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ABSTRACT

Can Risk Aversion Explain Schooling Attainments? Evidence from Italy*

Using unique Italian panel data, in which individual differences in behavior toward risk are measured from answers to a lottery question, we investigate if (and to what extent) risk aversion can explain differences in schooling attainments. We formulate the schooling decision process as a reduced-form dynamic discrete choice. The model is estimated with a degree of flexibility virtually compatible with semi-parametric likelihood techniques. We analyze how grade transition from one level to the next varies with preference heterogeneity (risk aversion), parental human capital, socioeconomic variables and persistent unobserved (to the econometrician) heterogeneity. We present evidence that schooling continuation probabilities decrease with risk aversion at low grade levels, but increase with risk aversion at the time when the decision to enter higher education is made. However, differences in attitudes toward risk account for a modest portion of the probability of entering higher education. Differences in parental human capital and ability(ies) are much more important.

JEL Classification: J24

Keywords: risk aversion, education, human capital, dynamic discrete choices

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1 Introduction and Motivation

The connection between individual attitudes toward risk and investment behavior has been widely analyzed in financial economics. This is true both at the theoretical and at the empirical level.[1] Although human capital is undoubtedly the main component of individual assets, the link between risk aversion and human capital accumulation, and in particular schooling, remains largely hypothetical. Most of the work is theoretical and often confined to relatively simple two-period models. In general, the results stress that earnings uncertainty may depress human capital investment.[2]

Empirical work remains scarce and is rather inconclusive. There is one main reason for this. At the empirical level, determining which asset is more risky is a relatively straightforward econometric question. However, quantifying the marginal risk which characterizes the transition from one level of schooling to the next is a more difficult research agenda. Not surprisingly, economists are currently unable to say if (and to what extent) schooling acquisition is a risky investment although the issue is starting to raise a significant level of interest. Moreover, the degree of education selectivity based on individual differences in risk aversion is completely unknown.

In this paper, we investigate whether risk aversion can explain differences in schooling attainments. We ask three simple questions. Does risk aversion increase or decrease investment in higher education? Does the effect of risk aversion change as individuals progress toward higher levels of schooling? How does the effect of risk aversion compare with the effects of ability and family human capital?

In order to answer these questions, we take an approach completely different from what is found in the literature. Using unique Italian panel data, in which an individual specific measure of risk aversion is inferred from an answer to a lottery question, we formulate the schooling decision process as a (reduced-form) dynamic discrete choice problem. Using discrete duration model techniques, we analyze how grade transition from one level to the next varies with measured risk aversion. In particular, we decompose the probability of entering higher education into four groups of variables; preference heterogeneity (risk aversion), persistent unobserved (to the econometrician) ability heterogeneity, parental human capital (parents' education and occu-

[1] See Kocherlakota (1996) for a comprehensive survey.

[2] This is the case, for instance, in Lehvari and Weiss (1974) and Olson, White and Sheffrin (1979).

pation) and socioeconomic variables (sex, region, age cohort).

Our analysis is based on a sample of Italian individuals. Our methodology therefore relies on the fact that higher education in Italy must be a "reasonably" risky investment. While tuition fees are low in Italy (and typically everywhere in Europe), there is no reason to believe that Italian students face lower psychic costs than do students in other countries.[3] For the sake of comparison, Italian students face a relatively more incomplete capital market than do US students. Borrowing while in school is practically inexistent in Italy.[4] The US, on the other hand, has very high tuition rates but also has substantial student loan and fellowship programs. Interestingly, both Italy and the US are characterized by a relatively high level of inequality. Although cross sectional wage dispersion is higher in the US than in Italy, long run (lifetime) inequality is thought to be higher in Italy and, in particular, among the highly educated.[5] To the extent that the riskiness of the education investment may be at least correlated with the individual's lifetime inequality, these institutional facts seem to indicate that investing in higher education may be as risky in Italy as in the US.

Aside from its direct contribution to the revived debate on the schooling/risk trade-off, this paper also contributes to the already existing literature on the determinants of schooling attainments. As of now, labor economists have paid a particular attention to the importance of parental human capital and individual abilities (observed or unobserved). This paper adds a new dimension to the analysis of the determinants of schooling; namely the importance of preference heterogeneity.[6]

The paper is constructed as follows. In Section 2, we present some back-

[3]Empirical evidence for the US suggests that differences in psychic costs may be quite important. For instance, the large explanatory power of the individual specific differences in the per-period utility of attending school found in the structural literature is consistent with the existence of strong psychic costs (Keane and Wolpin, 1997, and Belzil and Hansen, 2002). See Heckman, Lochner and Todd (2005) and Belzil (forthcoming) for surveys.

[4]The Italian national statistical office (ISTAT, 2003, Table 1.8) reports that the total number of student loans in Italy in the academic year 1999-2000 was 97.

[5]In a recent paper, Flinn (2002) shows that after taking into account job offer probability while employed and while unemployed and unemployment incidence, lifetime welfare inequality is higher in Italy than in the US. His results are obtained in a search framework with risk-neutral workers.

[6]In the structural literature, the term "preference heterogeneity" is often used to refer to differences in taste for schooling and academic abilities (Keane and Wolpin, 1997). In our analysis, these unobserved factors are subsumed in the unobserved heterogeneity term.

ground material and review the most important literature. In section 3, we discuss the Bank of Italy Survey of Income and Wealth (SHIW) and provide details about the measure of risk aversion used in our analysis. The econometric model is described in Section 4. In Section 5, we present evidence that schooling continuation probabilities decrease with risk aversion at low grade levels, but increase with risk aversion at the time when the decision to enter higher education is made. In Section 6, we compare the effects of risk aversion with the effects imputed to unobserved heterogeneity and to parental education. Section 7 is devoted to a brief comparison of our results with those reported in the literature. The conclusion is found in Section 8.

2 Background an Relevant Literature

Fundamentally, the marginal risk associated to schooling has two distinct components. One component relates to the human capital accumulation process and is experienced by the individuals at the time schooling decisions are made. The second component relates to post-schooling labor market outcomes and is therefore associated to the (perceived) distribution of random variables which are realized much beyond actual schooling decisions.

With respect to the accumulation process, acquiring schooling should be unambiguously viewed as a risky investment. School (and especially college) attendance requires to sacrifice present consumption and to absorb substantial psychic costs in return for future rewards, but successful grade achievement is rarely a certain outcome. For this reason, the probability of losing the investment paid up front cannot be ignored and may act as a strong disincentive.

At the level of labor market outcomes, the argumentation becomes more complicated. In practice, life cycle earnings are affected by random events such as job offers, layoffs, risk sharing agreements between firms and workers (or unions) and many other events. Occupation choices may also affect earnings volatility. The ex-ante probability distribution of those labor market outcomes may depend on schooling but it is far from clear if accumulated schooling contributes to an increase in earnings dispersion or decreases volatility.[7] On top of this, uncertainty about labor market abilities may also

[7] For instance, schooling may reduce earnings dispersion by reducing the unemployment incidence or by raising the job offer probabilities (given unemployment) but it may increase wage volatility if more educated workers find jobs in sectors or occupations where wages

represent a certain form of risk.

In the long run, labor market productivity and earnings may be affected by structural changes in the economy. Potential technological changes affecting the return to schooling may be viewed as an additional element of risk from the perspective of the student. On the other hand, when schooling is viewed as facilitating adjustment to technological change, this uncertainty may turn out to favor schooling acquisition (i.e.: schooling becomes a form of insurance).[8]

Given this level of complexity, and taking into account both the accumulation process and labor market outcomes, it is difficult to say whether or not individuals perceive schooling acquisition as a truly risky investment. In the earlier literature, a few descriptive analyses of the variability of empirical age/earnings profile have been carried out. However, the notion of variability is usually an "ex post" notion which may have little to do with "ex ante" risk.[9] Ideally, evaluating the marginal risk would require a statistical analysis of the joint distribution of life cycle wages, unemployment, job offer probabilities and grade completion (or failure) probabilities. In particular, it would also require to disentangle persistent unobserved (from the econometrician perspective) heterogeneity from true dispersion, as in Cunha, Heckman and Navarro (2005). This would be difficult to achieve and indeed, as of now, such a comprehensive study does not exist.

On top of this, measuring the marginal risk associated to schooling for all relevant labor market outcomes may turn out to be irrelevant if individuals have imperfect information about the law of motion that generates labor market outcomes. If so, individual subjective probabilities may diverge from the Rational Expectation hypothesis and the use of post-schooling panel data on wages and employment outcomes may become irrelevant for the econometrician.

As it stands now, there is no strong empirical evidence on the effect of education on wage/earnings dispersion, but economists are starting to pay more and more attention to the issue. In a recent paper, Palacios-Huerta (2003)

(or marginal product) is more volatile.

[8]This argument is put forward in Gould, Moav and Weinberg (2001).

[9]Mincer (1974) investigates how the variance of earnings differs across schooling levels over the life cycle while Chiswik and Mincer (1972) use age earnings profile to investigate time series changes in income inequality. Kodde (1985) uses the Lehvari and Weiss model as a background for empirical work and tests predictions from the model from data on subjective estimates (self reported) of future earnings.

presents an empirical comparison of the properties of risk-adjusted rates of return to schooling within an intertemporal model, using mean-variance spanning techniques.[10] In line with the stream of the literature devoted to the increase in wage inequality, many individuals have analyzed the wage dispersion (basically the variance) within education groups in cross-section data rather than in panel data. The cross-section evidence shows that the variance of wages is higher within the educated group (Lemieux , 2005 and Chay and Lee, 2000). In an attempt to separate individual heterogeneity from ex-ante risk, Belzil and Hansen (2004) estimate a dynamic programming model in which the degree of risk aversion can be inferred from schooling decisions but they assume that the attitude toward risk is represented by a parametric (constant relative risk aversion) utility function. They identify the degree of risk aversion from the degree of heteroskedasticity in the idiosyncratic earnings shock but assume that all persistent unobserved heterogeneity is in the information set of the agent. As panel data on wages, earnings and schooling do not allow them to identify cross-sectional dispersion in risk aversion, they assume homogeneity of preferences and automatically rule out the possibility that differences in schooling are driven by differences in attitudes toward risk. Finally, Cunha, Heckman and Navarro (2005) develop a statistical method which distinguishes between heterogeneity and risk but also allow for a distinction between ex-ante risk and ex-post dispersion. Their method allows the econometrician to infer the set of variables upon which schooling decisions are based, but disregards heterogeneity in risk aversion.[11]

3 Measuring Risk Aversion: The Bank of Italy Survey of Income and Wealth

We use data from the 1995 wave of the Bank of Italy Survey of Income and Wealth (SHIW). The survey collects information on consumption, income and wealth in addition to several household characteristics for a representative sample of 8,135 Italian households. More importantly, the 1995 survey contains a question on household willingness to pay for a lottery which can

[10] Basically, the mean-variance spanning technique amounts to quantifying the effect of introducing a new asset on the mean-variance of another benchmark asset.

[11] On top of these few papers, a relatively large number of related working papers are being currently circulated. These include Hartog, Van Ophem and Bajdechi (2004), Chen (2003), Harmon, Hogan and Walker (2003) and Davis and Willen (2002).

be used to build a measure of individual risk attitudes. The interviews were conducted by professional interviewers at the respondents' homes and to help the respondent to understand the question the interviewers showed them an illustrative card and were ready to provide explanations.[12]

In the survey, each head of household is asked to report the maximum price he/she is willing to pay to participate to an hypothetical lottery. The question is worded as follows:

"We would now like to ask you a hypothetical question that we would like you to answer as if the situation was a real one. You are offered the opportunity of acquiring a security permitting you, with the same probability, either to gain a net amount of 10 million lire (roughly 5,000 dollars) or to lose all the capital invested. What is the most you are prepared to pay for this security?"[13]

The respondent can answer in three possible ways: 1) give the maximum price he/she is willing to pay, which we denote as *bet*; 2) don't know; 3) don't want to participate. Of the 8,135 heads of household, 3,458 answered they were willing to participate and reported a positive maximum price they were willing to bet (prices equal to zero are not considered a valid response).[14]

At a theoretical level, it is easy to show that there is a one-to-one correspondence between the value attached to the lottery and the degree of risk aversion. For a given of wealth, w_i, and a potential gain (g_i), the optimal bet, bet_i, must solve the expected utility equation:

$$U_i(w_i) = \frac{1}{2}U_i(w_i + g_i) + \frac{1}{2}U_i(w_i - bet_i) = EU(w_i + R_i) \tag{1}$$

where R_i represents the return (random) of the lottery. Taking a second-order expansion, and noting that R_i is also the maximum purchase price (bet_i), we get that

[12]More details may be found in Guiso and Paiella (2005).

[13]In other words, the expected value of entering the lottery is $0.5 \cdot (10,000,000 - bet)$.

[14]Guiso and Paiella (2005) also explain that the question has a large number of non responses because many respondents may have considered it too difficult. This does not mean that those who responded gave erroneous anwers. However, the literature in experimental economics (Kagel and Roth, 1995) underlines that individuals tend to report lower buying than selling prices when asked to price hypothetical lotteries. Since our question asks the buying price of the lottery, it is possible that our measure of risk aversion is biased upward. However, if the bias is proportional to the reported price and is constant across individuals, the results should be unaffected.

$$EU(w_i + R_i) \approx U_i(w_i) + U_i'(w_i)E(R_i) + \frac{1}{2}U_i''(w_i)E(R_i)^2 \tag{2}$$

It is therefore possible to express risk aversion (say the Arrow-Pratt measure given by $\frac{-U_i''(w_i)}{U_i'(w_i)}$) as a function of the parameters of the lottery and the the value of the bet of each individual. In general, the optimal bet depends on $U_i(.)$, on consumer endowment (w_i), and on background risk. The valid responses to the question - *bet* - range from 1,000 lire to 100 million lire and constitute our measure of individual risk aversion. Of the 3,288 heads in our final data set (see the sample selection criteria below), 3,131 reported a maximum price *bet* less than 10 million lire which implies that they are risk averse individuals, 117 reported *bet* exactly equal to 10 million lire (i.e. they are risk neutral) and 40 reported *bet* more than 10 million indicating that they are risk lovers. The empirical distribution of *bet* is reported in Table 2. Although the majority of the respondents are risk averse and only 5% of the sample is either risk-neutral or risk-loving, there is a large heterogeneity in the degree of risk aversion within the risk averse individuals which shows that preferences are very heterogenous with respect to risk.

It should be noted that this measure of risk requires no assumption on the form of the individual utility function and extends to risk-averse, risk-neutral and risk-loving individuals. This lottery question has been used to study the relationship between risk aversion and several household decisions. Guiso and Paiella (2005), use the question on risk aversion to analyze occupation choice, portfolio selection, insurance demand, investment in education (in the linear OLS case) and migration decisions. They find substantial effects of this measure of risk aversion in ways that are consistent with the theory i.e. that more risk averse individuals choose lower returns in exchange for lower risk. They find for example that being risk averse increases the probability of being self-employed by 36% of the sample mean and the probability of holding risky assets by 42% of the sample mean. They also find that being risk averse as opposed to being risk neutral or risk prone (i.e. they use a risk-averse dummy), lowers education by one year on average.

Guiso, Jappelli and Pistaferri (2002) show that risk aversion is negatively correlated with a measure of income risk (built from a question which asks about the expectations on future employment and income) i.e. risk averse individuals choose jobs with low income risk. Brunello (2002) estimates returns to schooling instrumenting schooling attainment with risk aversion under the hypothesis that risk aversion affects schooling costs but does not affect income if not through schooling. We will use the lottery question to explain schooling attainment and quantify the predictive power of risk aversion as opposed to other determinants of schooling.

Theoretically, the answer given by the individual may be partly affected by his/her time-invariant degree of risk aversion but also partly affected by time varying differences in wealth/income as well as ability endowments. Guiso and Paiella (2005) show that household income, wealth and individual characteristics have limited explanatory power.[15] Ultimately, they conclude that this measure of risk is a good proxy for the time-invariant individual specific component of the attitude toward risk.

Guiso and Paiella (2001) discuss in details the main advantages of this estimate of absolute risk aversion relative to those already in the literature. They underline that the lottery represents a relatively large risk. In fact, ten million lire corresponds to just over 5,000 dollars and the ratio of the expected gain of the hypothetical lottery to the annual average Italian household consumption is 16 percent. This is an advantage since expected utility maximizers may behave as risk neutral individuals with respect to small risks even if they are risk-averse to larger risks. Thus, facing consumers with a relatively large lottery may be a good strategy to elicit risk attitudes.

Apart from the lottery question, we use information on the level of education attained by the head of household, as well as variables such as age, gender, region of birth, parental education and parental occupation. This set of variables is comparable to those which are used in US studies based on the National Longitudinal Survey (NLS). We select the sample of all heads with a valid answer to the lottery question (3,458) and eliminate those who report a missing value in any of the following variables: education, age, gender, region of birth, education and occupation of the head's father and mother. This selection process leaves us with a final sample of 3,288 heads of household.

The schooling variable takes six possible values (1 to 6) corresponding to no education, elementary school (typically attained at 11 years of age), junior high school (attained at 14), high school (attained at 18), university degree (attained at 23-24) and post-university degree.

Table 1 in the Appendix shows the descriptive statistics of the sample. In the estimation we use dummy variables derived from the original variables. There are six dummy variables - *edu1* to *edu6* - for the level of education

[15] Interestingly, the main predictor of risk aversion is region of birth.

attained by the individual (no title = *edu6*=1, elementary school, junior high school, high school, university degree, post-college degree = *edu1*=1), three dummies - *north, centre* and *south* - for the region of birth, one age dummy (*age45more*=1 if age of head more than 45 in 1995) and one sex dummy (*female*=1).[16] In addition we have one dummy each - *edu_father* and *edu_mother* - respectively for the level of education attained by the individual's father and mother (less than high school=0, high school or more=1), and four occupation dummies for blue collar, white collar, self employed and unoccupied for parents' occupation. These variables are denoted *bc_father, wc_father, se_father, u_father* for the father and *bc_mother, wc_mother, se_mother, u_mother* for the mother.

4 The Econometric Model

In this section, we present the econometric model. As schooling attainments are reported according to six (ordered) levels, we model schooling decisions as a reduced-form dynamic discrete choice model and we use a hazard function model of grade transition. The grade transition model admits a semi-structural interpretation and may be regarded as an approximation to a sequential dynamic optimization model.[17] Our method is based on the fundamental assumption that choices be made sequentially

We see at least three main advantages to our approach. First, it does not require to specify individual preferences but only requires that the measure of preference heterogeneity is a good proxy for the ordering of the persistent degree of risk aversion across individuals.

Secondly, it neither requires to model the distribution of labor market outcomes, nor to assume that the distribution of the labor market outcome variables, which are realized in the post-schooling periods, is actually known by the agents at the time of the schooling decisions.

[16] The reason we introduce a dummy for the heads of household older than 45 in 1995 is that presumably they started college (if they ever attended it) before 1968. Before 1968 legal restrictions limited the accession to college only to those who had a high school degree in classical or scientific studies, since 1968 accession to college is open to any type of high school degree.

[17] In recent work, Heckman and Navarro (2005) proved non-parametric (or semi-parametric) identification of reduced-form dynamic discrete choice models, such as discrete hazard functions. They also show that similar identification results extend to structural dynamic programming models, under certain conditions.

Finally, we do not need to assume that the persistent unobserved (to the econometrician) heterogeneity term(s) affecting labor market outcomes belong(s) to the information set of the agent when schooling decisions were made. Our estimation strategy is therefore consistent with schooling decisions made under imperfect information about individual specific skills.[18]

4.1 Modeling Sequential Schooling Decisions

The model allows for different types of factors; measured preference heterogeneity, family characteristics (parents' education and occupation), gender, regional effects, cohort effects and, finally, persistent individual unobserved heterogeneity.

With six ordered levels (or grades) of schooling, we are able to estimate five different hazard rates. The conditional probability (hazard rate) of stopping at grade g for individual i, denoted H_{gi}, is denoted

$$H_{g,i} = \Lambda(U_{g,i}) \text{ for } g = 1, 2, ..5 \tag{3}$$

where

$$U_{g,i} = \alpha_{g,i} + \beta_g' X_i + \delta_g \cdot RA_i \tag{4}$$

The term $\alpha_{g,i}$ represents an individual/grade specific intercept term, X_i is a vector of observable characteristics, and β_g' represents a grade specific vector of parameters measuring the effects of these characteristics. The variable RA_i represents the time-invariant part of individual-specific risk aversion and δ_g is a parameter. We assume that the value attached to the lottery is a perfect indicator of the time-invariant part of risk aversion.[19] We therefore get that

$$RA_i = Bet_{i,95} \tag{5}$$

We assume that

$$\alpha_{g,i} = \alpha_{0g} + \alpha_{1g} \cdot \theta_i$$

[18]This issue is analyzed formally in Cunha, Heckman and Navarro (2005).

[19]Because the bet is measured after schooling decisions are made, this is equivalent to assuming that risk aversion is exogenous. In a companion project, we investigate the effect of risk aversion when wealth, and therefore risk aversion, is endogenous.

and that θ_i is drawn from an unknown distribution which is approximated by a discrete distribution with K points of support.[20] As we include an intercept term in the transition probability, we normalize one support point (namely θ_1) to 0.[21] In line with Heckman and Navarro (2005), we estimate $\Lambda(.)$ as flexibly as possible. As advocated in Geweke and Keane (2000), $\Lambda(.)$ is approximated with a mixture of 5 normal random variables; that is

$$\Lambda(.) = \sum_{m=1}^{M} P_m^* \cdot \Phi(\mu_m, \sigma_m)$$

where P_m^* is the mixing probability and $\Phi(\mu_m, \sigma_m)$ denotes the normal cumulative distribution function with mean μ_m and variance σ_m^2.

The hazard rate, $H_{g,i}$, is therefore

$$H_{g,i} = \sum_{m=1}^{M} P_m^* \cdot \Phi(\frac{\alpha_{0g} + \alpha_{1g} \cdot \theta_i + \beta_g' X_i + \delta_g \cdot RA_i - \mu_m}{\sigma_m}) \tag{6}$$

To obtain identification, we impose that for one of the components of the mixture is the standard normal $\Phi(0,1)$.[22]

We estimate the model by maximum (mixed) likelihood techniques. Defining six different schooling indicators from the lowest schooling level (d_{1i}) to the highest (d_{6i}), the contribution to the likelihood for an individual i who has completed level g, is denoted L_i, and is equal to

$$L_i = \sum_{k=1}^{K} p_k \cdot [\Pi_{s=1}^{g-1}(1 - H_{s,i}(X_i, \theta_k))^s \cdot H_{g,i}(X_i, \theta_k)] \tag{7}$$

where θ_k is the type specific support point and where the type probability, p_k, is specified as $\frac{\exp(p_{0k})}{1+\exp(p_{0k})}$. Given the form of the hazard specification (equation 3), it is important to note that the sign of the parameter estimates indicates

[20] As typically found in most empirical applications dealing with a univariate duration endogenous variable, it has been found that $K = 2$ is sufficient to characterize unobserved heterogeneity.

[21] Obviously, the probability of transiting from one grade level (g) to the next ($g + 1$), the grade transition (continuation) probability, is simply $1 - H_{g,i}$. We sometimes refer to the grade transition probability as a "continuation" probability. The hazard rate is sometimes referred to as a "termination" probability.

[22] This is because the hazard rate includes a grade specific intercept term. As is required in the statistical literature on normal mixtures, we also impose a labeling restriction.

the direction of the effect of a variable on the exit rate out of school. So a negative estimate will typically imply a positive effect on expected grade completion, and in particular, on the probability of reaching higher education.

4.2 An Overview of the Different Model Specifications

In order to obtain a clear picture of the effect of risk aversion on school attendance, we first estimate a simple version of the grade transition model with 5 grade specific intercept terms and with a common set of parameters assumed to be constant across all grade levels (where $\beta_g' = \beta \ \forall g$). Subsequently, we estimated the more flexible version of the model where the regressors have separated effects by grade level. As noted earlier, this specification allows us to infer the differentiated impact of risk aversion by grade level.[23]

5 How Do Risk Aversion and Parents Background Variables Affect Grade Progression?

In this section, we concentrate on the discussion of the parameter estimates of the grade transition model. We report that the effect of risk aversion varies at different grade levels: continuation probabilities decrease with risk aversion until high school grade and increase with risk aversion for college and post-graduate studies. We also stress that the range of higher education participation probabilities spanned by the 10th-90th percentile range of the risk aversion measure is much smaller than the differences between the two heterogeneity types and, especially, between the children of educated and low-educated parents.

5.1 The Effect of Risk Aversion

5.1.1 Single Effect Model

In the single effect model, we find that those individuals who attach a higher value to the lottery (those who are less risk averse) tend to have a lower grade termination rate. Table 3 shows the estimates of the effect of the value of the

[23] The estimations are performed using a FORTRAN program. However, they are easily doable using standard econometric softwares such as SAS or STATA.

lottery bet on the termination rate for both the model with one single level of schooling and the model where risk aversion is allowed to have a different effect at the five different levels. The estimate, equal to -0.304, is highly significant, and therefore indicates that more risk averse individuals obtain less schooling. This is in agreement with conventional wisdom. However, we do not know of any comparable results, where the degree of schooling selectivity is directly tied to an observable measure of risk aversion, in the empirical literature.[24]

5.1.2 Flexible Model

In the flexible model specification, it is possible to investigate the dynamic effects of risk aversion. Indeed, the results indicate that it is relevant to differentiate between lower and higher grade levels. While risk aversion is negatively associated with continuation probabilities at low grade levels, we note that the effect of the value of the lottery bet on the termination rate is positive (i.e. the less risk averse get less schooling) at high levels of schooling (level 4 and 5). These results seem to be consistent with a view of schooling as an insurance at higher grades and a risky decision at lower grades.

5.2 Parents Background Variables

As documented in many empirical studies, grade termination is lower for those whose parents have achieved higher education. Table 4 shows the coefficients on parents' education in both the models with one level of schooling and the model where parents' education is allowed to affect differently the termination rate at each schooling level. In the model with one schooling level, the parameter estimates for father's and mother's education are equal to -2.02 and -1.28 respectively and imply that school continuation probabilities raise with parents' education. The second column of Table 4 shows that parents' education affects negatively grade termination at all level of schooling, from elementary schooling (level 1) to post-graduate schooling (level

[24] For instance, in the theoretical model of Lehvari and Weiss, this relationship would be derived from differentiating the expected utility of staying in school with respect to a measure of concavity of the utility function. In Belzil and Hansen (2004), the effect of risk aversion on schooling is obtained upon differentiating the school attendance probability (involving a closed-form solution to the value function) with respect to a parameter representing absolute (or relative) risk aversion.

5).

5.3 Individual Heterogeneity

The results obtained for individual heterogeneity are found in Table 5. The importance of unobserved heterogeneity is readily seen from the support point estimate for type 2 individuals (-0.28) along with the type 1 probability equal to 0.06. This implies that the population is clearly split between a high schooling attainment (low hazard rate) sub-population made of type 2 individuals, and a lower schooling attainment (higher hazard rate) sub-population made of type 1 individuals. The second column of Table 5 shows the estimates of the support point in the model where individual heterogeneity is allowed to affect separately the different grades.

Among the other coefficients, not shown for reasons of space, we find that grade continuation is also higher for those who have a parent who worked in a white collar occupation. As expected, we find that individuals living in the North (the most economically developed region of Italy), when compared to those who live in central regions, obtain more schooling. Finally, both females and younger cohorts appear to have lower grade termination rates. However, given the objectives of the paper, these estimates do not raise immediate interest and we do not discuss them in detail.

6 How do Differences in Risk Aversion Compare with Family Background Variables and Unobserved Heterogeneity?

Tables 3, 4 and 5 show the coefficient estimates on the risk aversion and parental background variables and on unobserved heterogeneity. However the non-linearity of the model is preventing to see the clear effects that both the risk aversion measure and other attributes may have on schooling transition probability. In order to fix ideas, it is useful to compute average grade termination (hazard) rates over the relevant range of the risk aversion heterogeneity variable. To get a clear picture, we report the average hazard rates at the 10th and the 90th percentiles of the risk aversion variable. The 10th percentile of the risk aversion variable corresponds to the 90th percentile of the value attached to the bet, in the same way the 90th percentile of the risk aversion variable corresponds to 10th percentile of the value of the bet. These estimates are found in the left-hand side of Table 6. They illustrate clearly the weak effect of risk aversion on grade termination. As an example, the average probability of terminating at grade level 4 (i.e. just before entering higher education) fluctuates between 0.666 for someone endowed with a low value for the risk aversion indicator and 0.661 for someone at the 90th percentile. The equivalent ranges are slightly higher and of a different sign for the lower education level 3 and level 2 and for the higher education level 5, but they remain small.

For a sake of comparison, we perform a similar exercise with the distribution of unobserved heterogeneity and parental education. As our estimation procedure splits the population into two types according to unobserved heterogeneity, it is easy to compute an average hazard rate for each type of individuals, and for each grade level. This will allow us to obtain a relative measure of the importance of preference heterogeneity as opposed to ability heterogeneity. The same can be done with parental education.

The type-specific and parental education-specific grade termination rates are found in Table 6. The difference in probability of stopping school between type 1 and type 2 exceed the difference recorded between the 10th and 90th percentiles of the risk aversion measure at most grade levels. The difference in probability of stopping at grade level 4 (just before entering higher education) between type 1 and type 2 individuals is around 10 times larger than for the 10th/90th percentile difference. The difference in probability of stopping school between individuals whose parents have an high school or higher education and those whose parents have less than an high-school degree exceeds by far the difference recorded between the 10th and 90th percentiles of the risk aversion variable. The difference in probability of stopping at grade level 4 is around 50 times larger between the children of the high educated and of the low educated parents than for the 90/10 percentile difference in risk aversion.

Schooling decisions appear to be overwhelmingly dominated by parental education differences (and less by skill differences) as opposed to differences in attitudes toward risk. At this stage, there is clear evidence that schooling attainments are much more affected by differences in parental background (and less by individual heterogeneity) than by differences in attitude toward risk.

7 Comparing our results with the Existing Literature

Overall, our results are qualitatively consistent with those reported in the literature, and obtained for the US. In particular, the positive correlation between individual schooling attainments and parents education is well established in simple correlation analysis, in reduced-form dynamic models such as Cameron and Heckman (1998, 2001) as well as in structural dynamic models such as Eckstein and Wolpin (1999) and Belzil and Hansen (2002). At the same time, these studies also point out that permanent unobserved heterogeneity, which may represent unobservable factors such as individual specific taste for schooling, academic ability, motivation, or any other unobservable trait which is time-invariant, is indeed the major determinant.

However, it should be noted that our estimates indicate that the role of parents' education is much higher than what is typically found for the US.[25] Our findings suggest a more modest role for unobserved abilities and tastes.

It is also interesting to compare our results with those reported in a somewhat related literature that uses smoking behavior as an instrument for schooling, in order to estimate the return to schooling.[26] The first stage regressions often indicate that schooling is inversely related to smoking behavior. In the literature, this finding is often interpreted as evidence that risk averse individuals (those who smoke less), or individuals with higher discount rates, obtain more schooling. To the extent that risk aversion is a key determinant of smoking behavior, our results are consistent with these findings only at higher grade levels (before entering college).

However, it should be noted that smoking is an endogenous variable, which is likely to be affected by several factors including intrinsic taste for smoking, parents' background (including education), teenage schooling attainments (performance in school) and other individual specific factors such as risk aversion and discount rates. It is therefore not certain that changes in schooling induced by smoking differences are solely due to risk aversion and,

[25]For instance, an estimate of the variance decomposition indicated that more than 80% of the variation in school continuation probabilities explained by the model, is indeed explained by parents' education.

[26]Fersterer and Winter-Ebmer (2003), Chevalier and Walker (1999) and Evans and Montgomery (1994).

therefore, that standard assumptions (such as monotonicity and homogeneity) made in the IV literature would be valid in this context. Our results, on the other hand, illustrate a marginal effect of risk aversion, holding all other factors constant. They are certainly not incompatible with the hypothesis that young individuals coming from poorer background and less educated families tend to smoke more (given a fixed degree of risk aversion).

8 Concluding Remarks

In this paper, we present evidence that the relationship between risk aversion and schooling is negative at lower levels of schooling (up to high school grade) and reverts to positive for college and higher degrees. This is consistent with the view that college education may be seen as an insurance. Importantly, we show that, despite a statistically significant effect, differences in attitudes toward risk are not that important. Unobserved persistent factors and most of all family human capital play a substantially larger role.

While interesting, these answers deserve some interpretation and also raise one fundamental question; Why is the level of risk associated to schooling, as perceived by individuals, so small?

One possible answer is that despite the intrinsic risk faced by those who decide to enter higher education, workers may have the perception that schooling reduces wage (or earnings) dispersion. In other words, young individuals regard schooling as an insurance and the marginal risk associated to higher grade enrollment is small. If this is true, it would be interesting to see if this is specific to Italy only or if this may extend to other countries.

There is another possible answer. It is conceivable that entering higher education may preserve the option value of choosing occupations, sectors or jobs (firms) which are characterized by stable and safe earnings profiles. In other words, the relevant decisions that involve differences in attitudes toward risk are occupation and/or sectoral employment choices. If these choices are made posterior to the decision to enter higher education, schooling decisions, as such, will not reveal selectivity based on differences in risk aversion.

While we believe that the analysis presented in this paper is interesting in its own right, we recognize that answering these questions would be important. However, it would require a more sophisticated analysis and access to similar data from other countries. This may be an interesting, but challenging, avenue for future research.

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Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
bet	3288	2513.083	4798.066	1	100000
edu1	3288	0.006	0.078	0	1
edu2	3288	0.103	0.304	0	1
edu3	3288	0.320	0.467	0	1
edu4	3288	0.305	0.460	0	1
edu5	3288	0.238	0.426	0	1
edu6	3288	0.028	0.165	0	1
edu_father	3288	0.116	0.321	0	1
edu_mother	3288	0.073	0.260	0	1
north	3288	0.388	0.487	0	1
centre	3288	0.168	0.374	0	1
south	3288	0.443	0.497	0	1
female	3288	0.198	0.399	0	1
bc_father	3288	0.398	0.490	0	1
wc_father	3288	0.207	0.405	0	1
se_father	3288	0.361	0.480	0	1
u_father	3288	0.033	0.180	0	1
bc_mother	3288	0.089	0.285	0	1
wc_mother	3288	0.045	0.209	0	1
se_mother	3288	0.094	0.291	0	1
u_mother	3288	0.771	0.420	0	1
age45more	3288	0.609	0.488	0	1

Table 2: The Individual Specificic Value Attached to the Lottery: The Distribution of Bet

Deciles	*bet* (1,000 liras)
1	50
2	100
3	500
4	1000
5	1000
6	2000
7	3000
8	5000
9	5000

Table 3: Estimates of the Effect of the Lottery Value on Grade Termination

	Number of levels	
	1	5
bet_i (all levels)	-0.3047	
	(0.0420)	
bet_i (level 1)		-0.3443
		(0.0627)
bet_i (level 2)		-0.8919
		(0.0877)
bet_i (level 3)		-0.5656
		(0.0782)
bet_i (level 4)		0.1034
		(0.0642)
bet_i (level 5)		1.8825
		(0.1212)

Notes: level 5= post-graduate, level 4= graduate, level 3= high school, level 2 = middle school, level 1 = elementary school. Asymptotic standard errors in brackets.

Table 4: The Effect of Parents' Education

		Number of levels	
		1	5
edu_father	(all levels)	-2.0267	
		(0.1522)	
edu_mother	(all levels)	-1.2831	
		(0.1327)	
edu_father	(level 1)		-1.1615
			(0.0861)
edu_mother	(level 1)		-0.0113
			(0.1004)
edu_father	(level 2)		-8.7726
			(0.9039)
edu_mother	(level 2)		-7.3562
			(0.5819)
edu_father	(level 3)		-1.8180
			(0.1421)
edu_mother	(level 3)		-0.8614
			(0.1109)
edu_father	(level 4)		-2.1339
			(0.3054)
edu_mother	(level 4)		-1.2720
			(0.2135)
edu_father	(level 5)		-0.3717
			(0.0852)
edu_mother	(level 5)		-0.6814
			(0.1087)

Notes: level 5= post-graduate, level 4= graduate, level 3= high school, level 2 = middle school, level 1 = elementary school. Asymptotic standard errors in brackets.

Table 5: Unobserved Heterogeneity Parameter

	Number of levels	
	1	5
$\alpha_2\theta_2$ (all levels)	-0.2814	
	(0.0810)	
$\alpha_{21}\theta_2$ (level 1)		-1.3261
		(0.1948)
$\alpha_{22}\theta_2$ (level 2)		-0.2641
		(0.0781)
$\alpha_{23}\theta_2$ (level 3)		-0.2591
		(0.0707)
$\alpha_{24}\theta_2$ (level 4)		-0.9788
		(0.1199)
$\alpha_{25}\theta_2$ (level 5)		-1.2020
		(0.1430)
prob(type 1)	0.0634	0.2936
	(0.0027)	(0.0367)

Notes: prob(θ_1) is the type-specific population proportion and θ_2 is the support point ($\theta_1$is normalized to 0). Level 5= post-graduate, level 4= graduate, level 3= high school, level 2 = middle school, level 1 = elementary school. Asymptotic standard errors in brackets.

Table 6: Average termination probability by grade level, for different values of risk aversion, heterogeneity type and parents education

	Risk Aversion		**Unobs. Het.**		**Parents Educ.**	
	10th	**90th**	**Type 1**	**Type 2**	**low**	**high**
level 1	0.0299	0.0393	0.1035	0.0091	0.0176	0.0011
level 2	0.4543	0.5585	0.5554	0.4955	0.3049	0.0000
level 3	0.5152	0.5729	0.5820	0.5305	0.5608	0.0950
level 4	0.6666	0.6616	0.7246	0.6394	0.7248	0.2104
level 5	0.9335	0.8560	0.9531	0.8662	0.8830	0.7492

Notes: The 10th and the 90th percentile of risk aversion correspond respectively to the 90th and the 10th percentile of the lottery value. High parents' education is high school or higher. Level 5= post-graduate, level 4= graduate, level 3= high school, level 2 = middle school, level 1 = elementary school.