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Abstract: Using unique Italian panel data in which individual differences in attitudes toward risk are measurable (from a lottery pricing question), we investigate the effect of the individual specific time invariant risk aversion factor on the probability of entering higher education. Apart from the risk aversion factor, absolute risk aversion depends on various state variables (wealth, liquidity constraints, back- ground risk) and is assumed to be measured with non-classical error. We also take into account the endogeneity of the response to the risk aversion question, as well as potential non-classical measurement error in wealth. All model specifications point out to the fact that individual specific risk aversion acts as a deterrent to higher education investment.

Keywords: Risk Aversion, Ex-ante risk, schooling, subjective beliefs, dynamic discrete choices.

JEL Classification: J24.

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1 Introduction

This paper addresses the following question: assuming a homogeneous level of risk or uncertainty across agents, does individual risk aversion increase or decrease the probability of attending higher education? In other words, is education a risky investment, or an insurance? Until now, the empirical literature on the determinants of schooling decisions has focussed almost entirely on the importance of (i) cognitive skills, (ii) parents' background, and to a lesser extent, (iii) liquidity constraints. For the most part, fundamental preference parameters such the preference for risk or the rate of time preference have either been ignored, or treated within a representative agent framework.

In order to answer this question, we develop a methodology aimed at measuring differences in school continuation probabilities, conditional on an individual-specific risk aversion factor. Using unique Italian panel data (the Bank of Italy Survey of Income and Wealth) in which individual differences in attitudes toward risk are measurable (from a lottery pricing question), we construct the classical Arrow-Pratt measure of absolute risk aversion, and we develop a reduced-form econometric model of sequential schooling decisions.[1] Because the Arrow-Pratt measure is posterior to schooling decisions (it is measured in 1995), it depends on current wealth (also measured in 1995), which is endogenous, as well as liquidity constraints and background risk indicators. We also allow to be affected by non-classical measurement error.

Italy is an ideal country to investigate the effect of preference (for risk) heterogeneity since liquidity constraints are unlikely to be relevant (Checchi, Fiorio and

[1] Because we do not model how subjective distributions are inferred, or do not force individuals to know the true effect of education on the higher moments of the distribution of post-schooling outcomes, our approach is different from structural dynamic expected utility models, in which Bellman equations are solved explicitly, for a given set of beliefs. Keane and Wolpin (1997) is the seminal piece in the structural literature on schooling. See Belzil (2007) for a comprehensive survey of the literature.

Leonardi, 2008; Leonardi, 2007). In particular, college education is not as expensive as in other countries (tuition costs in public universities are around 1,000 US dollars per year at 1995 constant prices and still unchanged in real terms), private schools are not popular and direct costs are low because of geographical reasons, and because a very large proportion of college students live with their family of origin (see the Table 1 in the Appendix).

Our method is based on two fundamental assumptions; namely that preferences are time invariant (there must exist an individual specific, time invariant, risk aversion parameter, which characterizes individual preferences), and that individuals share common beliefs about the effect of education on marginal risk exposure. More specifically, we assume that measured absolute risk aversion is composed of two (separately additive) parts; one containing the effect of wealth, background risk and the individual-specific time-invariant risk aversion factor, and a residual non-classical measurement error component. As the incidence of non-response to the risk aversion question is important, we must model self-selection explicitly. To do so, we assume that both measured risk aversion and the response/non-response outcome may depend on various measures of the quality of the interview, and on unobserved heterogeneity possibly correlated with (i) the individual-specific time-invariant risk aversion parameter, and with (ii) unobserved heterogeneity affecting grade transition.

In order to allow for non orthogonality between the individual specific risk aversion parameter and wealth, we also model the distribution of wealth as a function of the risk aversion parameter, schooling, parents backgrounds, and various instruments affecting the transitory part of wealth (Guiso and Paiella, 2008). Different approaches to the interpretation of the wealth equation error term (whether it is interpreted as random fluctuations, or measurement error) provide us with the opportunities to estimate three versions of our model.

Given identification of the individual specific risk aversion parameter, we infer the subjective effect of continuing to a higher grade level on marginal risk exposure, from the estimated effect of the risk aversion parameter on the decision to attend higher education. To this extent we model explicitly unobserved heterogeneity affecting grade transition (the decision to attend higher education), and we allow it to be correlated with individual-specific risk aversion.

Finally we estimate the model separately for the cohorts born before and after 1950 because the younger cohorts were affected by the extension of compulsory schooling and the liberalization of access to universities which may have changed their perception of the risk attached to college education (see section 3).

Our econometric model is based on four separate components. Precisely, it maximizes the joint (mixed) likelihood of (i) educational choices, (ii) measured absolute risk aversion, (iii) observed wealth and (iv) the response/non-response outcome to the lottery question. For flexibility purposes, all idiosyncratic error terms are modeled using mixtures of normals. Obviously, the high degree of flexibility comes at the cost of parameter proliferation. Our contribution is therefore also methodological. For instance, our method could be used on a variety of data sets that incorporate some imperfectly measured information on individual risk preferences, such as the GSOEP (for Germany), and the PSID and the NLSY (for the US).

At the outset, it should be made clear that modeling grade progression as a function of individual specific risk aversion is not new.[2] Indeed, it is achieved in an earlier paper (Belzil and Leonardi, 2007). However, in that paper, grade progression is made function of the observed risk aversion measure. The paper therefore ignores (i) the endogeneity of risk aversion (because wealth is endogenous), (ii) the incidence of non-classical measurement error in the risk aversion measure, (iii) the

[2] Modeling schooling attainment as a transition (discrete duration) model is achieved in a seminal piece by Cameron and Heckman (1998).

possible correlation between wealth and risk aversion factor, and (iv) endogeneity of the response rate.

To our knowledge, this is the first empirical paper that finds both an explicit and a significant effect of risk aversion on the probability of entering higher education. Precisely, in all model specifications, risk aversion acts as a deterrent to higher education investment, conditional on senior high school completion. Although the relative importance of risk aversion (compared to parents' education) may vary across models, our results indicate clearly that risk aversion is a key determinant of the probability to continue to higher education. Indeed, after conditioning on access to senior high-school (the grade level preceding higher education in Italy), we find that individual risk aversion is almost as important as parental education in explaining access to higher education. We find no substantial difference across cohorts born before and after the liberalization of college access in Italy.

The paper is constructed as follows. In Section 2, we present some background material and review the most important literature. In Section 3, we present a brief description of the Italian schooling system. In Section 4, 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 and sample selection. The econometric model is described in Section 5. The main empirical results are in Section 6 and robustness exercises in Section 7. The economic interpretation of the results, along with the conclusion, are found in Section 8.

2 Background and Relevant Literature

Measuring the relationship between risk attitudes and educational choices is a long standing problem in economics. Early theoretical results (Lehvari and Weiss, 1974, and Olson, White and Sheffrin, 1979) stress that earnings uncertainty may depress human capital investment, but empirical work remains scarce and is rather inconclusive. This is largely explained by two main issues.

First, there is a multiplicity of channels by which schooling may affect risk exposure. Some of these may come from the supply side and have to do with the possibility of experiencing academic failure. Others come from the demand side, and have to do with the effect that education may have on earnings fluctuations and volatility.[3] In the long run, labor market productivity and earnings may be affected by technological changes, which 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 is a form of insurance). For all these reasons, it is difficult to say whether or not individuals perceive higher education as a truly risky investment, or as a form of insurance.

Second, accounting for heterogeneity in risk attitudes is still nowadays a major challenge for applied econometricians. In particular, individual differences in risk aversion are practically never measured in observational data. Furthermore, when such measures exist, they are available for time periods over which major schooling decisions have already been taken.

Taken broadly, the current paper may be viewed as a contribution to the literature devoted to the identification of the main determinants and barriers to educational attainment. In order to get a clear picture, it is useful to divide the literature into three distinct groups.

A first group of papers has documented the significant and stable correlation be-

[3]Focussing on the supply side, higher education requires to face both direct and psychic costs while academic success may have an inherent random component. On top of this, uncertainty about labor market abilities may also represent a form of ex-ante risk. At the same time, schooling may reduce earnings dispersion by reducing the incidence of unemployment 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 (or marginal product) is more volatile.

tween schooling attainments and parents' education, as well as a strong correlation between schooling attainments and parental income. These empirical regularities, which have not only been reported by economists, but also by many sociologists, are well documented in many countries (Cameron and Heckman, 1998). This branch of the literature is well known and need not be discussed further.

A second group is composed of papers devoted to the investigation of liquidity and borrowing constraints that may affect education choices (Cameron and Taber, 2004, and Keane and Wolpin, 2001). To a large extent, the main objective of this literature is to provide an economic foundation to the observed correlation between education and parental income. As this is not the topic of the current paper, we do not review it in details. It is however important to note that in this literature, which is surveyed in Keane (2002), it is customary to assume that all individuals share a common risk aversion parameter, but that they face different degrees of liquidity constraints because of differences in parental income or parental transfers. One of the most important consequences of allowing for liquidity constraints, is that individuals who are subject to liquidity constraints react differently to changes in the direct cost of higher education than those who can more or less borrow freely. As of now, it is fair to say that there is very little evidence supporting the liquidity constraints hypothesis. In Keane and Wolpin (2001), the weak incidence of liquidity/borrowing constraints is largely explained by the allowance for an endogenous labor supply while in school. In Cameron and Taber (2004), it comes out from the lack of significant difference between IV estimates of the return to schooling using a direct cost instrument and those obtained using an opportunity cost instrument. It is important to note that in this segment of the literature, individual differences in risk preference are totally ignored.

A third set of papers is concerned with the explicit role that risk aversion and risk exposure may play in schooling decisions. This is the focus of our paper.

Shaw (1996) develops a model of the joint investment in financial wealth and human wealth to show that human capital investment is an inverse function of the degree of relative risk aversion, but does not address the endogeneity issue between education and risk aversion and does not attempt to measure an individual specific risk aversion factor[4]. Palacios-Huerta (2003) presents an empirical comparison of the properties of risk-adjusted rates of return to schooling within an intertemporal model, using mean-variance spanning techniques, but does not model individual decisions.[5] Belzil and Hansen (2004) estimate a dynamic programming model of schooling decisions in which the variance of the earnings distribution depends on accumulated human capital. They fit their model on a sample taken from the NLSY 1979 but, for technical reasons, they disregard heterogeneity in risk aversion.

Although each of these papers have investigated at least one aspect of the relationship between risk, earnings uncertainty, and schooling, they also disregard heterogeneity in attitudes toward risk.[6] More recently, several economists have tried to use directly (or indirectly) observable measures of individual risk aversion and relate cross-sectional dispersion in risk aversion to observed schooling choices. This literature is currently in its infancy. Until now, those who have used this

[4]Using data from the Survey of Consumer Finances, Shaw (1996) finds that wage growth is positively correlated with preferences for risk taking. She measures individual-specific risk aversion using information on the allocation of wealth to risky financial assets or from a survey question about that desired allocation. She also finds that more educated individuals are also more likely to be risk-takers.

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

[6]There also exists a related literature in which descriptive analyses of empirical age/earnings profile have been performed. In the earlier empirical literature, Mincer (1974) investigates how the variance of earnings differs across schooling levels over the life cycle while Chiswick and Mincer (1972) use age earnings profile to investigate time series changes in income inequality. However, the notion of variability is usually an "ex post" notion which may have little to do with "ex ante" risk. In the more recent wage inequality literature, it is customary to analyze wage dispersion (basically the variance) within education groups. Lemieux (2006) shows that the variance of wages is higher within the more educated group and discusses the increase in college enrollments that took place during the period over which rising wage inequality has been documented for the US.

approach have ignored the endogeneity of most risk aversion information. The most important complications hinge on the fact that risk aversion measures, obtained from self-reported survey items such as lottery pricing and the like, (i) are usually available after schooling decisions have been exercised, (ii) are most likely subject to (non-classical) measurement error, and (iii) are often characterized by a high rate of non-response. This is exemplified in Belzil and Leonardi (2007), in which a grade progression function is specified conditional on an observed transformation of the lottery pricing, regardless of endogeneity issues.[7]

As it stands now, the relationship between risk preference and education is unknown.[8] Nevertheless, and as indicated by the recent surge in empirical papers devoted to the issue, the link between risk and education is now regarded as an important topic.[9] Knowing the degree of education selectivity based on individual differences in risk aversion is fundamental. For instance, the relatively insignificant change in college enrollment that has been observed in the 1990's after the increase in returns to schooling that took place over the 1980's in the US (and in other countries) suggests that behavior toward risk may be a possible explanation.[10]

3 The Schooling System in Italy

The Italian schooling system is composed of four levels: elementary, lower high school, upper high school and college. Elementary school is typically completed at age 11 (equivalent to 5th grade in the US), lower secondary school at age 14

[7]However, in the final section of Belzil and Leonardi (2007), we stress that a more rigourous treatment of risk aversion endogeneity, non-classical measurement error, wealth endogeneity, and possibly non-response endogeneity is called for.

[8]More recently, a literature concerned with the separation of ex-ante risk and heterogeneity in schooling decisions has also emerged. Cunha, Heckman and Navarro (2005) and Belzil (2007) are two representative examples.

[9]See for instance the special issue of Labour Economics, 14(6), 2007.

[10]A descriptive analysis of college enrollment trends in the US is presented in Card and Lemieux (2000). A structural general equilibrium analysis is found in Johnson and Keane (2008).

(equivalent to 8th grade), upper high school at age 19 and college at age 23-24. Our study looks at the effect of individual-specific, time-invariant risk aversion on the decision to continue after senior high school and enroll in college. We estimate the effect of risk aversion separately for the cohorts born before and after 1950 because they were differently affected by two education reforms which may have an effect on their decision to go to college.

For the period under consideration the compulsory schooling was elementary school until 1962 and lower secondary afterwards i.e. the reform of the compulsory school leaving age affected the cohorts born after 1950. Table 1 lists the education variables in form of dummies of the highest attained degree. The change in compulsory schooling laws largely explain the increase in education attainment across cohorts. Among those born before 1950, a high percentage of individuals stopped at elementary school (37%). The proportion of those who stop at elementary school drops dramatically within the cohort born after 1950 to 9% in Table 1 and the proportion of those who stop at lower secondary school increases to 38%.[11] The reform of compulsory schooling in 1962 does not need to have direct implications on our analysis because we look at the effect of risk aversion only on the decision to continue to college education and neglect its effect on compulsory schooling levels. However it is possible that the risk attached to the choice of continuing schooling after high school was perceived differently by the cohorts born before 1950 whose compulsory schooling stopped at the elementary grade and by later cohorts whose school leaving age was moved forward to lower high school grade.

We have another reason to analyze separately the cohorts born before and after 1950: the restrictions to access to college were lifted in 1969 and affected the cohorts born after 1950 which at the time were aged 18-19. An easier access to university may have led to changes to the perception of risk attached to college. In

[11] The fraction (not equal to 0) of people born after 1950 reporting elementary school as the highest attained degree may be due to non-compliance or to grade repetitions.

Italy there are four types of 5-year secondary schools: Liceo, technical, vocational schools or art schools and schools for teachers. Liceo are the traditional high schools to access university level education and until 1969 access to college was restricted to these schools. All other choices (technical, vocational schools or art schools and schools for teachers) develop professional and technical skills and only after 1969 give also an optional access to university.[12] Table 1 shows that the percentage of the population with a college degree is much lower in Italy (10%) than in the US and that a large fraction (31%) of the Italian population holds a secondary school degree. Notwithstanding the easier access to university granted after 1969, the proportion of college graduates in the population in Italy is still very low (12%) even in the younger cohorts born after 1950.

4 The Bank of Italy Survey of Income and Wealth

The 1995 survey of SHIW collects information on consumption, income and wealth in addition to several household characteristics for a representative sample of 8,135 Italian households.

4.1 Measuring Risk Aversion

The 1995 survey contains a question designed to elicit risk aversion attitudes. 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

[12] After lower secondary school, one may also choose professional 3-years courses which do not grant access to university but provide skills for determined professions. In our data these are coded as lower secondary.

amount of 10 million lire (roughly 5,000 euros) 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, 3,483 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 and are coded as non response as typically in this kind of questionnaires zero usually indicates that they do not know responses).

The question has a large number of non responses because many respondents may have considered it too difficult. For our purposes the relationship between non-response and schooling is of particular interest. Those who responded to the lottery question are on average 6 years younger than the total sample and have higher shares of male-headed households (79.8 compared to 74.4 percent), of married people (78.9 and 72.5 percent respectively), of self-employed (17.9 and 14.2 percent) and of public sector employees (27.5 and 23.3 percent respectively). They are also somewhat wealthier and slightly better educated (1.3 more years of schooling). The difference in education between the total sample and the sample of respondents seems to suggest that, in so far as education is also a proxy for better understanding, non-responses can be ascribed partly to differences in the

[13] In other words, the expected value of entering the lottery is $0.5 \cdot (5000 - bet)$ becuase with probability 1/2 the respondent gets 5,000 euros and with probability 1/2 he loses his *bet*. 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. Guiso and Paiella (2008) 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, the ratio of the expected gain of the hypothetical lottery (5,000 euros) 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 (Rabin, 2000).

ability to understand the question. Therefore, because non-responses may induce selection bias, we model the response probability directly. To this extent, we assume that the probability of responding to the lottery question may depend on various measures of the quality of the interview given by the interviewer, on education, and on other exogenous individual characteristics (see section 5.2).

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 wealth w_i, and a potential gain $g_i = 5000$ euros, the optimal bet bet_i, must solve the expected utility equation:

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

where P_i represents the return (random) of the lottery.

One way to derive a measure of the implied risk aversion would be to take a second-order Taylor expansion of the second equality in equation 1 around w_i and then obtain an estimate of the Arrow–Pratt measure of absolute risk aversion in terms of the parameters of the hypothetical security of the survey:

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

It is therefore possible to express risk aversion as a function of the parameters of the lottery and the value of the bet of each individual. Substituting 2 into 1, we obtain the following expression for the Arrow-Pratt measure of absolute risk aversion (Gollier, 2001):

$$A_i(w_i) \simeq \frac{-U_i''(w_i)}{U_i'(w_i)} = 2(5000 - bet_i)/(5000^2 + bet_i^2) \tag{3}$$

In general, the degree of absolute risk aversion $A_i(w_i)$ 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 (0.5 euros) to 100 million lire (50,000 euros), in equation 3 the variables are in euros. Of the 3,483 heads with a positive *bet*, 3,358 have an $A_i(w_i) > 0$ which implies that they are risk averse individuals, 125 are risk neutral and 44 are risk lovers. 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.[14]

An alternative way to measure risk aversion (pursued in the robustness Section 7), implies the assumption of a specific functional form for the utility function such that the coefficient of absolute risk aversion tends to infinity as the maximum reported price tends to zero. Following Belzil (2007) and Guiso and Paiella (2008), we use the exponential utility to compute the implied absolute risk aversion for each individual in the sample:

$$-\exp(-R_i w_i) = -\frac{1}{2}\exp(-R_i(w_i + 5000)) - \frac{1}{2}\exp(-R_i(w_i - bet_i)) \tag{4}$$

Equation 4 uniquely defines the Arrow–Pratt measure of absolute risk aversion in terms of the parameters of the hypothetical security of the survey. Obviously, $R(w_i) = 0$ for risk-neutral individuals (i.e., those reporting $bet_i = 5000$ euros) and $R(w_i) < 0$ for risk-loving individuals (those with $bet_i > 5000$ euros).

It is important to note that both measure of risk aversion are unlikely to be a perfect indicator of the true individual specific risk aversion parameter. For

[14] 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. The problem with this approach is that the risk aversion at low levels of the price bet_i is underestimated, because as bet_i approaches zero, this measure of $A_i(w_i)$ tends to 0.2, whereas the true measure of risk aversion tends to infinity.

instance, the answers may be affected by some contextual measurement error, or by background risk, liquidity constraints and the like. For this reason, the econometric model must be designed so to avoid estimating a grade transition model that depends directly on either of these measures. These issues are discussed in details in Section 5.[15]

4.2 Wealth

Since absolute risk aversion $A_i(w_i)$ is measured posterior to the schooling choice (in 1995), we need to model its dependence on current wealth, in order to extract the time-invariant individual-specific part of risk aversion (which we will denote as θ_i^{ra}). It is well known that wealthier individuals are also less risk averse, but also that accumulated wealth itself depends on risk aversion.

The SHIW data are particularly accurate in the measurement of household wealth. Wealth is defined as the total of financial and real assets net of household debt. Financial wealth is given by the sum of cash balances, checking accounts, savings accounts, postal deposits, government paper, corporate bonds, mutual funds and investment in fund units and stocks. Real assets include investment real estate, business wealth, primary residence and the stock of durables.

The SHIW data also provide various measures of "unexpected" changes in wealth. Following Guiso and Paiella (2008), we use information on the self-reported value of one's home property and the average price of housing in the province of

[15] This lottery question has been used to study the relationship between risk aversion and several household decisions. Guiso and Paiella (2006) 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.

residence to build a measure of windfall gains (or losses) on housing. This measure is constructed using data on house prices at the province level over the years 1980-1994. For homeowners, we compute the house price change since the year when the house was acquired or since 1980 if it was acquired earlier. To tenants, we attach a capital gain equal to zero. We model wealth using the capital gain on one's first house property and the sum of settlements received related to life, health, theft and casualty insurance. These variables are denoted *capitalgain house* and *insurance money* in Table 1. Older cohort born before 1950 have higher wealth, a higher average capital gain on their house but receive on average a lower amount of money in form of insurance settlements.

4.3 Background Risk and Liquidity Constraints

Apart from individual differences in wealth and from differences in utility function curvature, measured absolute risk aversion may also depend on background risk and from the presence of liquidity constraints. When markets are incomplete, risk aversion may vary not only because of heterogeneity in tastes but also because individuals face environments that differ in terms of background risk (Gollier, 2001). The measure of background risk is intended to be a measure of aggregate risk at the local level. It is obtained in the following way: For each province we regress the log of GDP per capita in 1980-1995 on a time trend and compute the variance of the residuals. We then attach this estimate (the variable *variance provincial gdp* in Table 1) to all households living in the same province.[16]

The presence of liquidity constraints may also affect risk aversion if they constitute an impediment to consumption smoothing. We build a direct measure of liquidity constraints as a dummy to indicate one of three types of constraints

[16] This variable is more likely to be exogenous rather than measures of the coefficient of variation of the distribution of future earnings based on subjective expectations like in Guiso, Jappelli and Pistaferri (2002).

(Guiso and Paiella, 2008). Discouraged borrowers and rejected loan applicants (3% of the sample) are people who answer yes to either of the following questions: "during the year did you or a member of the household think of applying for a loan or a mortgage to a bank or other financial intermediary, but then changed your mind on the expectation that the application would be turned down?" or "during the year did you or a member of the household apply for a loan or a mortgage to a bank or other financial intermediary and have it turned down?". We also defined as liquidity constrained people who belong to a family with liquid assets <1% of total assets (18% of the sample) and those with debt >25% of total net worth (6% of the sample). Overall the liquidity-constrained individuals constitute 30% of the sample (the variable *liquidity constraint* in Table 1).

4.4 Sample Selection

Apart from the lottery question used to build the measure of absolute risk aversion, 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 of Youth (NLSY). We eliminate from the original sample of 8,135 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. Due to the many missing observations on parents' education the final size of the sample is 7,563 (5,166 born before 1950 and 2,397 born after 1950).

Figure 1 shows the empirical distribution and the estimated kernel density of our measure of risk aversion $A_i(w_i)$ separately for the two cohorts. The distribution of risk aversion is more skewed to the right for the younger cohort, but the mean is approximately equal (the Kolmogorov-Smirnov test of equality of the distributions is rejected at the 1% probability level but the T test of equality of the means is accepted).

Figure 2 compares the distribution of absolute risk aversion among the college graduates and those individuals with a lower education degree. Basic summary statistics indicate clearly that college graduates are less risk averse on average. Although this negative correlation is consistent with conventional wisdom (namely that risk aversion is detrimental to higher education), it is not sufficient to establish the link between individual specific preferences and higher education for two main reasons; first, absolute risk aversion depends on wealth (which may vary with completed education), and second, the decision to enter college may be driven also by individual unobserved cognitive ability which may also be correlated with individual specific risk aversion. As will be clear later, we deal with this issue by modeling explicitly the role of individual heterogeneity in grade achievement (see section 5.5).

Table 1 shows the descriptive statistics of the sample. The original schooling variable takes five possible values (1 to 5) corresponding to no education, elementary school (typically attained at 11 years of age), junior high school (attained at 14), senior high school (attained at 18), university degree (attained at 23-24).[17] In the estimation we use five dummy variables derived from the original education variable, three dummies - north, centre and south - for the region of birth and one sex dummy (female=1). In addition we have one dummy each - *highschool father* and *highschool 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 each parents' occupation.

[17] We actually have information about post-university degree, but the number of individuals being too small, we cannot really estimate the transition to post-graduate studies.

4.5 Interview Quality

In order to allow for non-classical measurement error in our analysis, we make use of five dummy variables which indicate the quality of the interview. These variables are in Table 1. *No_ understand* is a dummy equal to 1 if, according to the interviewer, the level of understanding of the questionnaire by the head is poor or just acceptable (as opposed to satisfactory, good or excellent). *Difficult answer* is a dummy equal to 1 if, according to the interviewer, it was difficult for the head to answer questions. *No_ interest* is a dummy equal to 1 if, according to the interviewer, the interest for the questionnaire topics was poor or just acceptable (as opposed to satisfactory, good or excellent). *No_ reliable* is a dummy equal to 1 if, according to the interviewer, the information regarding income and wealth are not reliable. *No_ climate* is a dummy equal to 1 if, according to the interviewer, the overall climate when the interview took place was poor or just acceptable (as opposed to satisfactory or good).

All five variables indicate that the quality of the interview among the younger generation born after 1950 is on average better and the proportion of non-responses to the risk aversion question is much lower. The variable *response*=1 in Table 1 indicates that 62% of the cohorts born after 1950 responded to the risk aversion question while only 35% responded among the older generations born before 1950. Simple linear probability models estimated on each interview quality variable in turn, show that wealth, schooling, father's education and measured risk aversion are often significant predictors of those variables and constitute evidence that non-classical measurement error is likely to be important (see Table 2 in Appendix).

5 The Econometric Model

Our econometric model is based on four separate components. These are (i) the grade transition model, (ii) the response/non-response outcome model, (iii) the absolute risk aversion equation, and (iv) the wealth equation.

5.1 A Model of Grade Transition

We model schooling decisions as a reduced-form dynamic discrete choice model in which the hazard function (the drop-out rate) depends on measures of parental background, individual-specific heterogeneity and an individual-specific parameter measuring permanent risk aversion. We assume that individual specific risk aversion affects only the transition from high school to college because earlier transitions are more likely to be affected by parents' decisions.

The grade transition model may be regarded as the reduced-form of a sequential dynamic programming model, in which subjective beliefs are not specified by the econometrician. It is therefore faithful to our objective not to dictate how higher education affects the second (or higher) moment of future state variables, as perceived by the agent. This particular aspect of the grade transition model is the cornerstone of our econometric methodology.

The conditional probability (hazard rate) of stopping at grade g for individual i, denoted H_{gi}, is denoted:

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

where

$$U_{g,i} = \alpha_g \theta_i^S + \beta_g' X_i + \delta_g \theta_i^{ra} \tag{6}$$

and where G is the second highest grade level (senior high school), or in other words, the highest grade level at which continuation is possible. In our framework, $H_{G,i}$ is the probability of dropping out after having completed senior high school. Therefore, the probability of entering higher education is $(1 - H_{G,i})$. Similarly, $H_{G-1,i}$ is the drop out probability after completing junior high school. The term θ_i^S represents an individual-specific intercept term whose effect varies with grade level (according to parameter α_g). The variable θ_i^{ra} represents the permanent part of individual-specific risk aversion and δ_g is a grade-specific parameter. Further details on the treatment of unobserved heterogeneity are presented below. X_i is a vector of observable characteristics (parents' educational and occupational background, sex and region dummies), and β_g' represents a grade specific vector of parameters measuring the effects of these characteristics. Note that the model is general enough to take into account that the marginal effect of risk aversion may be positive or negative. In this paper we allow risk aversion to affect only the transition from high school to college.

$\Lambda(.)$ is approximated with a mixture of 5 normal random variables:

$$\Lambda(.) = \sum_{m=1}^{M=5} P_m^g \cdot \Phi(.; \mu_m^g, \sigma_m^g)$$

where P_m^g is the mixing probability and $\Phi(\mu_m^g, \sigma_m^g)$ denotes the normal cumulative distribution function with mean μ_m and variance σ_m^2.[18] Further details are presented in the Appendix.

[18]Because the grade transition model is actually a sequence of binary choices, we follow Geweke and Keane (2000), who advocate using normal mixtures in binary choices. Ferguson (1983) discusses the capacity of normal mixtures to approximate any distribution.

5.2 A Model of Non Response

As stated earlier, one of the key features of our analysis is the introduction of non-classical measurement error. This is achieved by conditioning on the full set of interview quality variables denoted by the vector Q. We therefore assume that the decision to respond or not depends on some individual characteristics (age, sex) in vector X^R.[19] In order to take into account selectivity, individual propensity to respond is affected by unobserved heterogeneity (θ_i^R), which is allowed to be correlated with individual-specific risk aversion (θ_i^{ra}), individual heterogeneity affecting grade transition (θ_i^S) and individual wealth measured in year 1995 ($Wealth_{i,95}$). Precisely, the probability of response is

$$\Lambda^R(\varkappa_X' X^R + \varkappa_W Wealth_{i,95} + \varkappa_Q' Q + \theta_i^R) \tag{7}$$

where

$$\Lambda^R(.) = \sum_{m=1}^{M=5} P_m^R \cdot \Phi(.; \mu_m^R, \sigma_m^R)$$

and where $(P_m^R, \mu_m^R, \sigma_m^R)$ are defined as those equivalent parameters introduced for grade transition.

5.3 Modeling Absolute Risk Aversion

As risk aversion information contained in the SHIW is posterior to the period when schooling decisions were made, we construct a non-linear factor model that allows to identify individual-specific permanent risk aversion.

We first specify a flexible model of the Arrow-Pratt measure of risk aversion, $A_{i,95}(.)$, where the subfix 95 (which we report only in this section for clarity reasons) indicates that risk aversion is measured in year 1995:

[19] We could also include parents education and occupation, but we found their effect so small that we decided to exclude them.

$$A_{i,95}(.) = \bar{A}_{i,95}(Wealth_{i,95}; Background\ risk_{i,95}; Liquidity\ constraints_{i,95}; \theta_i^{ra}) + \varepsilon_{i,95}^A \tag{8}$$

where $\bar{A}(.)$ denotes a second degree polynomial, and where $\varepsilon_{i,95}^A$ is an error term motivated by the presence of measurement error. Total measurement error ($\varepsilon_{i,95}^A$) depends on quality interview variables (Q) as well as a purely idiosyncratic error component ($\tilde{\varepsilon}_{i,95}^A$). That is

$$\varepsilon_{i,95}^A = \varepsilon_Q^{A\prime} \cdot Q + \tilde{\varepsilon}_{i,95}^A$$

where $\varepsilon_Q^{A\prime}$ is a vector of parameters measuring the effect of interview quality variables, and where he residual error term, $\tilde{\varepsilon}_{i,95}^A$, is distributed with density $f^A()$. Again, θ_i^{ra}, is the time-invariant degree of risk aversion, upon which, schooling decisions depend. The background risk and liquidity constraint variables are measured in 1995 and were described earlier in section 4.3.

5.4 Modeling Wealth

The wealth equation takes into account the key distinction between observed wealth ($obs.Wealth_{i,95}$), which is possibly be measured with error, and true wealth ($Wealth_{i,95}$), which is the relevant quantity from the perspective of the agent. Precisely, we have

$$\begin{aligned} obs.Wealth_{i,95} &= \gamma_X' X_i + \gamma_S' S_i + \gamma_Z' Z_{i,95} + \gamma_R \theta_i^{ra} + \varepsilon_{i,95}^W && (9) \\ &= \gamma_W' W_i + \varepsilon_{i,95}^W && (10) \end{aligned}$$

with

$$\varepsilon_{i,95}^{W} = \varepsilon_{Q}^{W\prime} \cdot Q + \tilde{\varepsilon}_{i,95}^{W}$$

where $\varepsilon_{Q}^{W\prime}$is a vector of parameters measuring the effect of interview quality variables, and where $\tilde{\varepsilon}_{i,95}^{W}$ is distributed with density $f^{W}(.)$. The vector of parameter, γ_X, measures the effect of parents' background variables on wealth while the vector of parameters γ_S allows us to detect if (or to what extent) wealth (and indirectly risk aversion) is explained by education of the individual (S_i is a vector of education dummies). The vector $Z_{i,95}$ contains a set of variables measured in 1995 which may explain the transitory part of risk aversion. These variables include the capital gain on house property and the amount of money received as insurance settlements.

To close the model, we approximate both $f^{A}(.)$ and $f^{W}(.)$ with a mixture of 5 unrestricted normal densities:

$$f^{s}(.) = \sum_{m=1}^{M=5} P_{m}^{s} \cdot \phi(.; \mu_{m}^{s}, \sigma_{m}^{s}) \text{ for } s = W, A \tag{11}$$

where $\phi(.; \mu_{m}^{s}, \sigma_{m}^{s})$ denotes the normal density with mean μ_{m}^{s} and standard deviation σ_{m}^{s}.

Different interpretations of the error term of the observed wealth equation ($\varepsilon_{i,95}^{W}$) will lead to different model specifications. In the paper, we consider three possible interpretations. There are described as follows.

- Model with both measurement error and random fluctuations in wealth

$$Wealth_{i,95} = \gamma_{W}' W_i + \tilde{\varepsilon}_{i,95}^{W} \tag{12}$$

- Model with measurement error only

$$Wealth_{i,95} = \gamma'_W W_i \tag{13}$$

- Model with exogenous wealth

$$Wealth_{i,95} = obs.Wealth_{i,95} \tag{14}$$

Throughout the paper, we focus the presentation on the model that incorporates both measurement error and random fluctuations, since it appears to be the most general (at least conceptually). The generality of this specification is obtained at the cost of assuming that measurement error is deterministic (explained solely by interview quality variables).

The second one imputes all the error term to measurement error. Although the relevant wealth equation has no error term, it is still endogenous from the perspective of the econometrician because it still depends on the unobserved risk aversion factor. Both model specifications assume non-classical measurement error in wealth.

Finally, the third one is the simplest specification. It is obtained assuming that observed wealth coincide with relevant wealth, and therefore enforces pure exogeneity of the wealth component. Estimating the third model will not require to estimate the likelihood of observed wealth

5.5 Heterogeneity

Because we have a relatively complicated non-linear factor structure, and we have only a limited number of measurements on risk aversion, the distribution of the time-invariant portion of risk aversion is difficult to identify. To perform estimation, we partition the domain of the permanent risk aversion factor into 8 points;

$$\{\theta_1^{ra} = -0.02, \theta_2^{ra} = 0.05, \theta_3^{ra} = 0.08, \theta_4^{ra} = 0.12, \theta_5^{ra} = 0.14, \theta_6^{ra} = 0.16, \theta_7^{ra} = 0.18, \theta_8^{ra} = 0.20\}$$

These points are chosen to cover the same region as the Arrow-Pratt measure obtained in 1995. These support points, along with their respective type probabilities, define the degree of heterogeneity in risk aversion.

To close the model, we assume that the heterogeneity components $\{\alpha_i^S, \theta_i^{ra}, \theta_i^R\}$ may be approximated by a tri-variate discrete distribution. We estimate the model with 8 types of individuals. Altogether, a type k is defined as the subset of the population endowed with $\{\alpha_k^S, \theta_k^{ra}, \theta_k^R\}$. The support points $\{\alpha_k^S, \theta_k^R\}$ are freely estimated.

5.6 Estimation

We estimate the model by maximum (mixed) likelihood techniques. For an individual who does not respond to the lottery, the contribution to the likelihood, L^{NR}, is simply

$$L_i^{NR} = \sum_{k=1}^{K} p_k \cdot (1 - \Lambda^R(. \mid type_k)) \tag{15}$$

The contribution to the likelihood for a respondent i, who has completed level g, who is endowed with a wealth level $Wealth_{i,95}$ and who reports a degree of absolute risk aversion $A_{i,95}(.)$, is denoted L_i^R, and is equal to

$$\begin{gathered} L_i^R = \textstyle\sum_{k=1}^{K} p_k \cdot [\Lambda^R(. \mid type_k) \cdot \Pi_{s=1}^{g-1} \cdot (1 - H_{s,i}(X_i \mid type_k))^s \cdot H_{g,i}(X_i, \mid type_k) \\ \cdot f^A(A_{i,95} - (\bar{A}_{i,95} \mid type_k)) \cdot \\ f^W(obs.Wealth_{i,95} - (\gamma_W' W_i \mid type_k))] \end{gathered}$$

where both $f^A(.)$ and $f^W(.)$ are given by equation 11.

6 Empirical Results

As there exists a large literature which documents the determinants of schooling attainment, we focus our discussion on the effect of relative risk aversion on grade transitions from senior high school to higher education. The actual and predicted drop-out rates at all schooling levels are found in Table 2. The predicted values are on the basis of the average values of the independent variables. The results show that the model predicts accurately the termination rates at all levels of schooling and in both cohorts (born before and after 1950). Since the extension of compulsory schooling to the junior high school level affected the cohorts born after 1950, the termination rates at schooling levels lower than junior high school is much lower in these cohorts.

6.1 The Effect of Non-Response

Before discussing the parameters, it is informative to examine the correlation between the heterogeneity term affecting the decision to respond θ_i^R, and other heterogeneity components (individual-specific risk aversion θ_i^{ra}, and grade transition heterogeneity θ_i^S). Those are found in Table 3. For both cohorts, the correlation between response heterogeneity and risk aversion heterogeneity is negative (-0.47 and -0.38). Taken as such, this indicates that self-selection is important, and in particular, that an analysis that would ignore the endogeneity of the response decision would lead to improper inference about individual risk aversion factor. The correlation between response and grade transition heterogeneity is also found to be important (-0.61 for the older cohort and -0.21 for the younger one).

Table 4 shows the parameters of the estimated response equation. The probability of responding increases with age (within cohort) and decreases with wealth within each cohort. Female head of households are less likely to respond. Most variables which indicate the (low) quality of the interview (the variables *no_ understand, difficult answer, no_ reliable, no_ interest* and *no_ climate* are explained in the Section 5.2) are negative and significant in the response equation in both cohorts except for the variable *no_ interest* (positive significant) and *no_ climate* (insignificant) in the equation of the older cohort. These results imply that the lower the quality of the interview, the lower the probability that they respond to the risk aversion question. Although education is not introduced as a determinant of the response equation, the incidence of response is increasing indirectly with education, through the effect of the interview quality indicators.

6.2 The Distribution of Individual Specific Risk Aversion and Measurement Error

In order to estimate the model, we must also estimate the distribution of the time-invariant part of the risk aversion measure (Table 5). This allows to separate the degree of absolute risk aversion measured in 1995 $A_{i,95}(.)$ into three different components, one component that depends on wealth and background risk, another component representing the time-invariant portion of risk aversion θ_i^{ra}, and a residual term capturing non-classical measurement error. It is therefore interesting to compare the distribution of this time-invariant risk aversion factor to the actual Arrow-Pratt measure inferred in 1995 and evaluate the importance of measurement error. In the last row of Table 5 we report the average values and the standard deviations of the absolute risk aversion factor for both cohorts. The estimates are equal to 0.1307 for the cohort born before 1950 and 0.1318 for the cohort born after 1950. The standard deviations (between 0.03 and 0.04) are also comparable across cohorts. When compared with the actual measure measured in 1995, the estimates are close to the mean and standard deviation of the observed Arrow-Pratt risk aversion measure (mean 0.147 and standard deviation 0.055 for the cohort born after 1950 and mean 0.15 and standard deviation 0.057 for the cohort born before 1950).

The correlations between the heterogeneity components (Table 3) indicate that individual-specific risk aversion is positively correlated with individual heterogeneity explaining grade termination for the older cohort (the correlation is close to 0.10). For the younger cohort, it is negative (-0.23). These correlations are also difficult to evaluate because there are practically no equivalent estimates in micro-econometrics.[20]

As is evident from the absolute risk aversion equation (Table 6), measurement error is found to be most important. The estimates for the effect of interview quality are all positive (when significant) and indicate that those who tend not to be in control during the interview appear to over-estimate their degree of risk aversion.

In total, we find that the variance of the error term is larger as the variance of the regression. Obviously, this high degree of measurement error explains the very weak correlation between risk aversion measures and grade completion reported in the empirical literature. Indeed, as reported in Belzil and Leonardi (2007), there is a very weak correlation between grade attainment and the betting price.

6.3 The Effect of Wealth and Background Risk on Absolute Risk Aversion

Because of the flexible polynomial structure of the absolute risk aversion equation, the effect of the variables are difficult to infer upon examination of the parameter estimates. To measure the marginal effect, we computed a predicted absolute risk

[20]Dohmen et al. (2008) is a recent exception. In their paper, the authors investigate the relation between individual risk aversion and the rate of time preference. However, their estimates are obtained from various measurements available in the German Socio Economic Panel, and do not use a factor structure.

aversion for every individual, and regressed it on all variables (within a linear regression specification). In general, we find that the estimates of Table 6 are consistent with what is reported in Guiso and Paiella (2008); absolute risk aversion decreases with wealth, increases with the measure of liquidity constraints, and increases with our measure of background risk (the variance of the province GDP). However, the parameter estimates cannot rule out that absolute risk aversion may decrease with background risk at very low level of background risk, or at very high levels of wealth.

6.4 The Effect of Time Invariant Risk Aversion and Schooling on Wealth

The estimates of Table 7 indicate that wealth is positively associated with the individual level of education, as documented by the four dummy variables associated to different grade levels (higher education is the reference variable). Not surprisingly, it is also positively correlated with parents' education. Wealth is positively and significantly associated with the two variables which we use as exogenous instruments: the amount of money received as payment from insurance and the capital gain on the property house. Finally, our model allows us to measure the effect of the individual-specific time-invariant degree of risk aversion on wealth. As more risk averse individuals may sometimes save more, but also invest in less risky assets, the sign of risk aversion on wealth is ambiguous. Our estimates indicate that risk aversion and wealth are positively correlated. This result is difficult to evaluate since there exist very few empirical estimates of the individual-specific degree of risk aversion in the micro-econometric literature.[21]

Finally, the impact of interview quality on wealth are not as clear as in the

[21] Evaluating individual-specific risk aversion is more common in the experimental literature, but its relation with wealth is rarely investigated.

risk aversion equation. Some of the quality variables have a positive impact on wealth, while others are negative. Overall, their level is small when compared to other binary indicators.[22]

6.5 What is the Effect of Risk Aversion on Grade Transitions?

Given the form of the hazard specification, the sign of the parameter estimates indicates the direction of the effect of a variable on the exit rate out of school. So, for instance, a positive (negative) estimate for the effect of risk aversion will imply that individuals who are more risk averse tend to have a higher (lower) drop out rate. For a particular grade level already completed, a positive effect of risk aversion therefore indicates that individuals regard entering the next grade level as risky, while a negative estimate would be consistent with the reverse argument (the insurance hypothesis). Tables 8 and 9 show the parameter estimates at all grade transitions, risk aversion is assumed to affect only the transition to college and enters positively both for the older cohort (0.81) as well as the younger cohort (0.99).

Because the model is highly non-linear and contains a large number of parameters (more than 200), it is more appealing to focus the discussion on the illustration of the marginal effects on the grade transition probabilities.[23] The marginal effects associated to risk aversion are found in Table 10 for the transition from senior high school to college. Without loss of generality, we calculate these hazard rates for type 1 individuals and for the modal occupation and region. The marginal effects implied by the model parameters, and found in Table 10 are very close to 0.03-0.04

[22] Indeed, for this reason, and for the sake of robustness checks, we will later estimate a model where wealth is exogenous.

[23] The degree of flexibility reached by using mixture of normals when modeling grade transition, wealth, and relative risk aversion is the main reason for the proliferation of parameters.

both the young and the old cohort. These values indicate a fairly large effect for risk aversion in the transition from senior high school to college. Given senior high school completion, more risk averse individuals are more likely to drop after senior high school and disregard the higher education option. Returning to the first objective of this paper, this result is therefore consistent with the standard view that individuals regard higher education as risky.

Table 10 does not show significant differences across cohorts in the marginal effect of risk aversion on drop out rates at senior high school level. We interpret this result as follows. The reform of the school leaving age (extended to lower high school in 1962) and the 1969 liberalization of access to college, which affected differently the cohorts born before and after 1950, does not seem to have affected the level of ex-ante risk, or at least, has not induced a different perception of the risks attached to investment in higher education.

6.6 How Important is Risk Aversion?

The effect of parental education is the natural benchmark marginal effect to use for comparison. The marginal effect of parents' education on children drop-out rates is computed in Table 10 for the drop-out rate at the senior high school level. As documented in Table 10, having a single parent with a high school degree has often an insignificant effect on the drop out rate. For the older cohort, the marginal effects are -0.0009 and 0.0064 for the father and the mother with high school education. For the older cohort, the effects are -0.0140 (father) and 0.0052 (mother). However, having both parents educated has a much bigger and significant effect on the drop out probability. The effect is close to -0.20 for both cohorts.

In order to get a clearer picture, we also decomposed the predicted individual differences in drop out rates into two separate components: risk aversion and parents education and occupation. Table 11 shows that between 30% and 32% (depending on the cohort) of the total variation in drop out rates at the senior high school level is accounted by differences in risk aversion. In summary, our results indicate that risk aversion is a key determinant of the decisions to enter higher education conditional on having completed senior high school (although not as important as parents' educational background). Finally, the results displayed in Table 11 do not reveal any significant cohort effects.

7 Further Model Specifications and Robustness

In order to evaluate the robustness of the main results, we estimated two other model specifications that use the approximated degree of absolute risk aversion. First, we estimated the version of the model in which the entire error term of observed wealth is interpreted as measurement error. As a second step, we re-estimated the model under the maintained assumption that wealth is exogenous. We did so mostly because endogenizing wealth brings an extra degree of complication in our model, which translates into further parameter proliferation. This may therefore tend to obscure the results.

Finally, and as mentioned in Section 4, we re-estimated the model using an alternative approach based on the solution to the expected utility equation obtained when preferences belong to the CARA family.

In order to save space, we report the distribution of risk aversion (mean and standard deviations) as well as marginal effects and variance decomposition. (Tables 12 and 13). Our presentation stresses the distribution of risk aversion because it is the main channel by which it may affect the results.

7.1 Measurement Error in Wealth

In the model where all the wealth error term is imputed to measurement error, the spread of the risk aversion factor distribution has increased slightly for both cohorts (the standard deviations are now above 0.04 in both cases). Overall, the results are still indicative of the importance of risk aversion, although the impact is reduced. The marginal effects of the individual-specific risk aversion factor are now below, but very close, to 0.03. The contributions of risk aversion to the total variations in grade termination rates are also slightly lower (20% and 25%).

7.2 Exogenous Wealth

Obviously the model with exogenous wealth is the one that departs the most from those specifications reported earlier. Because it ignores measurement error in wealth, the model explicitly assumes that a larger portion of measured risk aversion is explained by wealth. The consequence appears to be a narrowing of the spread of the estimated distribution of risk aversion. This is illustrated by a reduction in the standard errors, now below 0.03 for both cohorts. The marginal effects of risk aversion (between 0.034 and 0.036) are now back to levels that are now only slightly below those reported in the previous section.

7.3 An Alternative Approach

As mentioned in Section 4, we may also obtain a measure of risk aversion, if we use the one-to-one correspondence between the value attached to the lottery, and the degree of risk aversion (given wealth). In order to infer the individual-specific risk aversion factor, we therefore solve the expected utility equation for a given preference structure (Belzil, 2007). However, in order to take into account that the answer to the lottery may not be fully reliable, we incorporate non-classical measurement error, and we also take into account that differences in risk aversion error may reflect differences in background risk and/or differences in liquidity constraints.

Given the static (single period) nature of the lottery, we assume that the per-period utility function, along with the value of the bet, recovers an imperfectly measured degree of risk aversion, denoted $\tilde{\theta}_i^{ra}$. We interpret the maximum bet offered by a given individual as the solution to the expected utility equation driven by a Constant Absolute Risk Aversion functional form (CARA). The solution is obtained from the following expression

$$\frac{1}{2}\phi_i(w_i + g, \tilde{\theta}_i^{ra}) + \frac{1}{2}\phi_i(w_i - bet_i, \tilde{\theta}_i^{ra}) = \phi_i(w_i, \tilde{\theta}_i^{ra}) \tag{16}$$

where g=5000 euros is the potential lottery gain and $\phi_i(.) = -\exp(-\tilde{\theta}_i^{ra} \cdot w)$.

Given a value of $\tilde{\theta}_i^{ra}$ for each individual, the objective is to infer the relevant (true) individual specific risk aversion parameter (θ_i^{ra}). The left-hand side variable $\tilde{\theta}_i^{ra}$, depends on background risk, liquidity constraints and also on a random component that may represent measurement error. Obviously, it also depends on the functional form of ϕ_i. That is

$$\tilde{\theta}_i^{ra}(95) = \theta(Background\ risk_{i,95}; Liquidity\ constraints_{i,95}; \theta_i^{ra}) + \varepsilon_{i,95}^{ra} \tag{17}$$

where θ denotes a second degree polynomial.

This measurement error term, $\varepsilon_{i,95}^{ra}$, depends explicitly on the quality interview variables (Q) as well as a purely idiosyncratic error component ($\tilde{\varepsilon}_{i,95}^{ra}$). That is

$$\varepsilon_{i,95}^{ra} = \varepsilon_Q^{ra\prime} Q + \tilde{\varepsilon}_{i,95}^{ra}$$

where $\varepsilon_Q^{ra\prime}$ is a vector of parameters measuring the effect of interview quality variables, and where the residual error term, $\tilde{\varepsilon}^{ra}_{i,95}$, is distributed with density $f^{ra}()$ like in equation 11. Again, θ^{ra}_i, is the time-invariant degree of risk aversion, upon which, schooling decisions depend. The background risk and liquidity constraint variables are measured in 1995 and were described earlier in section. Note that this tightly specified utility function obviates the need for modeling the wealth equation. We proceed as before by maximizing the joint likelihood of education choices (equation 5), non-response (equation 7), and the relative risk aversion equation 17 which was just introduced.[24]

The specification that used the specific CARA functional form is comparable both in terms of the marginal effect of risk aversion (0.0320 and 0.0373) and in the importance attributable to preference heterogeneity (29% and 32%). However, it appears to be the specification in which parents' educational achievements account for the largest share of the probability of accessing higher education. Although the spread in the degree of relative risk aversion across cohort is higher than before (0.1241 vs. 0.1445), it does not seem too exagerated.

8 Economic Interpretation and Concluding Remarks

In conclusion, all model specifications that we have considered imply that, given senior high school completion, the decision to continue to higher education is negatively correlated with risk aversion. This result is consistent with standard theoretical arguments (for example Lehvari and Weiss, 1974). It is also interesting to note that, conditional on senior high school completion, individual differences in risk aversion are almost as important as parents' educational background (the

[24] However, it would still be possible to consider wealth as a useful measurement of the individual risk aversion factor, and therefore maximize the joint likelihood of education choices, non-response, risk aversion and wealth. To avoid over-paramaterization, we chose not to do so.

factor most often cited as the principal determinant of schooling attainments).

We analyzed separately the effects on older (born before 1950) and younger cohorts (born after 1950) because both the extension of the school leaving age to lower high school in 1962 and the liberalization of access to college in 1969 affected directly the cohorts born after 1950 and may therefore have induced a different perception of the risks attached to investment in senior high school and college. However we do not find significant differences across cohorts in the marginal effect of risk aversion on drop out rates at senior high school level.

At this stage, four remarks should be made. First, our results are not inconsistent with the conventional wisdom that educational attainments are largely explained by parents background. Because important differences in children achievements are known to emerge at a very young age, only a small subset of the population actually exercise the decision to enroll in higher education.

Second, and on a similar note, our results are also not incompatible with the existence of liquidity constraints. Effectively, the impact of risk aversion on higher education enrollment reported in the paper should be seen as a reduced-form effect. If individual are facing different levels of financial constraints, their individual willingness to choose higher education may simply reflect the conjunction of preference heterogeneity and financial restriction heterogeneity. Indeed, more generally, although we find an important effect of risk aversion on the decision to enroll in higher education, our semi-structural approach does not allow us to identify the sources of risk perceived by the agent.

Finally, regardless of liquidity constrainsts, the econometric model is based on an argumentation that omits heterogeneity in subjective risk evaluation. In a world where agents differ not only with respect to risk aversion, but also with respect to subjective probability distributions (some regard higher education as risky, others regard it as an insurance), the effect of risk aversion would be more difficult to evaluate. This is a difficult problem to tackle. Disentangling individual differences in preferences from differences in beliefs is currently at the frontier of micro-econometrics. As a consequence, future research targeting this issue appears an interesting avenue for future research.

Appendix: Further Parameterization

In order to estimate the model with normal mixtures and unobserved heterogeneity, the following parametrizations have been adopted. Basically, we formulate the grade transition model as a mixture of normals with unit variance. To obtain identification, we impose the standard labeling condition (the components are ordered in ascending order in terms of their means: $\mu_1^g < \mu_2^g ... < \mu_5^g$), and for one component (the 3rd one), we set the mean (μ_3^g) to 0. We do this because X_i contains an intercept term (the individual specific heterogeneity term).

Finally, we proceed similarly for the wealth and the risk aversion equations. However, for both cases, we also estimate the variance (the σ_m^r and σ_m^w) for each mixture component. Tables 3 to 5 in the Appendix list the estimated parameters.

Type probabilities:

$$p_k, = \frac{\exp(p_{0k})}{\sum_{j=1}^{6} \exp(p_{0j})} for\ k = 1, 2, ..6 \text{ and } p_{06} = 0$$

Grade transition equation (normal mixtures):

$$P_m^g = \frac{\exp(p_m^{g*})}{\sum_{j=1}^{5} \exp(p_j^{g*})} for\ m = 1, 2\ , ..5 \text{ and } p_5^{g*} = 0$$

$$\mu_1^g = -\exp(\mu_1^{g*}) - \exp(\mu_2^{g*}),$$

$$\mu_2^g = -\exp(\mu_2^{g*}),$$

$$\mu_3^g = 0,$$

$$\mu_4^g = \exp(\mu_4^{g*}),$$

$$\mu_5^g = \exp(\mu_4^{g*}) + \exp(\mu_5^{g*})$$

$$\sigma_m^g = 1\ for\ m = 1, 2, 3, 4, 5$$

Absolute Risk aversion equation (normal mixtures):

$$P_m^A = \frac{\exp(p_m^{A*})}{\sum_{j=1}^{5}\exp(p_j^{A*})} for\ m = 1, 2\ , ..5 \text{ and } p_5^{A*} = 0$$
$$\mu_1^A = -\exp(\mu_1^{A*}) - \exp(\mu_2^{A*}),$$
$$\mu_2^A = -\exp(\mu_1^{A*}),$$
$$\mu_3^A = 0,$$
$$\mu_4^A = \exp(\mu_4^{A*}),$$
$$\mu_5^A = \exp(\mu_4^{A*}) + \exp(\mu_5^{A*})$$
$$\sigma_m^A = \exp(\sigma_m^{A*})\ for\ m = 1, 2, ..5$$

Wealth equation (normal mixtures):

$$P_m^w = \frac{\exp(p_m^{w*})}{\sum_{j=1}^{5}\exp(p_j^{w*})} for\ m = 1, 2\ , ..5 \text{ and } p_5^{w*} = 0$$
$$\mu_1^w = -\exp(\mu_1^{w*}) - \exp(\mu_2^{w*}),$$
$$\mu_2^w = -\exp(\mu_2^{w*}),$$
$$\mu_3^w = 0,$$
$$\mu_4^w = \exp(\mu_4^{w*}),$$
$$\mu_5^w = \exp(\mu_4^{w*}) + \exp(\mu_5^{w*})$$
$$\sigma_m^w = \exp(\sigma_m^{w*})\ for\ m = 1, 2, ..5$$

Response Equation (normal mixtures):

$$P_m^R = \frac{\exp(p_m^{R*})}{\sum_{j=1}^{5}\exp(p_j^{R*})} for\ m = 1, 2\ , ..5 \text{ and } p_5^{R*} = 0$$
$$\mu_1^R = -\exp(\mu_1^{R*}) - \exp(\mu_2^{R*}),$$
$$\mu_2^R = -\exp(\mu_1^{R*}),$$
$$\mu_3^R = 0,$$
$$\mu_4^R = \exp(\mu_4^{R*}),$$
$$\mu_5^R = \exp(\mu_4^{R*}) + \exp(\mu_5^{R*})$$
$$\sigma_m^R = \exp(\sigma_m^{R*})\ for\ m = 1, 2, ..5$$

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Table 1: Descriptive statistics

	Full sample	Cohort born before 1950	Cohort born after 1950
risk aversion $A(.)$	0.148	0.149	0.147
college or more (d)	0.103	0.090	0.119
senior highschool (d)	0.312	0.234	0.404
junior highschool (d)	0.309	0.250	0.380
elementary school (d)	0.239	0.367	0.087
no education (d)	0.034	0.057	0.008
highschool father (d)	0.100	0.082	0.121
highschool mother (d)	0.063	0.047	0.082
north (d)	0.398	0.398	0.398
south (d)	0.434	0.440	0.427
female (d)	0.179	0.186	0.172
bluecollar father (d)	0.478	0.469	0.488
selfemployed father (d)	0.304	0.336	0.266
unoccupied father(d)	0.012	0.016	0.006
bluecollar mother (d)	0.134	0.130	0.139
selfemployed mother (d)	0.118	0.128	0.106
unoccupied mother (d)	0.695	0.709	0.679
age	48.312	58.177	36.509
wealth (000 euros)	123.626	132.554	104.384
insurance (000 euros)	0.215	0.180	0.291
capitalgain house (000 euros)	67.098	73.717	53.404
variance provincial gdp	2.018	2.254	1.735
liquidity constrained (d)	0.306	0.285	0.350
response (d)	0.434	0.346	0.622
no understand (d)	0.174	0.215	0.086
difficult answer (d)	0.055	0.070	0.022
no interest (d)	0.222	0.255	0.151
no reliable (d)	0.122	0.135	0.096
no climate (d)	0.063	0.072	0.044
N obs	7,563	5,166	2,397

notes: (d) indicates a dummy.

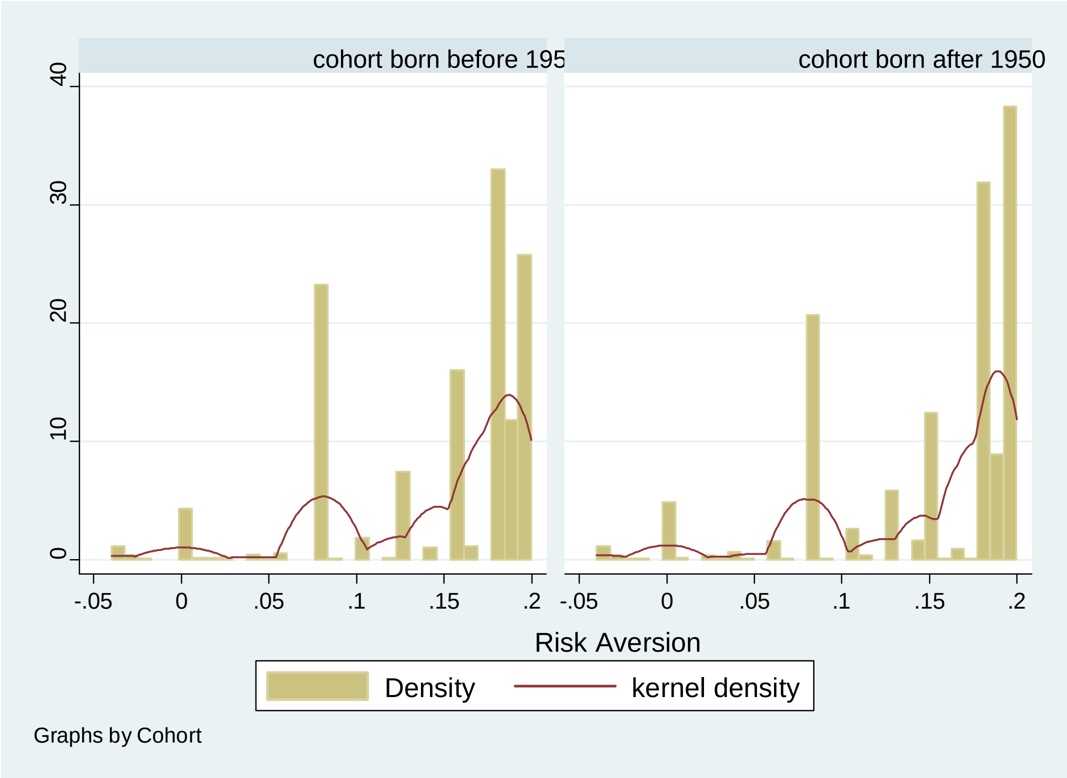

Figure 1: The distribution of absolute risk aversion $A(.)$ by cohort

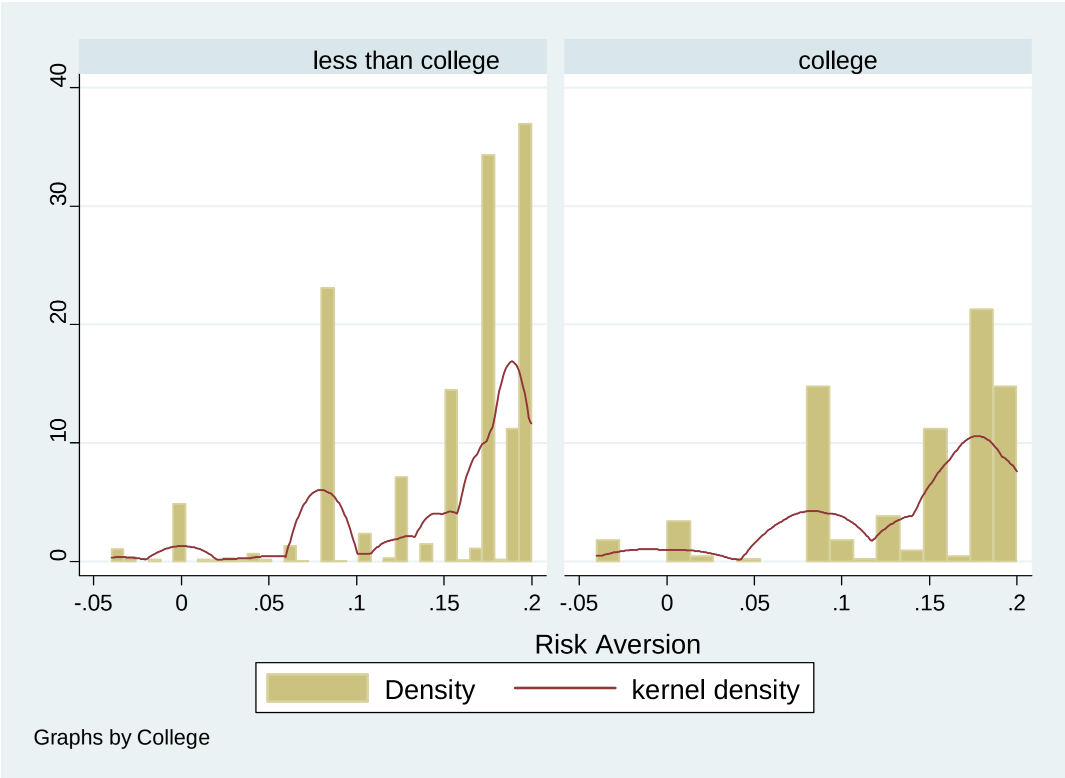

Figure 2: The distribution of absolute risk aversion $A(.)$ by education level

Table 2: Actual and Predicted grade termination probabilities

	Cohort born before 1950		Cohort born after 1950	
	actual	predicted	actual	predicted
no qualification	0.0572	0.0714	0.0083	0.0120
elementary school	0.3894	0.4234	0.0878	0.0990
junior high school	0.4358	0.4650	0.4205	0.4560
senior high school	0.7229	0.6743	0.7718	0.7245

Note: The predicted termination (hazard) probabilities are computed from the model specification.

Table 3: correlation between heterogeneity components

	grade transition $\alpha_4^S\theta_i^S$	non response θ_i^R	risk aversion θ_i^{ra}
		cohort born before 1950	
grade transition $\alpha_4^S\theta_i^S$	1.0000		
non response θ_i^R	-0.6130	1.0000	
risk aversion θ_i^{ra}	0.0964	-0.4727	1.0000
		cohort born after 1950	
grade transition $\alpha_4^S\theta_i^S$	1.0000		
non response θ_i^R	-0.2107	1.0000	
risk aversion θ_i^{ra}	-0.2342	-0.3847	1.0000

Table 4: The response equation

	Cohort born before 1950	Cohort born after 1950
wealth	0.0020*	-0.0666
no understand (d)	-0.2024	-0.6045
difficult answer (d)	-0.3763	-0.7345
no interest (d)	0.0406	-0.2843
no reliable (d)	-0.0807	-0.2296
no climate (d)	0.0020*	-0.2534
age	0.0364	0.1345
age square	-0.0211	-0.0524
female (d)	-0.2106	-0.0932
type 1 θ_1^{nr}	0.2712	-0.1356
type 2 θ_2^{nr}	-0.2792	0.1012
type 3 θ_3^{nr}	0.3860	0.1276
type 4 θ_4^{nr}	-0.0508	0.1064
type 5 θ_5^{nr}	0.4877	0.1924
type 6 θ_6^{nr}	-0.5022	-0.0356
type 7 θ_7^{nr}	-0.6325	0.1024
type 8 θ_8^{nr}	-0.4512	0.1523

Note: The parameters reported with a (*) are those not significant at 5% level. No_understand is a dummy equal to 1 if, according to the interviewer, the level of understanding of the questionnaire by the head is poor or just acceptable (as opposed to satisfactory, good or excellent). Difficult in answering is a dummy equal to 1 if, according to the interviewer, it was difficult for the head to answer questions. No_interest is a dummy equal to 1 if, according to the interviewer, the interest for the questionnaire topics was poor or just acceptable (as opposed to satisfactory, good or excellent). No_reliable is a dummy equal to 1 if, according to the interviewer, the information regarding income and wealth are not reliable. No_climate is a dummy equal to 1 if, according to the interviewer, the overall climate when the interview took place was poor or just acceptable (as opposed to satisfactory or good).

Table 5: The distribution of time invariant risk aversion

Type	θ^{ra}	Estimated proportions	
		Cohort born before 1950	Cohort born after 1950
1	-0.02	0.0018	0.0009
2	0.05	0.0412	0.0345
3	0.08	0.1611	0.1556
4	0.12	0.2731	0.2812
5	0.14	0.2534	0.2395
6	0.16	0.1356	0.1316
7	0.18	0.0611	0.1002
8	0.20	0.0727	0.0538
average		0.1307	0.1318
st. dev.		0.0375	0.0368

Table 6: The absolute risk aversion equation

	Cohort born before 1950	Cohort born after 1950
wealth	-0.1253	-0.1183
wealth square	$\simeq$0.0000*	0.0008*
variance gdp	0.0050*	-0.0283
variance gdp square	-0.0007	0.0004
liquidity constr.	0.0902	0.3012
wealth*variance gdp	-0.0010	$\simeq$0.0000*
wealth*liquidity constr.	0.0099	$\simeq$0.0000*
liquidity constr.*variance gdp	-0.0090	0.0545
θ_i^{ra}	0.1286	-0.0880
θ_i^{ra} square	-0.0634	0.0347
θ_i^{ra} *wealth	0.0450	0.0256
θ_i^{ra} *liquidity constr.	0.0976	-0.1430
θ_i^{ra} *variance gdp	-0.0055	0.0008*
no understand (d)	0.1233	0.1412
difficult answer (d)	0.1316	0.1245
no interest (d)	0.1237	0.1003
no reliable (d)	0.1134	-0.0337*
no climate (d)	-0.0601*	0.1321
Variance measurement error	0.9245	0.8623
Variance regression	0.6233	0.7422

Note: The measurement error indicator is the ratio of the variance of the error term of the variance of observe absolute risk aversion. All parameters, except those identified by a (*) are significant at 1%. The variance of the regression includes the effect of the interview quality variables.

Table 7: The wealth equation

	Cohort born before 1950	Cohort born after 1950
senior highschool (d)	-1.9112	-1.9181
junior highschool (d)	-2.6870	-1.9814
elementary (d)	-2.7451	-2.2727
no qualification (d)	-2.9857	-3.0350
highschool father (d)	0.8305	-0.5126
highschool mother (d)	1.7645	1.9076
bluecollar father (d)	0.0586	-0.4012
bluecollar mother (d)	2.8611	1.0057
selfemployed father (d)	0.6040	0.0893
selfemployed mother (d)	2.8297	2.0443
unemployed father (d)	-0.5618	-0.4093
unemployed mother (d)	2.6353	1.2124
north (d)	-0.0476	0.0107
south (d)	-0.5180	-0.7326
female (d)	-0.7420	-0.1902
insurance money	0.0112	0.0146
capitalhouse gain	1.5259	0.6779
risk aversion (θ_i^{ra})	0.3001	0.4566
no understand (d)	0.0123	0.0118
difficult answer (d)	0.0284*	0.0322*
no interest (d)	-0.0235	0.0119
no reliable (d)	0.0021	-0.0128
no climate (d)	-0.0213*	-0.0015*

Note: All parameters, except those identified by a (*) are significant at 5%.

Table 8: Grade transition: cohort born before 1950

	Transition to elementary	Elem. to junior high	Junior to senior high	Senior high to college
α_{g1}	-3.1533	-1.9035	-0.3702	-0.1705
α_{g2}	-3.0221	-2.0822	0.0504	-0.2934
α_{g3}	-2.8426	-1.5001	-0.2276	0.5012
α_{g4}	-3.1528	-1.7216	-0.2629	0.5610
α_{g5}	-2.9056	-1.5728	-0.4140	-0.4600
α_{g6}	-3.1992	-2.0022	-0.5104	0.4004
α_{g7}	-3.2178	-2.0348	-0.7234	0.7111
α_{g8}	-3.2934	-2.0278	-0.3332	0.6612
highschool father (d)	-0.0676	-1.1293	0.0815	-0.1429
highschool mother (d)	-0.0726	-1.1132	0.0912	-0.1467
highsch. father and mother (d)	-1.4162	-1.5085	-1.2965	-1.2752
bluecollar father (d)	1.8778	0.9367	0.7237	0.5929
bluecollar mother (d)	-0.5552	0.1123	0.4442	0.8005
selfemployed father (d)	1.3745	0.6329	0.5924	0.4378
selfemployed mother (d)	-0.8823	0.1376	0.4003	0.3729
unemployed father (d)	0.0778	0.4418	1.5484	3.2222
unemployed mother (d)	-0.6737	-0.2721	0.2724	0.2937
north (d)	-0.0367	-0.1329	-0.2890	-0.2478
south (d)	0.6897	0.0732	-0.2239	-0.3993
female (d)	0.3425	0.3329	0.0009	-0.1923
risk aversion (θ_i^{ra})	-	-	-	0.8103

Note: All parameters, except those identified by a (*) are significant at 5%.

Table 9: Grade transition: cohort born after 1950

	Transition to elementary	Elem. to junior high	Junior to senior high	Senior high to college
α_{g1}	-3.4969	-2.2734	0.4034	0.1511
α_{g2}	-3.1962	-2.3278	0.1923	0.0366
α_{g3}	-3.9364	-2.6638	-0.4003	0.6011
α_{g4}	-3.0538	-2.1003	-0.3922	0.6613
α_{g5}	-3.0888	-1.8674	-0.4429	-0.4011
α_{g6}	-3.1025	-2.0035	-0.5562	-0.1037
α_{g7}	-3.1429	-1.9538	-0.4835	0.4556
α_{g8}	-3.0098	-1.8346	-0.4462	0.6016
highschool father (d)	-0.1278	-0.9821	-0.8037	-0.3133
highschool mother (d)	-0.1002	-0.5824	-0.1129	0.2648
highsch. father and mother (d)	-1.5214	-1.5512	-0.3227	-1.3023
bluecollar father (d)	1.2193	1.0626	0.8026	0.7324
bluecollar mother (d)	-1.5622	0.1088	0.4048	0.9178
selfemployed father (d)	1.1129	0.9724	0.8423	0.0032*
selfemployed mother (d)	-0.8924	-0.0422*	0.0739	0.7328
unemployed father (d)	-0.0321*	0.5823	0.8092	3.1221
unemployed mother (d)	-0.1794	0.1023	0.4421	0.0887
north (d)	-0.4398	0.3239	-0.1729	0.1328
south (d)	1.1005	0.8739	0.1826	0.3754
female (d)	-0.4493	0.1835	0.0835	0.2235
risk aversion (θ_i^{ra})		-	-	0.9932

Note: All parameters, except those identified by a (*) are significant at 5%.

Table 10: The Determinants of grade termination at senior high school: Marginal effects

	Cohort born before 1950	Cohort born after 1950
highschool father (d)	-0.0009*	-0.0140
highschool mother (d)	0.0064*	0.0052*
highschool father and mother (d)	-0.2236	-0.1867
risk aversion (θ_i^{ra})	0.0356	0.0302

Note: the marginal effects are computed at the average value (or mode) of the regressors and at the average value of the grade transition heterogeneity term. All marginal effects, except those identified by a * are significant at 5%.

Table 11: The relative explanatory power of risk aversion and parents' education: The decision to terminate at senior high school

	Cohort born before 1950	Cohort born after 1950
parents' background	50%	56%
risk aversion	30%	32%

Note: To obtain the explanatory power of parent's background variable and risk aversion, we used simulated hazard rates at level 3 and level 4, and evaluated the relative variance for each component with respect to the total variance of predicted hazard rates.

Table 12: Robustness check: Marginal effects of the determinants of grade termination at senior high school

	measurement error only		exogenous wealth		CARA preferences	
	Cohort ≦1950	Cohort >1950	Cohort ≦1950	Cohort >1950	Cohort ≦1950	Cohort >1950
Distribution of risk aversion						
Mean	0.1296	0.1364	0.1286	0.1397	0.1241	0.1445
St- dev.	0.0549	0.0503	0.0273	0.0228	0.0303	0.0318
Marginal effects						
highschool father (d)	0.0005*	-0.0238	0.0003*	-0.0082	0.0009*	-0.0225
highschool mother (d)	0.0030*	0.0040	0.0066*	0.0038*	0.0025*	0.0046*
highsch. father and mother (d)	-0.2002	-0.2206	-0.2001	-0.2319	-0.1922	-0.2352
risk aversion (θ_i^{ra})	0.0281	0.0290	0.0338	0.0356	0.0320	0.0373

Note: The marginal effects are computed at the average value (or mode) of the regressors and at the average value of the grade transition heterogeneity term. All marginal effects, except those identified by a * are significant at 5%.

Table 13: Robustness checks: The relative explanatory power of risk aversion and parents' education in the decision to terminate at senior high school

	measurement error only		exogenous wealth		CARA preferences	
	Cohort ≦1950	Cohort >1950	Cohort ≦1950	Cohort >1950	Cohort ≦1950	Cohort >1950
parents' background	49%	55%	50%	54%	63%	60%
risk aversion	20%	25%	31%	34%	29%	32%

Note: In the model "insurance settlement" wealth is instrumented using only the amount of money received as insurance settlements. To obtain the explanatory power of parent's background variable and risk aversion, we used simulated hazard rates at level 3 and level 4, and evaluated the relative variance for each component with respect to the total variance of predicted hazard rates.

Table 1: Appendix. Percentage of children aged 19-29 living at home. Source: SHIW 1995

age	% who live at home	% student	% students who live at home
19	98.5%	45.0%	45.0%
20	98.5%	43.1%	42.8%
21	96.0%	39.9%	39.3%
22	92.8%	30.6%	30.3%
23	90.6%	30.1%	29.5%
24	86.2%	26.7%	26.2%
25	72.8%	30.1%	27.5%
26	73.5%	26.8%	25.1%
27	65.5%	21.3%	18.9%
28	56.5%	19.5%	15.0%
29	45.0%	17.7%	13.2%

Source: SHIW 1995.

Table 2: Appendix. Linear probability models of interview quality variables

	nounderstand	difficult	nointerest	noreliable	noclimate
college	-0.298***	-0.016	-0.169***	-0.038	-0.001
	(0.035)	(0.018)	(0.043)	(0.036)	(0.024)
high school	-0.280***	-0.016	-0.165***	-0.050	-0.021
	(0.031)	(0.016)	(0.038)	(0.032)	(0.021)
junior high school	-0.231***	-0.023	-0.136***	-0.008	0.005
	(0.030)	(0.016)	(0.037)	(0.031)	(0.021)
elementary	-0.139***	-0.005	-0.045	-0.002	0.000
	(0.029)	(0.015)	(0.036)	(0.030)	(0.020)
age	0.002***	0.001**	0.002***	0.001	0.001**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
female	0.013	0.001	0.043**	-0.024	-0.002
	(0.013)	(0.007)	(0.016)	(0.014)	(0.009)
father education	-0.008	0.002	-0.024*	-0.024**	-0.002
	(0.009)	(0.005)	(0.011)	(0.009)	(0.006)
mother education	-0.002	-0.005	0.008	0.011	-0.009
	(0.010)	(0.005)	(0.012)	(0.010)	(0.007)
wealth	-0.012***	0.000	-0.010**	0.003	-0.004*
	(0.003)	(0.001)	(0.003)	(0.003)	(0.002)
risk aversion	0.062*	-0.011	0.048	-0.042	0.023
	(0.027)	(0.014)	(0.034)	(0.028)	(0.019)
constant	0.248***	0.019	0.223***	0.125**	0.027
	(0.040)	(0.021)	(0.050)	(0.041)	(0.027)
N	3285	3285	3285	3285	3285
r2	0.106	0.008	0.055	0.014	0.015

Note: Linear probability models: each column corresponds to a different regression. *,**,*** correspond to 10%, 5% and 1% significance levels.

Table 3: Appendix. Type probabilities and Normal Mixtures

	Cohort born before 1950	Cohort born after 1950
	type probabilities	
	coeff	coeff
P_{01}	-3.2805	-4.9723
P_{02}	0.4045	1.2842
P_{03}	0.1863	1.2184
P_{04}	0.0132	0.9676
P_{05}	0.7455	0.8056
	grade transition	
P_1^{g*}	-0.1002	-0.5041
P_2^{g*}	0.6634	-0.3338
P_3^{g*}	3.5537	-0.2443
P_4^{g*}	-2.4355	0.1934
P_5^{g*}	0	0
μ_1^{g*}	1.8031	-0.2936
μ_2^{g*}	-1.9045	-0.6005
μ_3^{g*}	0	0
μ_4^{g*}	32.0001	2.0516
μ_5^{g*}	23.5523	1.1002

Table 4: Appendix. Normal Mixtures: risk aversion equation and wealth equation

	Risk aversion equation			Wealth equation	
	Cohort born before 1950	Cohort born after 1950		Cohort born before 1950	Cohort born after 1950
	coeff	coeff		coeff	coeff
P_1^{A*}	-0.6057	-0.3256	P_1^{w*}	-0.8148	-0.8184
P_2^{A*}	0.1003	0.1374	P_2^{w*}	-0.1258	-0.1727
P_3^{A*}	0.1467	0.0354	P_3^{w*}	-0.4221	-0.4318
P_4^{A*}	0.1553	0.0748	P_4^{w*}	-0.5323	-0.5258
P_5^{A*}	0	0	P_5^{w*}	0	0
μ_1^{A*}	-1.9856	-1.9004	μ_1^{w*}	-1.4988	-1.4989
μ_2^{A*}	-2.0012	-1.9251	μ_2^{w*}	-1.4928	-1.4955
μ_3^{A*}	-1	-1	μ_3^{w*}	0	0
μ_4^{A*}	-1.9026	-1.9812	μ_4^{w*}	-1.5122	-1.5092
μ_5^{A*}	-1.0035	-1.3287	μ_5^{w*}	-1.5048	-1.5045
σ_1^{A*}	0.2172	0.3026	σ_1^{w*}	0.9648	1.2227
σ_2^{A*}	-0.0316	0.0056	σ_2^{w*}	0.4957	0.9929
σ_3^{A*}	-0.1689	-0.0555	σ_3^{w*}	0.7937	1.1485
σ_4^{A*}	-0.2846	-0.0349	σ_4^{w*}	0.9523	1.2398
σ_5^{A*}	-0.2623	-0.0773	σ_5^{w*}	1.6648	1.6153

Table 5: Appendix. Normal Mixtures: non-response equation

	Cohort born before 1950	Cohort born after 1950
	coeff	coeff
P_1^{R*}	-0.6342	-0.3689
P_2^{R*}	0.1402	0.0836
P_3^{R*}	0.1552	0.0902
P_4^{R*}	0.1701	0.0973
P_5^{R*}	0	0
μ_1^{R*}	-1.8826	-1.9903
μ_2^{R*}	-1.4724	-1.9951
μ_3^{R*}	-1	-1
μ_4^{R*}	-1.6542	-1.9956
μ_5^{R*}	-1.0006	-1.0016
σ_1^{R*}	0.2233	0.3246
σ_2^{R*}	-0.0045	0.0178
σ_3^{R*}	-0.1899	-0.033
σ_4^{R*}	-0.2278	-0.0777
σ_5^{R*}	-0.2945	-0.0773