleles (2001) who also find that the effect of "ability" is very small (performing in the top quartile of the exam at the end of the second year in medical school only increases expected income as medical specialist by 5.9%) and to Brunello, Lucifora and Winter-Ebmer (2004), who find that individually expected benefits from a university education, relative to high school is unrelated to parental background, reason for choosing their selected university or self-assessed relative ability.

4. Do students expect compensation for wage risk?

4.1 Core results

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:

$$\ln w_i = X_i\beta_x + \beta_r r_i + \beta_s s_i + \varepsilon_i \qquad (1)$$

[25] See Webbink and Hartog (2004) for such confrontation.

In the literature (see Hartog 2007 for a survey and Hartog and Vijverberg, 2007 for an application), risk r_i has been measured as the variance around the mean wage in the particular group to which individual i belongs, i.e. education or occupation. The argument is that individuals build wage expectations for alternative educations and occupations by just looking at the wage distributions they observe on the labour market for the particular groups. The variance around the mean, within schooling-education groups, is a measure of the individual's ignorance, of the unpredictability of wages and hence, of risk.. Typically, the regression also contains a measure for the skewness s_i 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 favourable odds of large gains relative to large losses (Tsiang 1972), and they are willing to pay for it by accepting lower wages, thus exhibiting skewness affection. Different authors (see King 1974, McGoldrick 1995, McGoldrick and Robst 1996, Hartog and Vijverberg 2007 for the US and Hartog et al. 2003, Diaz-Serrano et al. 2003 for Europe) have chosen the risk augmented Mincer approach and have found that mean income in an occupation or education is positively related to the variance and negatively to the skewness.[26]

Typically, the equation is estimated in two steps, with variance and skewness defined on the residuals (within occupations/educations) from an ordinary Mincer equation in the first stage and then added to a re-estimation in the second stage. The main criticism applying to this approach is that ex-post wage realizations are not a valid proxy for the ex-ante wage risk r_i (and skewness s_i) faced by the agents (Cunha et al. 2005, Cunha and Heckman 2007). 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 private information about their own ability and other productivity-related variables, they form

[26] The mentioned papers did not analyze the case of Switzerland. We have replicated their work with data of the Swiss Labour Force Survey and find the same qualitative results as these authors: variance has a negative sign, skewness a positive sign in a risk augmented Mincer earnings regression. Detailed results are available from the authors.

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) and Cunha and Heckman (2007) 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). Instead of reconstructing the information set from observed behaviour, as Cunha and Heckman did, one might also exploit the direct observations on expectations that we have at our disposal here. In particular, we can see if individuals' expectations reflect the risk compensation that is supposed to be established by the Risk Augmented Mincer equation.

With the expected variance and skewness measures at hand, the risk augmented Mincer earnings equations can be estimated on individuals' expectations. There is no need for a two-stage procedure as we have direct observations on risk and skewness and we can proceed immediately. We will start with pooled results, i.e., the data for 4 scenarios for each of 252 individuals has been combined, giving 1008 cases.

[table 4 about here]

Table 4 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 at age 40 than at 30 if they would go working immediately. Completing tertiary education, they think to earn a good 30 percent more at age 30 than without tertiary education. At 40, they expect another 30 percent on top of that when finishing tertiary education. Year dummies reflect the boom in 2000/2001[27]. Men expect somewhat higher wages than women. Higher wages for men and steeper age-wage profiles for higher education are stylised facts that students are clearly aware of.

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

[27] On the effects business cycles can have on expectations see also Wolter and Weber 2003.

(for descriptives see Appendix A). We find a significant positive effect on median wage, which mirrors the findings with data from actual, ex-post wage realizations. The mean expected effect of risk on wages is substantial: An increase in the interquartile range by 1,000 CHF will increase earnings by 4 percent. McGoldrick (1995, 221) found that “a $1,000 increase in the standard deviation of unsystematic earnings [the risk measure; note from the authors] will increase men’s earnings by 2.5% and women’s earnings by 3.1%” in the US.[28]

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 in some specifications, meaning that also the expected return on tertiary education becomes lower. In Hartog et al. (2003, table 1), the education variable remained unaffected by the risk and skewness variables. Our differing result could have important implications concerning the interpretation of expected, ex ante rates of return to education, as part of the ex ante return may have to be re-interpreted as risk compensation. However, this effect depends on using fixed or relative interval width.

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 hardly changes when the skewness coefficient is added (column IV).

Adding controls for individual background (column V) does not influence the coefficients for either variance or skewness. Thus there are no spurious correlations or biases if omitted. 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[29]) is associated with a more than 40 percent higher median wage. Although this calculation is based on the maximum possible difference in variance, the order of magnitude shows that the effect is substantial even for smaller variance differences.

Column VI 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 the coefficients’ size as well as the goodness of fit are reduced.

[28] The exchange rate was 1.182 CHF/USD in 1995 (source: Swiss National Bank).

[29] This case is theoretical and means an infinite variance.

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

Using expectation (i.e. ex-ante) data, we can thus fully replicate the results of the literature on risk augmented Mincer earnings equations which uses actual ex-post wage data: expected risk variables show a positive effect, expected skewness variables a negative effect on expected median wage. In fact, we even get similar values for the elasticities. Multiplying the regression coefficient with the mean values of risk and skewness (0.28535 and 0.13711, respectively) we find a risk elasticity of 0.12 and a skewness elasticity of –0.011 (for fixed interval width), values that are in the middle of the interval of values found in the empirical literature (Hartog 2007). The elasticities for the case of variable interval width are lower (at 0.035 and –0. 009, respectively), but still within the range found for market wages.

4.2 Robustness checks

Different objections might be raised against our interpretation of the results in table 4. We will discuss the following four possible shortcomings in turn: a) the wage expectation data might be unreliable, b) pooling across scenarios might hide heterogeneous results across the scenarios, c) there might exist unobserved heterogeneity across students and d) the results are not externally valid and therefore not relevant.

a) Unreliable wage expectation data?

As pointed out in section 2.1, 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 – which again, is an advantage over paper and pencil survey data. 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 4 does not influence the results; neither does the exclusion of the (small) share of people who committed several errors. Given the high data quality, the plausible descriptive results of the survey and the stability of the results using different specifications in table 4, we are confident that our results are not an artefact caused by unreliable data.

b) Does pooling obscure heterogeneity in scenarios?

Pooling the observations for four different scenarios per person might hide heterogeneous results for regressions run separately for every scenario. These four separate regressions all show the same results for our variables of interest (positive sign for the variance coefficient, negative for the skewness coefficient), however (not shown).

c) Unobserved heterogeneity across students?

Although we control for different individual characteristics in the regressions of table 4, there might still exist student fixed effects, i.e. unobserved student characteristics that are correlated with expected median as well as with expected risk and skewness. Therefore, we estimated a fixed effects model where the students' means over the four scenarios have been subtracted from each variable. All variables that are fixed for a student drop out of the estimation. Table 5 therefore only includes 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 4, although the coefficients for variance and skewness are slightly reduced.

[table 5 about here]

5. Conclusions

We have investigated students' perceptions on the benefits of education, by using data from direct questioning rather than deduced from imposed econometric modelling. We believe we have presented evidence for the case that students derive their information on benefits and risks of possible educations from observations on individuals with such educations already active in the labour market. We think that private information, in the sense of information that students use to assess the consequences of educational choices but that we as researchers cannot observe, plays no dominant role. Our case rests on our finding that differences in perceived earnings effects for those already in the market have a large impact on what individuals expect for themselves, much larger than the impact of ability and family background. Similar results are reported by Nicholson and Souleles (2001) and Brunello, Lucifora and Winter-Ebmer (2004).

In our view, individuals find it hard to make sharp predictions on what an education will bring them personally, in deviation from what they observe on average in the contemporaneous labour market. They can observe structures in compensation (means, dispersions, by education) and they will use them for their predictions. As Nicholson and Souleles (2001) show, they can predict general market trends in compensation. According to the results we report here, they are also aware of risk compensation, with implicit elasticities remarkably close to those actually observed in the labour market. Thus, we will continue our research on the hypothesis that potential students focus on key parameters of earnings distributions associated with schooling alternatives, that they perceive these parameters with errors, but that they have little private information to warrant a sharp prediction on where in these distributions they would eventually end up.

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Appendix A

N = 252 in all tables

Individual fixed variables (no variance between scenarios)

variable	mean	standard deviation
year 1998	.274	
year 1999	.198	
year 2000	.187	
year 2001	.341	
age	23.6	2.49
male	.706	
part time study	.099	
father's education high	.071	
father's education middle	.830	
father's education low	.099	
mother's education high	.032	
mother's education middle	.357	
mother's education low	.611	
upper class	.028	
upper middle class	.369	
middle class	.540	
lower class	.063	
Second. school grade French[30]	4.88	.435
Second. school grade German	4.97	.368
Second. school grade Math	4.80	.639
High wage: important	.782	
Secure job: important	.687	

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

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 wage (CHF)	5294	842	6619	1228	7346	1220	9852	2209
interquartile range (log-normal distrib.; CHF)	1085	657	1532	905	1826	1131	2810	2316
variance coefficient (fixed interv. width)	.172	.124	.245	.166	.288	.175	.437	.200
variance coefficient (relative interv. width)	.263	.159	.289	.163	.301	.166	.342	.171
skewness coefficient (fixed interv. width)	.176	.283	.137	.291	.152	.254	.083	.279
skewness coefficient (relative interv. width)	.189	.289	.141	.296	.154	.254	.099	.282
median wage difference: expectation – estimation	709	759	1035	1041	363	847	675	1579
variance coefficient: expectation - estimation	-.126	.183	-.079	.195	-.009	.152	.015	.162

Appendix B: phrasing of questions on wage expectations and perceptions

The following questions were introduced by a section explaining the meaning of probabilities and the median, and by specifying details about the wages asked (per month, full-time equivalent, no inflation).

Own wage expectation

Scenario secondary education:

Imagine you stop studying now and do not start another education. Think about the kind of occupations, industries, hierarchy levels etc. in which you will be working under these conditions.

What is the median amount of money that you think you will earn by the time you are 30 (40) years old?

What do you think is the probability that you will earn more than X / less than Y? At age 30: ... / At age 40: ...

[Stellen Sie sich vor, Sie brechen Ihr jetziges Studium ab und absolvieren keine zusätzliche Ausbildung. Beantworten Sie die folgenden Fragen, indem Sie sich Berufe, Branchen, Hierarchiestufen etc. vorstellen, in denen Sie unter dieser Voraussetzung arbeiten würden.
Wie hoch schätzen Sie Ihren Medianlohn im Alter von 30 bzw. 40 Jahren ein?
Wie schätzen sie die Wahrscheinlichkeit ein, dass Ihr Lohn höher wäre als X / niedriger wäre als Y? Mit 30 Jahren: ... / Mit 40 Jahren: ...]

Scenario tertiary education:

Imagine you have successfully finished your education at the University of Applied Sciences before age 30. Think about the kind of occupations, industries, hierarchy levels etc. in which you will be working under these conditions.
What is the median amount of money that you think you will earn by the time you are 30 (40) years old?
What do you think is the probability that you will earn more than X / less than Y? At age 30: ... / At age 40: ...

[Stellen Sie sich vor, sie haben die Ausbildung an der Fachhochschule vor dem 30.Lebensjahr absolviert. Beantworten Sie die folgenden Fragen, indem Sie sich Berufe, Branchen, Hierarchiestufen etc. vorstellen, in denen Sie unter diesen Umständen arbeiten würden.
Wie hoch schätzen Sie Ihren Medianlohn im Alter von 30 bzw. 40 Jahren ein?
Wie schätzen sie die Wahrscheinlichkeit ein, dass Ihr Lohn höher wäre als X / niedriger wäre als Y? Mit 30 Jahren: ... / Mit 40 Jahren: ...]

Perceived market wages

Scenario secondary education

Think about persons of your sex whose highest education is a apprenticeship (no specific degree). Think about the kind of occupations, industries, hierarchy levels etc. in which these persons will be working today.
What is the median amount of money that you think they will earn? 30 year olds: ... / 40 year olds: ...
What is the share of people earning more than X / earning less than Y? 30 year olds: ... / 40 year olds: ...

[Denken Sie an Personen Ihres Geschlechts, deren höchste abgeschlossene Ausbildung eine Berufslehre ist (kein bestimmter Abschluss). Beantworten Sie die folgenden Fragen, indem Sie sich Berufe, Hierarchiestufen etc. vorstellen, in denen diese heute arbeiten.
Wie hoch schätzen Sie den Medianlohn von Frauen/Männern mit Lehrabschluss ein? 30jährige: ... / 40jährige: ...
Wie gross ist der Anteil derjenigen, die mehr verdienen als X / die mehr verdienen als Y? 30jährige: ... / 40jährige: ...]

Scenario tertiary education

Think about persons of your sex who successfully finished an education at the University of Applied Sciences (no specific degree). Think about the kind of occupations, industries, hierarchy levels etc. in which these persons will be working today.
What is the median amount of money that you think they will earn? 30 year olds: ... / 40 year olds: ...
What is the share of people earning more than X / earning less than Y? 30 year olds: ... / 40 year olds: ...

[Denken Sie an Personen Ihres Geschlechts, welche nach der Lehre einen Fachhochschulabschluss absolviert haben (kein bestimmter Abschluss). Beantworten Sie die folgenden Fragen, indem Sie sich Berufe, Hierarchiestufen etc. vorstellen, in denen diese heute arbeiten.
Wie hoch schätzen Sie den Medianlohn von Frauen/Männern mit Fachhochschulabschluss ein? 30jährige: ... / 40jährige: ...
Wie gross ist der Anteil derjenigen, die mehr verdienen als X / die mehr verdienen als Y? 30jährige: ... / 40jährige: ...]

Appendix C: fitting log-normal distributions

The log-normal distribution is completely determined by two parameters, typically expressed as the mean μ and standard deviation σ of the underlying normal distribution. The log of the median m of the log-normal distribution equals μ by definition of the log-normal distribution: $\ln m = \mu$.

The interquartile range r of the log-normal distribution can be calculated by estimating σ. Since the median and two additional points of the wage distribution are known, σ can be estimated.

Starting from the z-transformation

$$\frac{x-\mu}{\sigma} = z(p),$$

rearranging and substituting the known log wages for x and μ gives:

$$\ln w - \ln m = \sigma * \Phi^{-1}(p)$$

We have two observations for w and p each, such that σ can be estimated as the coefficient in an OLS with N=2 using the equation above (adding an error term at the right hand side).

With σ at hand, the interquartile range of the fitted log-normal distribution can be computed:

$$iqr = m * (e^{z_{.75} * \sigma} - e^{z_{.25} * \sigma})$$

where $z_{.75} = \Phi^{-1}(0.75) = -z_{.25}$.

Figures and Tables

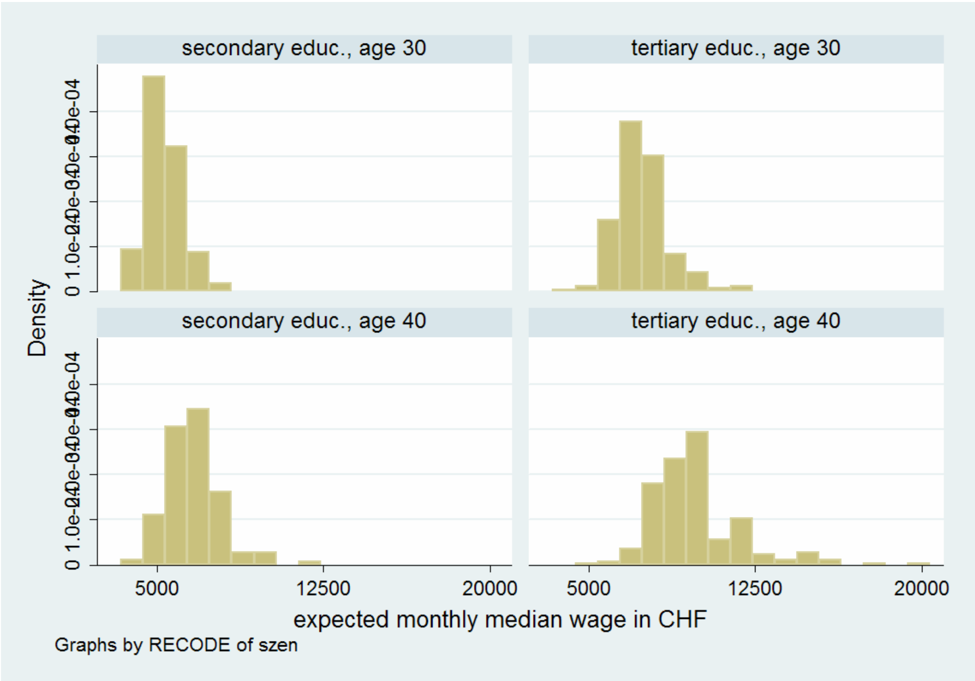

Figure 1: distribution of median of students' expected wage distributions

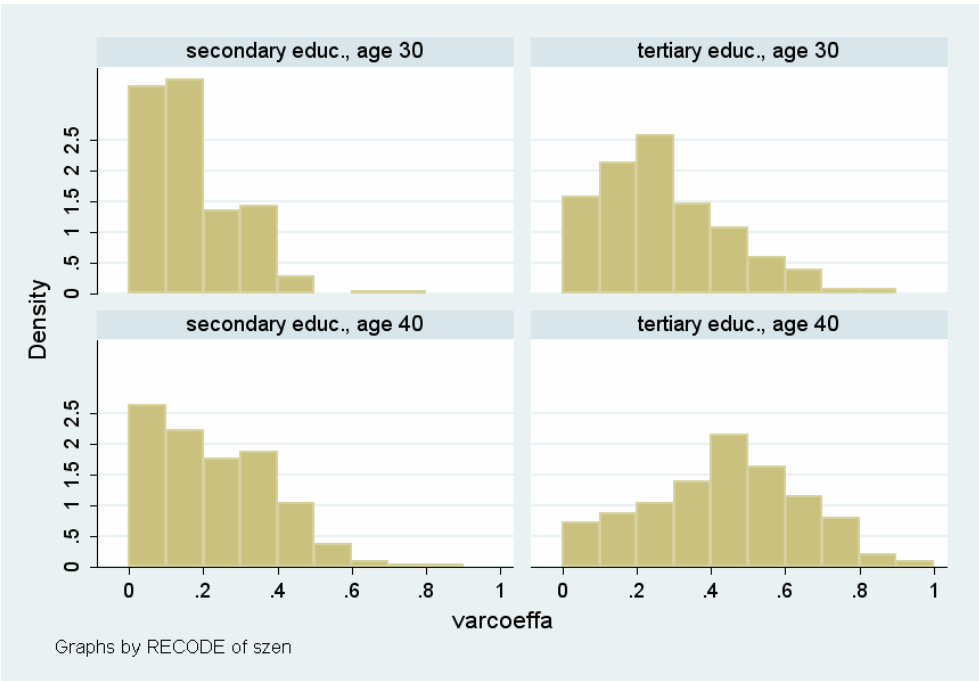

Figure 2: distribution of variance coefficients of students' expected wage distributions

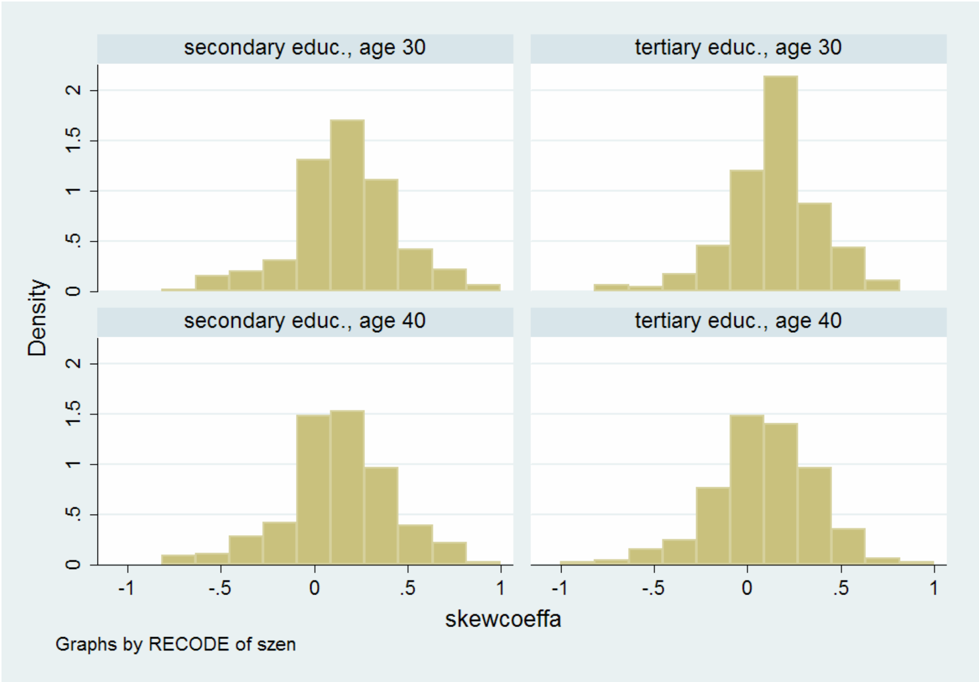

Figure 3: distribution of skewness coefficients of students' expected wage distributions

Table 1: Regressing personally expected median, dispersion and skewness on perceived actual values

	slope	t(0)	t(1)	R2
median, 30, secondary	0.67	9.03	4.40	0.24
idem, ln	0.58	9.05	6.57	0.24
median 40, secondary	0.74	10.87	3.82	0.31
idem, ln	0.61	10.85	6.87	0.31
median, 30, tertiary	0.85	16.96	3.02	0.53
idem, ln	0.78	16.79	4.65	0.52
median,40,tertiary	0.89	15.70	1.86	0.49
idem, ln	0.82	17.34	3.75	0.54
iqr, 30, secondary	0.24	5.24	16.82	0.10
variance coeff. (fixed int.)	0.37	7.16	12.12	0.17
variance coeff. (relative int.)	0.36	6.80	11.86	0.16
iqr, 40, secondary	0.44	9.70	12.41	0.27
variance coeff. (fixed int.)	0.40	6.68	9.92	0.15
variance coeff. (relative int.)	0.37	6.30	10.55	0.14
iqr, 30, tertiary	0.91	14.70	1.42	0.46
variance coeff. (fixed int.)	0.68	11.55	5.54	0.35
variance coeff. (relative int.)	0.63	10.32	6.11	0.30
iqr, 40, tertiary	0.67	7.47	3.67	0.18
variance coeff. (fixed int.)	0.69	12.38	5.59	0.38
variance coeff. (relative int.)	0.61	9.88	6.26	0.28
skewness coeff. (fixed int.), 30 , secondary	0.21	3.44	12.81	0.05
skewness coeff. (relative int.)	0.21	3.40	12.85	0.04
skewness coeff. (fixed int.), 40 , secondary	0.16	2.67	14.38	0.03
skewness coeff. (relative int.)	0.16	2.78	14.06	0.03
skewness coeff. (fixed int.), 30 , tertiary	0.36	5.61	10.12	0.11
skewness coeff. (relative int.)	0.36	5.63	10.22	0.11
skewness coeff. (fixed int.), 40 , tetriary	0.48	6.90	7.39	0.16
skewness coeff. (relative int.)	0.48	6.90	7.36	0.16

Note: t(0): t value against zero; t(1): absolute t value against unity.

Table 2: quartiles of distributions of differences between expectations and perceptions for median wage, wage variance and wage skewness

differences in median wages, 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
Differences in variance coefficients			
scenario age 30/secondary education	-.241	-.125	.002
scenario age 40/secondary education	-.224	-.064	.048
scenario age 30/tertiary education	-.116	-.021	.079
scenario age 40/tertiary education	-.067	-.017	.088
Differences in skewness coefficients			
scenario age 30/secondary education	-.115	.090	.306
scenario age 40/secondary education	-.128	.084	.326
scenario age 30/tertiary education	-.197	-.001	.107
scenario age 40/tertiary education	-.185	.002	.202

Table 3: OLS regressions of the variables "difference between expected median wages and estimated actual median wages" and "difference between expected variance coefficient and estimated actual variance coefficient" and "difference between expected skewness coefficient and estimated actual skewness coefficient" for different scenarios.

(see next page)

	median wage: ln expected median - ln estimated current median				wage risk: expected variance coeff. - estimated variance coeff.				wage skewness: expected skewness coeff. – estimated skewness coeff.			
	scenario age 30/secondary education	scenario age 40/secondary education	scenario age 30/secondary education	scenario age 40/secondary education	scenario age 30/tertiary education	scenario age 40/tertiary education	scenario age 30/tertiary education	scenario age 40/tertiary education	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	-0.045	-0.044	-0.048	-0.016	**-0.042***	**-0.049***	-0.012	0.007	0.000	0.009
year 2000	-0.012	-0.042	0.049	0.065	-0.004	0.009	-0.035	-0.019	-0.021	0.004	-0.015	0.032
year 2001	0.019	-0.006	0.032	**0.214****	-0.016	0.032	-0.025	-0.013	-0.012	-0.012	0.015	0.038
age	-0.006	-0.007	-0.001	0.000	**-0.015+**	0.000	-0.001	-0.000	-0.004	-0.006	0.001	-0.000
male	-0.018	-0.024	-0.045	-0.036	0.007	0.020	0.019	0.008	0.031	-0.008	**0.064****	**0.038+**
part time study	**0.084***	**0.119***	-0.113	**-0.153+**	-0.024	**-0.199***	-0.016	0.042	-0.060	-0.045	-0.051	-0.000
father's education high	0.056	0.048	**-0.248***	-0.090	0.068	0.036	-0.038	-0.005	0.035	-0.044	-0.005	0.037
father's education low	0.016	0.014	-0.079	**-0.122***	-0.015	-0.029	-0.022	**-0.040***	-0.006	-0.039	-0.013	-0.023
mother's education high	-0.045	-0.037	**0.354****	**0.261***	**0.092+**	0.047	-0.016	0.001	-0.035	-0.019	0.042	0.024
mother's education low	-0.037	0.033	0.016	-0.022	0.035	0.010	0.014	-0.010	**0.082****	**0.066+**	0.021	-0.040
upper class	0.084	0.084	-0.033	0.016	-0.066	0.042	**0.067***	0.049	0.022	0.004	-0.003	0.061
upper middle class	-0.005	-0.003	-0.055	-0.061	0.012	0.021	0.021	**0.034+**	**-0.046+**	-0.017	0.013	0.005
lower class	0.005	-0.013	-0.061	0.010	0.051	-0.003	-0.007	-0.026	0.043	0.033	-0.010	-0.054
Second. school grade French	-0.003	0.030	-0.014	-0.007	0.059	0.010	-0.021	-0.037	-0.011	0.023	-0.038	-0.015
Second. school grade German	0.018	-0.013	0.073	0.102	-0.011	0.043	**0.044***	0.047	-0.002	0.010	0.035	0.027
Second. school grade Math	0.007	-0.015	-0.021	-0.039	0.020	-0.010	-0.011	-0.009	0.005	-0.009	-0.001	-0.005
High wage: important	0.019	0.023	-0.087	-0.071	0.019	0.008	**0.053****	**0.039+**	**0.055+**	**0.093****	**0.049***	0.026
Secure job: important	-0.027	-0.022	-0.029	-0.044	0.002	0.007	-0.009	-0.023	-0.026	-0.039	0.016	0.004
Constant	0.184	0.325	0.095	-0.054	-0.013	-0.239	-0.005	0.063	-0.006	-0.066	-0.101	-0.066
F-Test	1.21	1.30	1.11	2.44	0.93	0.66	1.59	1.16	1.53	1.13	1.86	0.60
Adj. R-squared	0.025	0.028	0.041	0.079	-0.018	-0.023	0.052	0.018	0.007	0.005	0.029	-0.029
N	252	252	252	252	252	252	252	252	252	252	252	252

Table 4: Risk augmented Mincer earnings equations using individual wage expectations

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
Intercept	**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; standard errors are corrected for clustering of students due to pooling. Reference group: scenario age 30/secondary education, year 1998, female, father's education medium, mother's education medium, middle class

Table 5: Fixed effects estimation of risk augmented earnings equations

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. R-squared	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