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Absolute Risk Aversion and the Returns to Education*

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Abstract

Individual absolute risk aversion is measured for a sample of 1373 male household heads, using the 1995 wave of the Survey on the Income and Wealth of Italian households. This measure, conditional on financial and real wealth and household income, is used as an instrument for attained education in a standard log earnings equation. I find that, in line with the literature, the gap between IV and OLS estimates of the returns to education is large.

- JEL: J24, J31

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1 Introduction

It is well known that the estimation of the returns to education is difficult both because of measurement error and because unobserved ability can affect both educational choice and the returns to education. One of the strategies used to deal with this problem consists of selecting instrumental variables, that are correlated with schooling but not with earnings (conditional on schooling). The typical instruments used in the literature are school reforms, family background variables and smoking. An alternative is to use data on twins. See Card (1999) for a review of the existing evidence. In this note I add to the current list an additional candidate, the absolute degree of risk aversion. I start by showing in a simple static model that risk aversion affects in a natural way educational choice by influencing the marginal utility of schooling. Perhaps one reason why this variable has not been used so far is that it is difficult to measure risk aversion in survey data (see Barsky et al (1997) for an attempt). I use the 1995 wave of the Survey on the Income and Wealth of Italian households and previous work on these data by Guiso and Paiella (2000) to measure individual absolute risk aversion in a sample of 1373 married Italian male household heads. This variable is then used as an instrument for education in a standard Mincerian earnings function. In line with most of the current literature, I find that the gap between IV and OLS estimates is substantial.

2 Schooling Choice

Following Card (1999) I assume that an individual chooses S, the years of schooling, in order to maximize the following utility function[1]

$$U(y) - \phi(S) \tag{1}$$

where y is (hourly) earnings, U is a concave function and ϕ is a convex function of S. Hourly earnings are related to S by the following function

$$y = g(S) = e^{\lambda S} \tag{2}$$

The first order condition associated to the maximization of (1) is

$$U' g'(S) = \phi'(S) \tag{3}$$

where the prime if for the first order derivative[2].

Using a first order Taylor approximation of U' around $y = 0$, Eq. (3) can be re-written as follows

$$U'(0)\left[1 - ARAg(S)\right] g'(S) = \phi'(S) \tag{4}$$

where ARA is the Arrow Pratt coefficient of absolute risk aversion (see Laffont (1990)). Let $\phi'(S) = r$, the marginal cost of an additional year of schooling. If the utility function belongs to the CARA class and

$$U(y) = -\frac{1}{\sigma}\exp(-\sigma y) \tag{5}$$

the coefficient ARA is equal to σ[3] and schooling choice is given by

$$S^* = S(\lambda, r, \sigma) \tag{6}$$

[1] This assumption ignores the importance of parental choice in the education of children.

[2] The sufficient condition for an interior maximum is

$$U'' g'(S)^2 + U' g''(S) - \phi''(S) < 0$$

[3] Card uses a CRRA utility function $U(y) = \ln y$.

Claim 1 *The selected years of schooling S decrease when absolute risk aversion ARA increases.*

Proof. Differentiation of (4) with respect to ARA and S yields

$$\left\{g''(S)(1 - ARAg(S) - ARAg'(S)^2 - \frac{\phi''(S)}{U'(0)}\right\}\partial S = g(S)g'(S)\partial ARA$$

The expression within parentheses is negative because of the second order conditions for a maximum. ■

Individual differences in educational attainment can be explained in this simple model both by differences in marginal returns λ and marginal costs r and by differences in the absolute degree of risk aversion.

3 The Empirical Model

Consider the standard regression model

$$\ln y = \alpha_0 + \alpha_1 S + \alpha_2 A + \alpha_3 A^2 + \varepsilon \tag{7}$$

$$S = X\beta + Z\gamma + \eta \tag{8}$$

where A is age, ε and η are error terms, (7) is the Mincerian earnings function[4] and (8) is the attainment function, that depends both on variables affecting marginal benefits (X) and on variables affecting marginal costs and measuring individual preferences (Z).

It is well known that the ordinary least squares (OLS) estimate of (7) yields a consistent estimate of α_1 only when ε and η are uncorrelated. Unobserved ability and measurement error are two well known factors that affect both schooling S and earnings y conditional on schooling. This problem can be dealt with by identifying

[4] I use age rather than potential experience because the former variable can be treated as exogenous. See Harmon and Walker (1995).

a set of variables that affect schooling but not (conditional) earnings. These variables can be used as instrumental variables (IV) to estimate returns to education.

Card (1999) presents a detailed review of previous studies based on instrumental variables and discusses the validity of the instruments used in each study. Briefly, these instruments include school reforms and features of the school system, family background and the use of samples of twins. Another instrument recently used but not discussed by Card is smoking. The argument here is that smoking habits are likely to be highly correlated with the discount rate, that affects r, but do not influence earnings directly[5]. Therefore, they can be used as a valid instrument for schooling S.

The simple model presented in the previous section suggests that a measure of individual absolute risk aversion ARA is another potential candidate. In the model, the variable ARA affects the schooling decision because it affects the marginal utility of income, but does not affect the marginal returns to schooling λ.

4 Measuring risk aversion

Following Laffont (1990), the coefficient of absolute risk aversion at a given level of wealth W is twice the risk premium per unit of variance for small risk. The risk premium is the maximum amount that an agent is willing to pay to have the sure return rather than the expected return from a lottery ticket. According to this definition, risk aversion is not easy to measure and this perhaps explains why it has never been used as an instrument for attained education. A survey that contains detailed information on individual attitudes towards risk is the Italian Survey on Household Income and Wealth ($SHIW$), conducted every two years by the Bank of Italy. The survey

[5] See Fersterer and Winter-Ebmer (2000) for a recent discussion.

is very useful for my purpose because it includes information on earnings, educational attainment, household wealth and attitudes towards risk for a nationally representative sample of households.

In the survey, each household head is offered a hypothetical lottery and is asked to report the maximum price that he would be willing to pay to participate[6]. The exact question is

> "We would 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 1/2, to either gain 10 million lire or to gain nothing. What is the most that you are prepared to pay for this security?"

Ten million lire corresponds to just over Euros 5,000 (or roughly \$5,000). Guiso and Paiella (2000) explain that the interviews were conducted personally by professional interviewers. In order to help the respondent understand the question, they were supposed to show an illustrative card and to provide explanations. The respondent could answer in one of three ways: a) declare the maximum amount he is willing to pay to participate, denoted here by M, known as the compensating certainty equivalent; b) don't know; c) unwilling to answer[7].

Using the information provided by the answers to this question we can measure the Arrow-Pratt index of absolute risk aversion for each household head. Let W denote the non-random household endowment and Π denote the random prize of the lottery, taking values 10 million lire and 0 with equal probability. The maximum entry price is given by:

[6] This section draws extensively from Guiso and Paiella (2000).

[7] Guiso and Paiella (2000) find that the sample selection effects induced by missing answers are small and unlikely to constitute a problem.

$$U(W) = \frac{1}{2}U(W + 10 - M) + \frac{1}{2}U(W - M) \tag{9}$$

Taking a second-order Taylor expansion of the right-hand side of (9) around W yields

$$ARA = 4(5 - M)/\left[10^2 + 2M^2 - 20M\right] \tag{10}$$

that uniquely defines the Arrow-Pratt measure of absolute risk aversion in terms of the parameters of the lottery in the survey.

For the current purpose, a problem with this measure of absolute risk aversion is that it could vary with individual wealth. Laffont (1990) argues that "..it is difficult to obtain sufficient information about an agent's preferences in order to know whether his absolute risk aversion increases or decreases..[with wealth]. However, ...since we must assume that absolute risk aversion decreases with wealth to obtain results that accord with both intuition and observations of rational behavior..we can infer that agents must satisfy this assumption in general..." (p.24).

Clearly, if absolute risk aversion varies with household wealth, and wealth is correlated with hourly (net) earnings, the variable ARA fails to meet the fundamental requirement for an instrumental variable and cannot be used as a valid instrument for schooling S. The availability of detailed information on household income and real and financial wealth in the $SHIW$ dataset, however, allow me to regress individual ARA on these measures of wealth and to use the residuals of this regression as instruments for schooling. Define this generated variable as $RISK$. By construction, $RISK$ is orthogonal to household wealth and reflect both individual differences in characteristics (age, education and region of birth) and innate differences in tastes.

A second problem is that absolute risk aversion can affect log earnings of individuals with the same educational attainment by influencing their occupational choice. For instance, individuals with lower risk aversion could choose riskier occupations, that yield higher expected income. In this case, the generated variable $RISK$ is not a valid instrument. I evaluate this possibility by estimating an ordered probit model of occupational choice and by checking whether $RISK$ significantly affects selection.

A third problem is that educational choice depends on absolute risk aversion at the time of the choice, not on current risk aversion. Therefore, my measure of risk aversion is meaningful only if the time invariant component of risk is important. Empirical evidence in support of the importance of innate preferences is provided by Guiso and Paiella (2000), who find that the main predictor of absolute risk aversion in the $SHIW$ sample is region of birth.

Finally, there is no particular reason to expect that risk aversion, conditional on household wealth, be correlated with unmeasured ability. The maintained hypothesis used in the model, that is kept also in the empirical exercise, is that the causal relation runs from absolute risk aversion to educational attainment, not viceversa.

5 Empirical Results

I estimate (7) on the sample of married male household heads aged between 30 and 55 years with at least primary education, who were employed full-time and for the full year in 1995. The summary statistics of the variables used in the regression and of other relevant variables are in Table 1. As a preliminary step, I regress ARA on three measures of wealth: financial wealth FW, that includes all financial assets held by the household in 1995, household net income FY, that includes earnings, pensions and income from real and financial capital[8], and the dummy H, equal to 1 if the household head owns the house he lives in.

Table 1. Means and standard deviations of the main variables.

	Mean	Std Dvt
$\log y$	2.678	0.34
S	10.432	3.63
A	43.132	6.60
ARA	0.153	0.09
FY	49.756	23.72
FW	30.751	62.28
H	0.669	-

Note: both FY and FW are in million lire.

The results of this regression are presented in Table 2. As expected, the measure of absolute risk aversion is negatively correlated both with financial wealth FW and with household income FY. House ownership, on the other hand, is positively but not significantly correlated to risk aversion.

Table 2. OLS regression of ARA on measures of household wealth. Dependent variable: ARA

	Coefficient	P-value
FW	-0.093	.100
FY	-0.324	.033
H	5.410	.340
$Nobs$	1373	
R^2	0.015	-

Note: Robust standard errors. All the coefficients are multiplied by 1000.

[8] Compare this with the variable y, that include only (hourly) earnings.

Notice that the selected measures of wealth absorb only 1.5% of the total variation of absolute risk aversion. I use the residuals from the regression in Table 2 to construct the variable $RISK$.

As mentioned above, $RISK$ could affect log earnings, conditional on schooling, by influencing occupational choice. Employment in the available data can be in any of the following occupations: blue collar employee, clerk, school teacher and managerial employee. I order these occupations in the variable OCC, using the hourly wage paid in 1995 as the ranking criterion, and I fit an ordered probit model that includes the following explanatory variables: three dummies for attained junior high school (JUN), attained upper secondary school ($HIGH$) and attained college degree ($COLL$), age and $RISK$. Table 3 shows that occupational choice is strongly influenced by educational attainment. Conditional on education, the choice of occupation is not significantly affected by $RISK$.

Table 3. Ordered probit of occupational choice. Dependent variable: OCC

	Coefficient	P-value
JUN	1.082	.000
$HIGH$	2.190	.000
$COLL$	3.703	.000
A	0.041	.000
$RISK$	-0.432	.193
$Nobs$	1373	
$Pseudo\ R^2$	0.25	

Note: robust standard errors are used.

An alternative classification of occupations is between riskier private jobs and safer public jobs. I estimate a probit model where the dependent variable is a dummy equal to 1 if the employee works in the public sector and to zero otherwise and the regressors are educational dummies, age and $RISK$, as in Table 3. Conditional on education, I do not find evidence that $RISK$ significantly affects choice. These results support the selection of $RISK$ as a valid instrument[9].

Table 4 presents the results of the reduced form schooling equation. As predicted by theory, I find that, conditional on age, years of schooling are significantly higher for individuals with lower absolute risk aversion, net of wealth effects.

Table 4. OLS estimate of the reduced form schooling equation. Dependent variable: S

	Coefficient	P-value
A	0.071	.72
A^2	-0.001	.48
$RISK$	-2.089	.04
$Nobs$	1373	
R^2	0.02	

Note: robust standard errors are used.

Both OLS and IV estimates of the returns to education are presented in the first four columns of Table 5. It turns out that the estimated returns to schooling based on the IV procedure are about 80% higher than the returns estimated by standard OLS. This substantial gap cannot be explained by measurement error, that according to Card (1999) accounts for only a 10% gap.

Since the estimated IV model is just identified, we cannot test for instrument validity. A classical test is the Sargan statistic. This test verifies whether the instruments play a direct role in explaining log wages, not just an indirect role, through predicting educational attainment. If the test fails, one or more of the instruments are invalid and ought to be included in the explanation of log wages.

[9] A possible objection is that the available classification of occupations is too gross to pick up the different riskiness of jobs. Needless to say, this objection can only by addressed with better data.

Table 5. OLS estimate of (7). Dependent variable: $\ln y$

	OLS	OLS	IV	IV	IV	IV
	[1]	[2]	[3]	[4]	[5]	[6]
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
S	0.048	.000	0.088	.039	0.088	.038
A	0.042	.009	0.039	.032	0.039	.032
A^2	-0.0003	.049	-0.0003	.079	-0.0003	.076
$Nobs$	1373		1373		1373	
$Sargan\ test$					0.93 (1)	
R^2	0.29		0.10		0.10	

Note: robust standard errors are used. Degrees of freedom within parentheses.

The additional instrument is provided by a school reform dummy. An important exogenous event in the recent history of Italian education is Law 910 of December 1969, that extended the possibility of enrolment in college to individuals with completed secondary education, independently of the curriculum chosen in secondary school[10]. Since expected age of completion of secondary school is in general 19 years, this opportunity was mainly open to the cohorts born from 1951 onwards. A rough indication of the impact of the reform can be obtained by comparing the percentage of 19 years old individuals enrolling in college shortly before and shortly after the reform. It turns out that enrolment rates were 16.3% of the relevant population for individuals born in 1949 and 27.3% for individuals born in 1952[11]. At the same time, the percentage of high school graduates enrolling in college was 54% for the 1949 cohort and 66% for the 1952 cohort.

[10] See Brunello, Comi and Lucifora (1999) for a discussion.

[11] I choose 1949 and 1952 to minimize the risk of including individuals born before 1951 who completed their secondary school later than at the expected age. By taking close years, we also try to reduce the impact of aggregate factors, such as the increase in real income per-capita and the general trend towards more education.

I define the dummy $D51$ as equal to one for individuals born from 1951 onwards and to zero otherwise and use this variable and the variable $RISK$ as instruments for educational attainment in the log earnings regression. The results in the last two columns of Table 5 can be summarized as follows: first, the Sargan test cannot reject the null of instrument validity; second, the estimated returns to education are almost identical to those obtained in the just identified model and are substantially higher than the OLS estimates. This finding confirms the main result in this literature.

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