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Childhood determinants of risk aversion: The long shadow of compulsory education

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We study the determinants of individual attitudes toward risk and, in particular, why some individuals exhibit extremely high risk aversion. Using data from the Panel Study of Income Dynamics, we find that policy induced increases in high school graduation rates lead to significantly fewer individuals being highly risk averse in the next generation. Other significant determinants of risk aversion are age, sex, and parents' risk aversion. We verify that risk aversion matters for economic behavior in that it predicts individuals' volatility of income.

Keywords. Intergenerational transmission, schooling reforms, preference formation.

JEL classification. E21, I29.

1. Introduction

Preferences vary across individuals—for potential implications, see Becker and Mulligan (1997)—and the transmission of preferences may be an important factor behind correlations in income and wealth across generations. However, there is little evidence on the intergenerational evolution of preferences. Charles and Hurst (2003) showed, using the Panel Study of Income Dynamics (PSID), that risk preferences of parents are positively correlated with those of their offspring, especially for very risk averse individuals, but they did not study the determinants of risk preferences in detail—a task that we take up in the present paper.[1]

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[1]In the PSID, risk aversion is measured by asking participants about their willingness to participate in a hypothetical lottery as suggested by Barsky, Juster, Kimball, and Shapiro (1997).

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The transmission of preferences across generations may be part of the explanation for family correlations in economic outcomes. The possibility that severe poverty is self-perpetuating across generations has received much academic and political attention—often under the heading of "poverty traps." Bowles and Gintis (2002) surveyed the economic research on the inheritance of income status and it appears that the intergenerational transmission of income is strongest for the most and the least well off. The PSID, which follows individuals and their children over time, is particularly well suited for studying intergenerational correlations of income and wealth. Using paired offspring–parent data from the PSID, Solon (1992) found an elasticity of income with respect to parental income of about 0.5, while Charles and Hurst (2003) found a slightly lower elasticity of wealth with respect to parental wealth.

Our study sheds light on one potential source of generational transmission by documenting that a large group of—typically disadvantaged—individuals are extremely risk averse and the probability of being extremely or very risk averse is significantly impacted by parental variables, in particular schooling. The pattern is readily visible in the raw data where 43 percent of respondents who have parents without high school degrees are extremely risk averse—a number which drops to 35 percent if one parent graduated from high school and to 24 percent if both parents graduated. The correlation between risk aversion and parental schooling may reflect a host of unobserved variables such as parents' intelligence and environment, and the contribution of our study is to trace the effect from exogenous changes in schooling laws to the probability of extreme risk aversion of the children of parents whose educational levels were elevated by those laws. Our estimates capture the gross effect of elevating parents' schooling, which would be a combination of children learning from their parents, educated parents investing more in the upbringing of children, and so forth. This is the impact that would be of interest to policymakers in a country at a level of development comparable to the United States in the early to mid-20th century considering compulsory schooling reforms.

It is hard to make normative statements about preferences, but we consider the high level of risk aversion revealed by many of the poorer PSID participants to be excessive and likely to be a contributing factor in perpetuating poverty within families. This, however, is one channel of transmission where policy has made headway. We find that changes in compulsory schooling laws that increased parental education lowered the risk aversion of offspring. Many participants in the PSID were middle-aged (or older) in 1996 when risk aversion was measured and their parents' schooling was many years ago—compulsory schooling laws "cast a long shadow."

"Culture," defined as typical preferences in a population, may well affect macroeconomic outcomes; see Fernández (2008) for a survey. This begs the question of how coordinated preferences may appear or, put differently, how culture is formed and transmitted across generations. According to Bisin and Verdier (2008) "... the empirical evidence aiming at distinguishing the different cultural transmission models of fundamental preference traits is almost non-existent." Our results provide one such mechanism: compulsory schooling laws affect a large number of residents in a state and, thereby, impact the preferences of residents in a coordinated fashion (i.e., schooling laws increase the educational level of residents and affect the culture of future generations by changing average risk tolerance, which then may affect macroeconomic outcomes). For example, starting a business is a risky venture, investing for retirement involves the balancing of risk with expected returns, and high paying occupations may have less predictable income streams. Consequently, economic outcomes are dependent on attitudes toward risk.

Why does parental schooling have an impact on children's risk attitudes? We can provide a partial answer to this question using matched children–parents pairs from the PSID. Children of parents with high education tend to also have high education, but our evidence suggests that the effect of parental education on children's risk aversion is not mainly caused by more educated children having lower risk aversion. Parents with low risk aversion and business owners tend to have children with low risk aversion—possibly due to children directly learning about financial risk-taking from their parents ("mimicking") or possibly due to a genetic component. However, including measures for parents' risk aversion and business ownership in our estimations does not lower the effect of schooling, making it unlikely that parents' schooling affects children's risk aversion through these channels. If we include variables that reflect attitudes, such as whether parents "want children to be leaders," these variables affect children's risk aversion in the expected direction (parents who are ambitious on behalf of their children have less risk averse children). Including parents' attitudes in our estimations makes the impact of parents' schooling smaller, but not insignificant, consistent with parental attitudes being an important channel through which parental high school graduation works.

Psychologists have studied risk attitudes extensively. In the early literature, risk-taking is seen as a personality trait.[2] Recent papers suggest that risk should be regarded as a "multidimensional construct." For example, Trimpop, Kerr, and Kirkcaldy (1998) differentiated between planned, reckless, or assertive forms of risky behavior. Zaleskiewicz (2001) distinguished between risk-taking behavior related to achievement motivation (instrumental risk) and risk-taking behavior caused by a need for stimulation (stimulating risk). In the first case—which is more related to risk aversion as economists measure it—risk is taken to achieve an economic goal in the future, while the second case relates to whether an individual is looking for immediate excitement. Zaleskiewicz (2001) found only moderate correlation between the two measures: some people are risk takers, some people avoid all risks, but many individuals clearly distinguish between the two types of risk. He also found a correlation between instrumental risk-taking, rational thinking, and future orientation. Thus, more analytical individuals would be more risk tolerant when facing instrumental risk. This result relates to Benjamin, Brown, and Shapiro (2005), who found that cognitively able individuals (particularly in the math sphere) tend to be less risk averse.[3] Loewenstein, Weber, Hsee, and Welch (2001) suggested people evaluate risks cognitively but react to risks emotionally. They showed that emotional reactions to risky situations in many cases differ from cognitive assessments and often drive behavior. Shiv, Loewenstein, Bechara, Damasio, and Damasio (2005),

[2]Bromiley and Curley (1992) provided an extensive summary of this literature.

[3]The PSID is not well suited to address this question. A measure of IQ is available, but it is not a robust predictor of risk aversion because the PSID's IQ measure is not intended to measure "mathematical intelligence."

in a fascinating paper using subjects with brain damage in areas that affect emotions, found that less emotional individuals tend to be less risk averse.

The literature, combined with our findings, suggests risk attitudes are determined by many channels, likely involving cognitive abilities, emotions, and mimicking of parental behavior. Our results provide support for some of these channels, but stop short of providing a complete map of the determinants of risk aversion.

Our secondary results are as follows. We find lower risk aversion for individuals growing up in "good" counties, using ordinary least squares (OLS) regressions or noninstrumented probit estimations, which indicates that the environment (culture) is important in shaping risk aversion. However, the county variables are not significant in instrumental variables (IV) estimations. Our interpretation is that risk aversion is shaped partly by the environment and partly by parental education, and that the compulsory schooling variables capture both effects. Other significant determinants of risk aversion are age and sex, with females being more risk averse. Similar results were found by Dohmen, Falk, Huffman, Schupp, Sunde, and Wagner (2011) using German data. These authors performed OLS estimations and, in particular, did not explore the effects of changes in compulsory schooling laws.

Finally, we briefly consider whether risk aversion as measured by the PSID predicts economic behavior.[4] In particular, we verify that risk aversion predicts the volatility of income in the direction expected from a priori reasoning: people who express less appetite for risk tend to avoid risk in real settings.

In Section 2, we describe our data and discuss the measure of risk aversion. In Section 3, we explain our econometric methods and analyze determinants of risk aversion, and in Section 4, we examine the role of risk aversion in explaining the volatility of income.

2. Data

We use data from the PSID, which is a large panel of individuals and their offspring. This survey started in 1968, interviewing about 4800 households. Sixty percent of the initial households belong to a cross-national sample from the 48 contiguous states, while the other portion is a national sample of low-income families from the Survey of Economic Opportunity. The PSID follows these original households and households initiated by their offspring over time, conducting annual interviews (biennial since 1997), thereby creating a panel data set on income, demographic information, food consumption, and so on. At irregular intervals, panel participants are interviewed about wealth and savings, and at times they are asked supplementary questions. A series of questions asked to elicit attitudes toward economic risk in 1996 are of central relevance for this study. We describe the questions and how we construct a measure of risk aversion next.

[4]Guiso and Paiella (2004) examined a related measure of risk aversion for Italy and found it predicts choices such as portfolio selection and occupation. Previous drafts of this paper confirmed those results.

2.1 *Measuring risk aversion*

In 1996, respondents in households with employed heads were asked about their willingness to take jobs with different income prospects.[5] The questions are very similar to those introduced and analyzed by Barsky et al. (1997).[6] The first question reads as follows:

> Now I have another kind of question. Suppose you had a job that guaranteed you income for life equal to your current, total income. And that job was [your/your family's] only source of income. Then you are given the opportunity to take a new, and equally good job, with a 50–50 chance that it will double your income and spending power. But there is a 50–50 chance that it will cut your income and spending power by a third. Would you take the new job?

Depending on the answer, the respondent is asked similar questions with job prospects that always double income with a 50 percent probability and cut income by a changing fraction $1 - \lambda$ (with $1 - \lambda$ equal to 10, 20, 50, or 75 percent, respectively). For example, if a participant answers "yes" to the first question (with an income loss of one-third), the next question presents a scenario with a possible 50 percent cut in income. However, if the participant answers "no" to the first question, the income loss is reduced to just 20 percent in the next lottery question. Figure 1 summarizes the sequencing of all questions.[7]

According to expected utility theory, if a respondent answers "yes" to a particular lottery question, then

$$\frac{1}{2}U(2c) + \frac{1}{2}U(\lambda c) \geq U(c).$$

If agents rank outcomes according to a constant relative risk aversion (CRRA) utility function, $U(c) = \frac{c^{1-\rho}}{1-\rho}$, there is a relationship between the Arrow–Pratt coefficient of relative risk aversion ρ and λ; for the indifferent individual, $\lambda = (2 - 2^{1-\rho})^{1/(1-\rho)}$. By changing the cutoff point $(1 - \lambda)$, one can bracket the respondent's willingness to take risk measured by the coefficient of relative risk aversion. To interpret the results, we calculate the conditional mean of ρ in each group following the methodology described in Barsky et al. (1997) and in the PSID documentation, but we do not otherwise condition our empirical analysis on CRRA utility.

The five questions allow us to classify respondents into six distinct risk aversion groups. Table 1 presents a mapping of the respondents' answers to the implied lower and upper bounds for relative risk aversion in each group, as well as the conditional mean that we compute. Respondents in the same group are assigned the (corresponding) conditional mean as their coefficient of relative risk aversion. Thus, our measure

[5] The respondent to the survey is not necessarily the head of household, although typically the head of household or the spouse answered the questions. We track who is the respondent to the risk aversion question to make sure that other variables, such as parental education, refer to the actual respondent.

[6] With the exception that in the PSID, the question indicates that the new job will be equally good—having the same nonmonetary attributes—as their current job.

[7] In our analysis, we only keep respondents with a complete answer record to the series of questions.

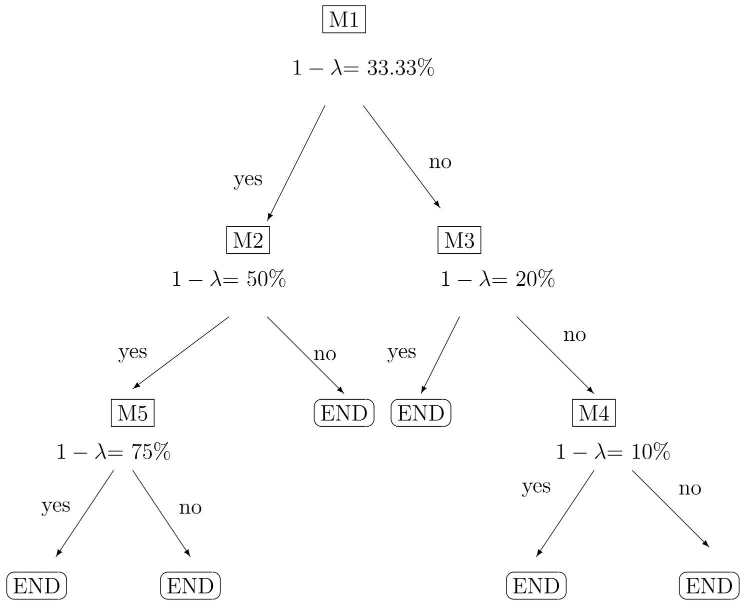

Figure 1. Sequencing of questions from the 1996 PSID supplement on risk aversion. In all questions, the proposed job doubles income with 50 percent probability and cuts income by the varying fraction $1-\lambda$.

of risk aversion only takes six different values. Table 1 shows that the coefficient varies from 0.18 to 33.9, with 49.46 percent of respondents having a coefficient of relative risk aversion above 5. While we do not condition the empirical analysis on CRRA, we believe that individuals who reject all the potential new jobs are extremely risk averse as these numbers suggest. From now on, we use the term "extremely risk averse" for individuals who refuse all lotteries offered (individuals labeled "group 66" in Table 1) and the term "very risk averse" for individuals who would refuse all lotteries offered or accept only the lowest amount of uncertainty (individuals labeled "group 66" or "group 55" in Table 1).

These questions have only been asked once in the PSID. This limits our sample size to approximately 5000 individuals to begin with. Moreover, unlike Barsky et al. (1997),

Table 1. Risk aversion mapping from the survey questions: 1996 PSID data.

		Relative Risk Aversion				
Group	Answers	Lower Bound	Upper Bound	Mean	N	Percent
11	Yes/Yes/Yes	0	0.31	0.18	365	6.56
22	Yes/Yes/No	0.31	1	0.63	756	13.60
33	Yes/No/—	1	2	1.46	828	14.89
44	No/Yes/—	2	3.76	2.83	861	15.49
55	No/No/Yes	3.76	7.53	5.44	1009	18.15
66	No/No/No	7.53	∞	33.9	1741	31.31

we cannot correct for possible measurement error by studying answers by the same individual at different points in time. Survey responses, such as the ones we utilize, may also be subject to systematic biases if they reflect different sets of unobserved constraints and opportunities or even different perceptions of such, in which case the actions of the respondents may be better interpreted as reflecting an indirect rather than a textbook, "deep" utility function. It is notoriously hard to disentangle such problems, but we believe that the deep utility interpretation is strengthened if the results are robust to inclusion of (endogenous) controls such as income and wealth.

2.2 *Environmental variables*

We use a series of retrospective questions about the respondent's background to construct variables that capture the environment in which the respondent grew up. Particularly relevant for our analysis are variables relating to parental education and the county where the individual grew up, which we describe next. Appendix A provides a brief description of all regressors.

Respondents are asked how much education their parents (or "substitute parents") had. The responses are classified into eight different categories ranging from "0–5 grades" of schooling to "graduate work/professional degree." We create high school dummies for each parent. The father high school dummy takes the value 1 if the respondent reports a father with a high school degree or more education. The dummies for the mother are constructed analogously.

Up to 1993, respondents were asked to provide information about the county where they grew up. We know the age of the individual at the time of the 1996 interview and this information, combined with county-level data, allows us to construct a series of variables to measure the "quality" of the county where and when the respondent grew up. We obtain county-level information from Haines (2004), who compiled county-level data for 1790–2000 from historical decennial census and county data books (for the more recent years). The county-level data are not annual but decennial. In the construction of our individual-specific county variables, we find the county-level data point closest to the year when the respondent was 10 years old. For example, if the respondent was 40 years at the time of the 1996 interview, he/she was 10 in 1966 and county-level information for 1970 is used. For each county, we collect median income, the percentage of urban population, the median house value, and the percentage of population 25 and older with a college degree.

We further construct variables that summarize state-level compulsory schooling laws that may have affected the education level of the respondent's parents. Acemoglu and Angrist (2000) compiled information on compulsory schooling laws. In particular, they produced a variable to summarize compulsory attendance laws, CA (the minimum years in school required before leaving school, taking into account certain age requirements), and a variable to summarize child labor laws, CL (the minimum years in school required before work is permitted). The CA variable is concentrated in the 8–12 range, and the CL variable is concentrated in the 6–9 range. Acemoglu and Angrist used four dummies for each variable to capture their respective distributions.[8] These authors documented that the compulsory schooling and child labor variables vary greatly by state and over time and correlate with individual educational attainment—in particular, they found compulsory schooling laws explain high school graduation rates well. We match their variables to our PSID respondents, which is possible because the PSID contains information on the state where the respondent's parents grew up and the age of the parents.[9] The compulsory schooling/child labor variables refer to the state where the respondent's father (or mother) grew up and we use the status of the laws at the time the respondent's parent was 15 years of age.

Other variables used are race, age, sex, whether the respondent grew up in a city, if he/she lived with both parents, and dummies for region or state of residence while growing up.

The sample size of our cross section is bounded by the number of people who gave complete answers to the risk aversion questions in 1996. Moreover, because some individuals choose not to answer other questions required for the construction of regressors (e.g., the parental education questions), the sample size is further reduced. A large number of observations are lost because in 1993 the PSID stopped reporting the county where the individual grew up and because information on spouses (who may answer the risk aversion question) is collected less often than information on heads of households.

3. Estimation: Determinants of risk aversion

3.1 *Instruments*

Parents choose their own education, and this choice is a function of unmeasured attitudes and innate abilities that may directly affect children's risk aversion. Therefore, a relation between parental education and children's risk aversion does not necessarily imply a causal effect. Put differently, various parental traits that we do not observe—such as parental intelligence—may affect the attitudes of offspring as well as parental educational choices. However, in the past there have been significant changes in educational policy that may help us identify the impact of policy-induced changes in schooling: U.S. states implemented child labor laws and school attendance laws—which we collectively refer to as "compulsory schooling laws"—as part of the "high school movement" in the early 20th century. These changes can be considered a "natural experiment," providing exogenous, policy-driven, variation in parental education. The potential effects of compulsory schooling on economic outcomes were first studied by Acemoglu and Angrist (2000), who estimated the monetary return to schooling in the United States. Other researchers studied the econometric validity and the economic implications of these laws: Lleras-Muney (2002) and Goldin and Katz (2003) found these laws indeed raised

[8]For the compulsory attendance laws: $CA8 = 1$ if $CA \leq 8$, $CA9 = 1$ if $CA = 9$, $CA10 = 1$ if $= 10$, $CA11 = 1$ if $CA \geq 11$. For the child labor laws: $CL6 = 1$ if $CL \leq 6$, $CL7 = 1$ if $CL = 7$, $CL8 = 1$ if $CL = 8$, $CL9 = 1$ if $CL \geq 9$.

[9]For parents whose age is not collected in the survey, we assume parental age equals the respondent's age plus 25. The fraction imputed is 57 percent for fathers and 37 percent for mothers. For parents with age available, we can also impute parents' age by our method. If we do so, imputed age has a correlation of 0.80 with actual age.

educational levels. Oreopoulos (2006) found similar effects from changes in compulsory schooling in the United Kingdom, while Lleras-Muney (2002) concluded that the changes in U.S. law were implemented as responses to exogenous political pressures. Oreopoulos, Page, and Stevens (2006) seem to be the first to examine the intergenerational effects of changes in compulsory schooling, finding an effect of parental education on children's grade retention and dropping-out rates, while Black, Devereux, and Salvanes (2005) found no intergenerational effect of compulsory schooling laws on children's education in Norway.

We now clarify the interpretation of our main IV results. Let RA_c denote risk aversion of person (child) c and let S_p denote parental schooling. We consider the relation

$$\mathrm{RA}_c = \beta_0 + \beta_1 S_p + u_c, \tag{1}$$

where u_c denotes unobserved components. (This equation should be interpreted as the relationship between risk aversion and parental schooling after partialing out exogenous regressors such as age.) S_p is exogenous in the sense that children's risk aversion cannot affect parental schooling; however, the amount of schooling is a choice for the parents, and it correlates with parents' cognitive skills and other preferences as well as with grandparents' attitudes, income, wealth, and so on. We are interested in the effect on risk aversion of an exogenous change in schooling and we, therefore, use as an instrument a variable SL_p which measures schooling laws in the state of residence of c's parent. Our first-stage regression is

$$S_p = \delta_0 + \delta_1 \mathrm{SL}_p + v_p. \tag{2}$$

An IV regression has the interpretation of measuring the overall impact of parental schooling on offspring's risk aversion through all channels, such as mimicking of parental behavior, parental investment in the amount and quality of their children's schooling, and higher wealth and inheritances. In other words, one may think of the IV estimate as capturing the projection of offspring's risk aversion on the exogenous variation in parents' schooling. For this interpretation to be valid, the main concern is whether the instrument satisfies the exogeneity condition that u_c is uncorrelated with schooling laws. To rule this out, two conditions need to be satisfied: (i) no causality from schooling to schooling laws and (ii) the exclusion restriction that schooling laws only affect children's risk aversion through parents' schooling. The first condition is likely to hold because the main impetus to changing schooling (and child labor laws) came from a general nationwide high school movement as explained by Goldin and Katz (2003) and because we use state dummies which neutralize any permanent differences between states which might correlate with the timing of schooling reforms as well as risk attitudes. The second (exclusion) restriction might be violated if schooling laws affect *children's* schooling in addition to that of their parents. However, this is unlikely to be important because there is very little variation in schooling requirements across states at the time when the children started high school.

Equation (1) suppresses some features of interest which we will explore in matched parent–children samples. Consider the expanded equation

$$\mathrm{RA}_c = \beta_0 + \beta_1 S_p + \beta_2 \mathrm{RA}_p + \beta_3 S_c + X_c' \beta_4 + v_c, \tag{3}$$

where RA_p is parents' risk aversion, S_c is child's schooling, X_c is a vector of other controls, and v_c is an error term. Parents' risk aversion is observable in a subsample and we examine, using noninstrumented estimations, whether this variable affects risk aversion and whether it lowers the impact of parental schooling, which might be the case if *parents*' risk aversion is a function of parents' education. (We will also use parental business ownership, which is available in a larger subsample, as an indicator of parental risk aversion and parental attitude measures rather than risk aversion.) Appendix B focuses on the potential effect of children's own education. We show that the schooling laws do not predict high school graduation for children which validates the exclusion restriction. (See Oreopoulos, Page, and Stevens (2006) for a more detailed discussion of this issue.) Further, we briefly attempt to estimate β_3 using instruments for own education from Currie and Moretti (2003). We find point estimates consistent with own education reducing risk aversion, but we are not able to obtain significant results—likely due to the small sample size available for these estimations.

Another important matter for the interpretation of the IV results is that schooling laws do not affect everybody to the same extent. For example, the child of a well-to-do professor would likely attend high school no matter what, while the child of a disadvantaged parent might not attend high school unless forced to by compulsory schooling laws. This heterogeneity in the impact of schooling laws is likely to create differences between noninstrumented and IV estimates of the impact of schooling, with larger IV estimates reflecting that schooling laws affect children of disadvantaged parents more. The survey article by Card (2001) shows that IV estimates being larger than noninstrumented estimates is the typical finding in the context of the returns-to-schooling literature. The theoretical explanation, given by Imbens and Angrist (1994), is that the IV estimates measure local average treatment effects (LATE), where the "treatment" (schooling laws) affects some individuals more than others. A comprehensive discussion of the treatment effects literature is given in Heckman and Vytlacil (2005). We give a pedagogical derivation in the simplest possible setup so as to provide an interpretation of our results.

Assume there are two groups of individuals which are differently impacted by schooling. For an individual c belonging to group j, parental schooling is $S_p^j = \delta_j \text{SL}_p^j + v_p^j$. We have in mind a disadvantaged group 1, where δ_1 is large, and an advantaged group 2, where δ_2 is small because offspring of advantaged (typically wealthy) families would attend high school independently of schooling laws. Assume for simplicity that the groups of advantaged and disadvantaged individuals are equally large. Then, in large samples, the first-stage OLS estimate from a regression using the combined sample is

$$\widehat{S}_p = \frac{1}{2}(\delta_1 + \delta_2)\text{SL}_p. \tag{4}$$

Consider also the case where the impact of parental schooling on children's risk aversion differs between groups: $\text{RA}_c^j = \beta_j S_p^j + \varepsilon_c^j$. It is reasonable to assume that the disadvantaged group 1 has a larger β_1. Schooling likely is more important for disadvantaged families compared to, say, a case where the parent is a successful small business owner who learns-by-doing how to manage risk and imparts some of this knowledge to his or her children.

An IV regression of RA_c^j on S_p^j, using compulsory schooling laws as an instrument, gives the coefficient $\frac{E[\mathrm{RA}_c^j \mathrm{SL}_p^j]}{E[S_p^j \mathrm{SL}_p^j]}$, which in large samples becomes

$$\frac{\delta_1\beta_1 + \delta_2\beta_2}{\delta_1 + \delta_2}, \tag{5}$$

that is, a weighted average of β_1 and β_2. Relatively larger coefficients δ_1 and β_1 imply that the IV estimate is larger than the OLS estimate which gives equal weight to δ_1 and δ_2. In the extreme case where $\delta_2 = 0$, the IV estimate reflects solely the impact of schooling on the risk aversion of disadvantaged individuals.

3.2 *Econometric implementation*

We mainly estimate the model using probit probability models, but the results are qualitatively similar if linear probability models are used. We include dummy variables for the state in which the father grew up because permanent differences between states may correlate with unobserved attitudes and we allow for clustering of standard errors by the state in which the father grew up. We also include dummies for the region in which the respondent grew up—using dummies for the state where the respondent grew up together with dummies for the state where the father grew up makes the dummies highly collinear, creating convergence problems for the nonlinear probit estimations. (We show the results are robust to using mother rather than father and to using dummies for where the mother grew up.) Our preferred specification involves variables that are exogenous to risk aversion, namely, age, sex, race, and parental variables including compulsory schooling and labor laws in the state where and when the parents grew up, but we verify the results are robust to the inclusion of potentially endogenous variables. For example, an individual may have high education due to, say, parents' high education. If individuals with high education have low risk aversion, we would find that parents' education appeared to directly explain their offspring's risk aversion, while the true effect is indirect—through children's education. Results that are robust to inclusion of such variables are likely to capture direct effects although we do not include such variables in the main regressions because we do not know the direction of causality between own education and risk aversion. Other potentially endogenous variables are the respondent's income and wealth.

We focus on modeling the probability of falling in the highest categories of risk aversion using probit and IV–probit estimators.

3.3 *Descriptive statistics*

Table 2 displays descriptive statistics for our main variables. The risk aversion measure has a mean of 12.5 with a large standard deviation of 14.7. About 32 percent of the respondents are extremely risk averse, while 50 percent are very risk averse. The average

Table 2. Summary statistics.[a]

Variable Name	Mean	Std. Dev.	Min.	Max.	N
Risk aversion	12.48	14.68	0.18	33.91	3390
Log risk aversion	1.46	1.65	−1.73	3.52	3390
Very risk averse	0.5	0.5	0	1	3390
Extremely risk averse	0.32	0.47	0	1	3390
Age	41.4	10.53	20	87	3390
Black	0.3	0.46	0	1	3390
Female	0.45	0.5	0	1	3390
Mother high school	0.69	0.46	0	1	3390
Father high school	0.6	0.49	0	1	3390
Parents' education/HS sum	1.29	0.83	0	2	3390
Lived with both parents	0.78	0.42	0	1	3349
County principal component	0.18	1.61	−5.12	5.29	3390
County med. income	19,669	6973	1954	43,062	3390
County urb. pop %	0.65	0.32	0	1	3390
% County college grad.	0.12	0.05	0.03	0.43	3390
County med. house value	39,412	18,089	3614	151,340	3390
County principal component	0.18	1.61	−5.12	5.29	3390
One's education (years)	13.31	2.22	2	17	3372
Log income (avg. 1984–1996)	10.03	0.86	2.59	12.79	3384
Log wealth (avg. 1984–1994)	4.43	3.06	−7.33	10.72	3312
Very risk tolerant parent	0.24	0.43	0	1	954
Yrs. fam. owned business (7–13)	0.61	1.51	0	7	1833
Log fam. income (avg. 7–13)	10	0.76	5.16	12.61	1567
Parents' planning score	3.16	1.56	0	6	1896
Parents' trust/hostility score	2.45	1.3	0	5	1896
Leader	0.61	0.49	0	1	1896
Parents hope college for kids	0.42	0.49	0	1	1896

[a]Amounts in 1982–1984 dollars. Variable definitions are given in Appendix A.

age of the PSID participants in our sample is about 41 years in 1998; the oldest is 87 and the youngest is 20 years old. In general, the table speaks for itself, but one may notice that blacks are oversampled at 30 percent. Females represent 45 percent of the sample, making females slightly underrepresented.[10]

To measure the "quality" of the county where respondents grew up, we compute a county principal component, a linear combination of four county-level variables—median income, education, percent of urban population, and median house value. These "components" all contribute positively to the principal component.

Compulsory schooling laws are important determinants of how many individuals in a state finish high school, and we define "parents' education/HS sum" to be the sum of the two dummy variables for mother's high school and father's high school.

Table 3 shows the correlation matrix for risk aversion, the variables included in our regressions, and the state-level instrumental variables. We see that risk aversion is pos-

[10]About 23 percent of households have a female head. However, the PSID reports the risk aversion of the individual filling out the questionnaire who in many instances is not the head. This explains why our sample includes a fraction of female respondents higher than the fraction of female heads.

Table 3. Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Log risk aversion	1.00								
(2) Parents' education/HS sum	−0.17	1.00							
(3) Age	0.20	−0.28	1.00						
(4) Black	0.08	−0.31	−0.07	1.00					
(5) Female	0.12	−0.16	0.06	0.19	1.00				
(6) County principal component	−0.18	0.34	−0.41	−0.07	−0.10	1.00			
(7) Lived with both parents	−0.03	0.02	0.08	−0.21	−0.04	−0.05	1.00		
(8) Compulsory attendance law	−0.12	0.23	−0.29	−0.21	−0.06	0.23	0.05	1.00	
(9) Child labor law	−0.09	0.17	−0.28	−0.09	−0.05	0.19	0.02	0.66	1.00

itively correlated with age and dummies for being a female or black, while it is negatively correlated with parents' education, the county principal component, dummies for whether the head lived with both parents, compulsory attendance laws in states where parents grew up, and labor laws.

Risk aversion is negatively correlated with indicators of wealth and education, and, importantly, the compulsory attendance and labor laws are positively correlated with parental education, which is a necessary condition for these variables to be useful instruments. Many regressors display nonnegligible correlations, implying a role for multiple regression in sorting out their relative effects.

3.4 *Results of probit and IV–probit estimations*

The leftmost two data columns of Table 4 report (first-stage) linear regressions of parental high school dummies' sum on compulsory schooling attendance laws (CA) and child labor laws (CL).[11] We include age, sex, whether the respondent lived with both parents, skin color, and the county principal component as controls, and we include dummies for the region where the respondent grew up and for the state where the respondent's father grew up. The two rightmost columns show (reduced-form) probit estimates of the probability of being very or extremely risk averse on compulsory attendance laws for the father.

The CA variables are all positive and significant for high school graduation, with the CA11 variable having the largest and most significant coefficient.[12] In the second col-

[11] The laws refer to the father when he was 15 years old and the observation will be missing if the father is absent.

[12] Acemoglu and Angrist (2000) found significant effects of both CA and CL dummies in a much larger data set. Intuitively, the CA dummies should have better explanatory power for high school graduation because they focus on years of schooling closer to the 12 years typically needed for high school graduation. Lochner and Moretti (2004) also found an effect of the CA dummies on high school graduation rates. Consistent with Acemoglu and Angrist (2000) and Lochner and Moretti (2004), we find (not tabulated) that the CA dummies do not affect college graduation rates in our sample.

TABLE 4. The effect of schooling laws on parental education and respondents' risk aversion.[a]

Dependent Var.:	Parental Education (OLS)		Respondents' Risk Aversion (Probit)	
	High School Dummy Sum		Very Risk Averse	Extremely Risk Averse
	(1)	(2)	(3)	(4)
CA9	0.13**	0.13**	−0.03	−0.05**
	(2.50)	(2.59)	(−1.14)	(−2.23)
CA10	0.10**	0.10*	−0.04	−0.08***
	(2.16)	(1.92)	(−0.82)	(−2.65)
CA11	0.20***	0.21***	−0.07*	−0.09***
	(3.46)	(2.72)	(−1.90)	(−3.17)
CL6		0.12*		
		(1.75)		
CL8		0.09**		
		(2.09)		
CL9		0.08		
		(1.62)		
Age	−0.02	−0.01	−0.01**	−0.01**
	(−1.58)	(−1.59)	(−2.08)	(−2.54)
$\text{Age}^2/100$	0.00	−0.00	0.02***	0.02***
	(0.06)	(−0.12)	(3.20)	(4.19)
Black	−0.36***	−0.36***	0.04*	0.05*
	(−6.40)	(−6.47)	(1.75)	(1.84)
Female	−0.09***	−0.08***	0.09***	0.07***
	(−3.20)	(−3.05)	(5.50)	(4.28)
County principal component	0.08***	0.08***	−0.03***	−0.02***
	(5.45)	(5.53)	(−3.73)	(−3.53)
Lived with both parents	−0.01	−0.01	−0.03	−0.05***
	(−0.29)	(−0.18)	(−1.58)	(−2.71)
Constant	1.89***	1.74***		
	(6.80)	(6.58)		
States dummies/father grew up	Yes	Yes	Yes	Yes
Region dummies/grew up	Yes	Yes	Yes	Yes
Adj. R^2	0.276	0.277	0.055	0.075
F (instruments)	4.38***	3.68***	3.92***	15.96***
N	3349	3349	3345	3344

[a]Very risk averse is 1 if the respondent's risk aversion is one of the two highest values for risk aversion and is 0 otherwise. Extremely risk averse is 1 if the respondent's risk aversion is the highest value and is 0 otherwise. CA9, CA10, CA11, CL6, CL8, and CL9 are dummies that capture compulsory schooling laws as proposed by Acemoglu and Angrist (2000) and defined in Appendix A. t-statistics are given in parentheses. Robust standard errors in the regressions are clustered by the state where the respondent's father grew up. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

umn, we include the CL dummies which add little to the explanatory power and are only marginally significant. The inclusion of these dummies does not change the coefficients to the attendance dummies.[13] We use the CA dummies only in the rest of our analysis.

[13]The magnitudes of the CL coefficients are also hard to interpret relative to the left-out dummy CL7.

From the probit estimations, compulsory attendance laws for the father explain the probability of children being very risk averse with marginal statistical significance and the probability of being extremely risk averse with very high significance. Clearly, children of parents who grew up in states that implemented more stringent compulsory attendance laws earlier are less likely to be extremely risk averse.

Table 5 displays the results of regular and IV–probit estimations of being very risk averse in the leftmost four data columns and of being extremely risk averse in the rightmost four columns. For easier interpretation, we display the implied marginal probabilities (the change in the probability from a unit change in the relevant variable). The two leftmost columns in each block of four show the results, for regular and IV–probit, respectively, of estimations that do not include the endogenous variables, own education, wealth, and income, while the rightmost columns in each block include those variables. Columns 1 and 5 show that parental education has a significant impact on off-

Table 5. Explaining risk aversion: Probit results (marginal effects).[a]

	Very Risk Averse				Extremely Risk Averse			
	(1) Probit	(2) IV–Probit	(3) Probit	(4) IV–Probit	(5) Probit	(6) IV–Probit	(7) Probit	(8) IV–Probit
Parents' education/ HS sum	−0.04***	−0.30**	−0.04***	−0.33**	−0.05***	−0.37***	−0.04***	−0.37***
	(−3.27)	(−2.03)	(−2.91)	(−2.30)	(−3.89)	(−4.33)	(−3.86)	(−4.15)
Age	−0.01**	−0.02***	−0.02**	−0.02***	−0.01***	−0.02***	−0.01**	−0.02***
	(−2.19)	(−3.05)	(−2.55)	(−3.54)	(−2.83)	(−3.53)	(−2.16)	(−3.47)
$Age^2/100$	0.02***	0.02***	0.02***	0.03***	0.02***	0.02***	0.02***	0.02***
	(3.31)	(3.12)	(3.42)	(4.39)	(4.63)	(3.58)	(3.64)	(4.34)
Black	0.03	−0.07	0.04	−0.05	0.03	−0.10*	0.03	−0.07
	(1.00)	(−1.10)	(1.54)	(−0.99)	(1.07)	(−1.71)	(0.94)	(−1.42)
Female	0.08***	0.05	0.09***	0.06**	0.06***	0.02	0.07***	0.04*
	(5.33)	(1.59)	(5.54)	(2.08)	(4.12)	(0.87)	(4.55)	(1.69)
County principal component	−0.03***	−0.00	−0.02**	−0.00	−0.02***	0.01	−0.01*	0.01
	(−3.12)	(−0.28)	(−2.56)	(−0.01)	(−2.72)	(1.33)	(−1.94)	(1.39)
Lived with both parents	−0.03	−0.03	−0.03	−0.04	−0.06***	−0.05***	−0.05***	−0.05***
	(−1.61)	(−1.40)	(−1.64)	(−1.56)	(−2.79)	(−2.59)	(−2.73)	(−2.58)
One's education (years)			−0.01***	0.01			−0.01***	0.01
			(−2.81)	(0.71)			(−3.23)	(1.34)
Log wealth (avg. 1984–1994)			0.01**	0.01***			0.01**	0.01***
			(2.16)	(2.59)			(2.26)	(2.96)
Log income (avg. 1984–1996)			0.02	0.03**			−0.01	0.01
			(1.47)	(2.07)			(−0.47)	(0.68)
State dummies/ father grew up	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies/ grew up	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3345	3254	3345	3254	3344	3253	3344	3253

[a] Probit and IV–probit estimates of the probability of being very or extremely risk averse as indicated. Instruments: dummies for compulsory attendance laws (when the respondent's father was 15 years old). Very risk averse is 1 if the respondent's risk aversion is one of the two highest values for risk aversion and is 0 otherwise. Extremely risk averse is 1 if the respondent's risk aversion is the highest value and is 0 otherwise. Robust standard errors in the regressions are clustered by the state where the respondent's father grew up. t-statistics are given in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

spring's risk aversion—the higher is parental education, the lower is the probability of being very risk averse or extremely risk averse—a result also found by Dohmen et al. (2011). Risk aversion initially declines with age and then increases; females are more risk averse, while race is not a significant determinant of risk aversion. Barsky et al. (1997) and Dohmen et al. (2011) also found that women are more risk averse.[14] The county principal component negatively predicts risk aversion, as does growing up with both parents, although the latter variable is only significant for extreme risk aversion.[15]

Columns 2 and 6 display IV–probit results. The marginal predicted impact of schooling is dramatically larger than found in the noninstrumented estimations—consistent with schooling laws affecting disadvantaged parents more at the same time as schooling having a higher impact for their children as explained before. The effect is large: if one parent, rather than none, finishes high school, the probability of being extremely risk averse plummets by 37 percent. The effect of age is slightly larger in the IV estimations, while the impact of race changes signs, becoming negative and borderline significant. Columns 3, 4, 7, and 8 of Table 5 address whether the effects of education may be indirect through educated parents having children who themselves are better educated, have higher income, or are wealthier. The estimated coefficients to education are very robust to the inclusion of these variables. In the noninstrumented estimations, higher own education marginally, but significantly, lowers risk aversion, but in the instrumented regressions, the coefficient is positive but not significant. (We study the role of own education in more detail in Appendix B.) There is a significant positive relation between wealth and risk aversion, but this likely reflects reverse causality from higher risk aversion to higher wealth due to precautionary saving. The estimated effect of own income is clearly not significant. Overall, these results indicate that parental schooling does not mainly affect risk aversion through a channel where children of better educated parents are wealthier or better educated and *therefore* less risk averse.

3.5 *Schooling laws and father's and mother's education*

Table 6 explores whether schooling laws affected fathers or mothers of the PSID respondents more. Column 1 repeats the column 1 of Table 4 for convenience. Column 2 explores whether the sum of the high school graduation dummies is explained by schooling laws when and where the mother grew up. The results are similar to, although somewhat stronger than, those found using the schooling laws for the father. If schooling laws are used for both mother and father, the schooling laws in the state where the mother grew up retain their explanatory power, while only the CA11 variable remains significant for the father. The latter result is robust to whether dummies are included for the state where the father grew up (column 3) or where the mother grew up (column 4).

Column 5 considers only father's high school graduation, and the results are less significant than in column 1, although all laws are estimated to have a positive impact,

[14]The PSID survey is not designed such that the selection of female respondents is representative for the total population, so our results regarding sex should be interpreted with care.

[15]Growing up with wealthy parents (as recalled by the subject) or in a city seems not to matter. The magnitudes of the coefficients on these variables are very small and their absolute t-statistics are below 1. We do not report these results for brevity.

Table 6. The effect of schooling laws on parental education: Father versus mother.[a]

	High School Dummy Sum				High School Father Dummy	High School Mother Dummy
	(1)	(2)	(3)	(4)	(5)	(6)
CA9, father	0.13**		0.05	0.09	0.05**	
	(2.50)		(0.96)	(1.59)	(2.09)	
CA10, father	0.10**		0.01	−0.05	0.04	
	(2.16)		(0.13)	(−0.72)	(1.53)	
CA11, father	0.20***		0.13**	0.12*	0.10***	
	(3.46)		(2.08)	(1.92)	(2.76)	
CA9, mother		0.20***	0.17***	0.17***		0.11***
		(4.32)	(4.35)	(2.89)		(3.55)
CA10, mother		0.13**	0.19***	0.15**		0.11**
		(2.44)	(2.79)	(2.06)		(2.54)
CA11, mother		0.21***	0.19***	0.15*		0.12***
		(3.04)	(2.99)	(1.70)		(2.82)
Age	−0.02	−0.02	−0.02*	−0.02*	−0.02***	−0.00
	(−1.58)	(−1.59)	(−1.73)	(−1.70)	(−2.78)	(−0.40)
$Age^2/100$	0.00	0.00	0.00	0.00	0.01	−0.00
	(0.06)	(0.07)	(0.35)	(0.29)	(1.30)	(−0.73)
Black	−0.36***	−0.35***	−0.36***	−0.35***	−0.19***	−0.16***
	(−6.40)	(−5.80)	(−6.48)	(−5.79)	(−5.48)	(−4.72)
Female	−0.09***	−0.10***	−0.09***	−0.10***	−0.03*	−0.06***
	(−3.20)	(−3.92)	(−3.31)	(−3.89)	(−1.94)	(−3.80)
County principal component	0.08***	0.08***	0.08***	0.08***	0.05***	0.03***
	(5.45)	(4.92)	(5.31)	(5.18)	(5.92)	(3.47)
Lived with both parents	−0.01	−0.02	−0.02	−0.03	−0.02	0.01
	(−0.29)	(−0.76)	(−0.40)	(−0.84)	(−1.47)	(0.43)
Constant	1.89***	1.86***	1.78***	1.82***	1.14***	0.77***
	(6.80)	(5.44)	(6.25)	(5.07)	(7.14)	(3.81)
States dummies/parent grew up	Father	Mother	Father	Mother	Father	Mother
Region dummies/grew up	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Father	Mother	Father	Mother	Father	Mother
Adj. R^2	0.276	0.269	0.282	0.272	0.220	0.205
F (instruments)	4.38***	6.64***	4.50***	6.17***	2.75**	4.99***
N	3349	3362	3301	3301	3378	3523

[a] Linear OLS regressions. The left-hand side variable is parental education (father, mother, or both) as indicated in each column. CA9, CA10, and CA11 are dummies that capture compulsory schooling laws as proposed by Acemoglu and Angrist (2000) and defined in Appendix A; t-statistics are given in parentheses. Robust standard errors in the regressions are clustered by the state where the respondent's parent grew up as indicated. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

and CA9 and CA11 are still significant. The last column reveals that schooling laws had stronger effects on female high school graduation. All three compulsory attendance variables are clearly significant and the estimated coefficients are all larger than the corresponding ones for fathers.

In Table 7, we study whether risk aversion is determined differently by mothers' or fathers' education. We further examine whether the results are robust to using as instru-

Table 7. Explaining risk aversion: Probit results (marginal effects) for father versus mother.[a]

	Very Risk Averse		Extremely Risk Averse		
	Parental Education Coefficient		Parental Education Coefficient		(Cluster, Instrument)
	(1)	(2)	(3)	(4)	
Parents' high school dummy sum					
Probit	−0.04***	−0.04***	−0.05***	−0.04***	(Father)
	(−3.27)	(−2.91)	(−3.89)	(−3.86)	
IV–Probit	−0.30**	−0.33**	−0.37***	−0.37***	(Father, Father)
	(−2.03)	(−2.30)	(−4.33)	(−4.15)	
IV–Probit	−0.24*	−0.26	−0.23**	−0.24*	(Father, Father + Mother)
	(−1.71)	(−1.45)	(−2.24)	(−1.93)	
Probit	−0.05***	−0.04***	−0.05***	−0.04***	(Mother)
	(−4.28)	(−3.85)	(−4.22)	(−4.04)	
IV–Probit	−0.24**	−0.26**	−0.17**	−0.19*	(Mother, Father + Mother)
	(−2.19)	(−2.08)	(−2.08)	(−1.95)	
IV–Probit	−0.21*	−0.20	−0.20**	−0.19*	(Mother, Mother)
	(−1.80)	(−1.44)	(−2.25)	(−1.71)	
Father high school dummy					
Probit	−0.06***	−0.05**	−0.06***	−0.05***	(Father)
	(−2.59)	(−2.30)	(−2.92)	(−2.68)	
IV–Probit	−0.52***	−0.56***	−0.64***	−0.64***	(Father, Father)
	(−3.91)	(−4.85)	(−6.08)	(−5.99)	
Mother high school dummy					
Probit	−0.06***	−0.06***	−0.07***	−0.07***	(Mother)
	(−3.20)	(−3.10)	(−3.78)	(−3.76)	
IV–Probit	−0.33*	−0.34*	−0.34**	−0.33*	(Mother, Mother)
	(−1.71)	(−1.65)	(−2.12)	(−1.79)	
Exogenous controls	Yes	Yes	Yes	Yes	
Endogenous controls	No	Yes	No	Yes	
States dummies/parent grew up	Yes	Yes	Yes	Yes	
Region dummies/grew up	Yes	Yes	Yes	Yes	

[a]Probit and IV–probit estimates of the probability of being very or extremely risk averse as indicated. Very risk averse is 1 if the respondent's risk aversion is one of the two highest values for risk aversion and is 0 otherwise. Extremely risk averse is 1 if the respondent's risk aversion is the highest value and is 0 otherwise. The instruments are dummies for compulsory attendance laws when the respondent's parent was 15 years old. "Parent" is father, mother, or both as indicated in each row. Robust standard errors in the regressions are clustered by the state where the respondent's father or mother grew up as indicated in the last column. Controls are as in Table 5: age, age squared, black and female dummies, a county principal component, and a dummy for living with both parents. Endogenous controls include own education and the log of wealth and income from 1984–1996. t-statistics are given in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

ments schooling laws for fathers, for mothers, or for both and whether the results are robust to clustering by the state where the mother or the father grew up. The table only displays the coefficient to the parental education variable; the first two rows redisplay the results of Table 5 for convenience. The third row displays results where schooling laws for both mother and farther are used as instruments. The results are similar, although the coefficient estimates are smaller and only marginally significant for the very risk averse. The fourth through sixth rows display results of probit estimates clustering by the state where the mother grew up. This results in slightly more significant estimates for the probit specification and very similar results for the IV–probits.

The middle panel uses the paternal high school graduation dummy as the measure of "parent's education." The probit coefficients become slightly larger, but less significant, compared to the baseline case, while the coefficients in the IV–probits become much larger than those found using the sum of the parents' high school graduation dummies. Using maternal education—see the lower rows—delivers slightly larger and more significant results in the probit estimation; however, the estimated (IV) coefficient for mother's high school dummy is much smaller than the coefficient found for father's high school graduation.

Overall, the results are robust to the use of mother's, father's, or combined dummies as instruments and the choice of clustering by mother's or father's state. The larger coefficient found for father's education in the instrumented estimations is likely due to different effects of heterogeneity between genders. There is some evidence that schooling reforms before World War II affected males more because males had higher earnings potential outside school (see Lleras-Muney (2002)) and, assuming that children from advantaged families always are affected little, this would imply that the ratio δ_1/δ_2 in equation (5) for males would be higher than for women. If the relative effect (between advantaged/disadvantaged families) of father's and mother's education on children's risk aversion is similar, this could explain the much larger coefficient in the IV–probit estimations for males—see equation (5).

3.6 *Results from matched samples*

The particular structure of the PSID, which follows households and their offspring, allows us to create a small matched sample with observations on risk aversion for an individual and that individual's father or mother. This matched sample can be used to examine which parental traits determine the risk aversion of children in more detail. For example, well educated parents may try to deliberately influence their children's risk tolerance or children may become more risk tolerant by interacting with risk tolerant parents. Our matched sample is relatively small and includes mainly the youngest respondents to the risk aversion question (the average age is 30 with a standard deviation of 7).

In Table 8, we estimate the marginal probabilities of being very risk averse (falling within the two highest risk aversion categories) or extremely risk averse (within the highest risk aversion category). We present noninstrumented regressions: in IV estimations, the parental education variable has the same sign but is far from significant (results not tabulated here for brevity) because the sample is smaller than that of our previous regressions and because compulsory schooling laws have less of an effect on the younger parents. While the interpretation of parental education in the noninstrumented regressions is subject to the caveats discussed earlier, the child–parent paired regressions will be informative about whether parental education might be capturing other parental characteristics. In particular, we would like to know if parental risk aversion affects the

Table 8. Parents' risk tolerance in a matched sample (probits; marginal effects).[a]

	Very Risk Averse		Extremely Risk Averse	
	(1)	(2)	(3)	(4)
Parents' education/HS sum	−0.05	−0.05	−0.05**	−0.05**
	(−1.54)	(−1.52)	(−2.11)	(−2.07)
Very risk tolerant parent		−0.13**		−0.06
		(−2.24)		(−1.17)
Black	0.02	0.02	−0.00	−0.00
	(0.33)	(0.35)	(−0.08)	(−0.06)
Age	0.00	−0.00	0.00	0.00
	(0.09)	(−0.23)	(0.59)	(0.44)
Female	0.07	0.08*	0.09**	0.09**
	(1.64)	(1.74)	(2.12)	(2.19)
Lived with both parents	−0.06	−0.07	−0.08**	−0.08**
	(−1.24)	(−1.29)	(−2.15)	(−2.18)
State dummies/grew up	Yes	Yes	Yes	Yes
Pseudo R^2	0.064	0.073	0.088	0.091
N	594	594	592	592

[a]Probit estimates of the probability of being very or extremely risk averse as indicated. Very risk averse is a dummy variable equal to 1 if the respondent's risk aversion is one of the two highest values and is 0 otherwise (roughly a 40–60 split of the sample). Extremely risk averse is a dummy variable equal to 1 if the respondent's risk aversion is the highest value and is 0 otherwise (roughly a 21–79 split of the sample). "Very risk tolerant parent" is a dummy variable equal to 1 if either the father of the mother reports a risk aversion lower than 1.5. Robust standard errors in the regressions are clustered by the state where the respondent grew up. t-statistics are given in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

risk aversion of children and whether its inclusion makes the educational variable insignificant.

Table 8 confirms the role of parents' education, although the results are not quite significant at the 10 percent level for very risk averse. Parents' risk tolerance has a significant impact—as also found by Charles and Hurst (2003)—on whether children are very (but not extremely) risk averse. Due to the smaller sample of about 600 observations, the only other significant variable is the sex of the respondent, where females are still found to be more risk averse. All in all, Table 8 provides at least tentative evidence that suggests parental risk attitudes matter for children's risk attitudes and that this effect is not highly correlated with parental education: it appears parental risk attitudes affect the level of risk aversion in the less extreme range, but the differences are minor and a larger data set would be needed to ascertain this.

In Table 9, we analyze the effect of family business ownership and family income when the respondent was a child using a matched sample of about 1200 observations.[16] Because business ownership involves risk, a negative effect of business ownership on risk aversion indicates that children's risk attitudes depend on parental risk-taking behavior. Having no instruments for business ownership, the results are only indicative,

[16]We do not show matched results that include both parents' business ownership and parents' risk aversion because this makes the data set very small. In unreported estimations on this smaller data set, we got similar point estimates, but the sample size was too small to obtain precise results.

Table 9. Business ownership and family income in a matched sample (probits; marginal effects).[a]

	Very Risk Averse				Extremely Risk Averse			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parents' education/ HS sum	−0.06**	−0.06**	−0.06***	−0.06**	−0.06***	−0.06***	−0.06***	−0.05***
	(−2.56)	(−2.40)	(−2.69)	(−2.55)	(−3.51)	(−3.31)	(−3.12)	(−2.72)
Yrs. fam. owned business (7–13)		−0.02**				−0.02*		
		(−2.09)				(−1.95)		
Log fam. income (avg. 7–13)				0.00				−0.03
				(0.04)				(−1.22)
Age	0.00	0.00	0.00	0.00	0.01*	0.01*	0.00	0.00
	(1.44)	(1.25)	(0.47)	(0.46)	(1.87)	(1.71)	(0.94)	(1.14)
Black	0.05	0.03	0.05*	0.05	0.03	0.02	0.03	0.01
	(1.47)	(1.07)	(1.67)	(1.64)	(0.72)	(0.42)	(0.64)	(0.32)
Female	0.07**	0.07**	0.06*	0.06*	0.05*	0.06*	0.06*	0.06*
	(2.01)	(2.06)	(1.81)	(1.81)	(1.81)	(1.85)	(1.92)	(1.89)
Lived with both parents	−0.02	−0.02	−0.03	−0.03	−0.06	−0.05	−0.06	−0.05
	(−0.66)	(−0.56)	(−0.90)	(−0.81)	(−1.47)	(−1.40)	(−1.54)	(−1.08)
State dummies/ grew up	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.038	0.041	0.045	0.045	0.056	0.059	0.064	0.066
N	1228	1228	1041	1041	1230	1230	1043	1043

[a] Probit estimates of the probability of being very or extremely risk averse as indicated. Very risk averse is a dummy variable equal to 1 if the respondent's risk aversion is one of the two highest values and is 0 otherwise (roughly a 50–50 split of the sample). Extremely risk averse is a dummy variable equal to 1 if the respondent's risk aversion is the highest value and is 0 otherwise (roughly a 31–69 split of the sample). The two family-level variables refer to the period when the risk aversion respondent was 7–13 years of age. Robust standard errors in the regressions are clustered by the state where the respondent grew up. t-statistics are given in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

but these regressions also serve to establish robustness of the role of parental education. We construct a variable that counts the number of years the respondent's parents report owning a business when the respondent was 7–13 years of age (i.e., the variable takes values from 0 to 7). Columns 1 and 5 repeat our baseline estimation on the sample for which we can construct business ownership and, from columns 2 and 6, parents' business ownership has an effect on risk aversion that is significant at about the 5 percent level for both levels of risk aversion. Columns 3 and 7 in Table 9 repeat the baseline estimation for the slightly smaller sample for which we can construct family income, and columns 4 and 8 show that parental income when the respondent was a child does not predict risk aversion once we control for parental education. The results of Table 9 indicate parental business ownership is not a main channel for parental education to affect risk aversion.

In our final set of paired regressions, we explore a series of questions in the 1972 wave of the PSID regarding parental attitudes by matching parents with valid answers to these questions to children with observations on risk aversion. To maximize sample size, we do not include parental risk attitudes or business ownership; about 1600 observations are available. The variables we consider are (i) a parental planning score, which measures parents' future orientation; (ii) a trust/hostility score; (iii) a dummy variable equal to 1 if parents report that they would prefer their children to be leaders as opposed to being popular with their classmates; (iv) a measure of parental educational aspirations for their children (a dummy variable equal to 1 if parents hope all their children will finish college). Exact variable definitions are provided in Appendix A.[17]

Table 10 presents these results. The leader dummy clearly has significant effects on children's risk aversion, with higher statistical significance for very risk averse respondents. The parents' planning score is significant at the 5 percent level for extremely risk averse individuals, but not significant for the very risk averse. The trust/hostility score is insignificant, while the educational aspirations variable is clearly significant for the

TABLE 10. Parents' attitudes in a matched sample (probits; marginal effects).[a]

	Very Risk Averse			Extremely Risk Averse		
	(1)	(2)	(3)	(4)	(5)	(6)
Parents' education/HS sum	−0.06***	−0.04**	−0.04**	−0.06***	−0.04**	−0.04**
	(−3.44)	(−2.57)	(−2.54)	(−3.73)	(−2.41)	(−2.41)
Parents' planning score		−0.01			−0.02*	
		(−1.32)			(−1.89)	
Parents' trust/hostility score		0.01			−0.01	
		(0.67)			(−1.25)	
Leader		−0.05**			−0.04*	
		(−2.10)			(−1.65)	
Parents hope college		−0.07**			−0.04	
		(−2.18)			(−1.42)	
Attitudes principal component			−0.03**			−0.04***
			(−2.57)			(−3.10)
Age	0.00*	0.00	0.00*	0.00	0.00	0.00
	(1.65)	(1.61)	(1.70)	(1.45)	(1.46)	(1.48)
Female	0.07**	0.07**	0.07**	0.07***	0.07**	0.07**
	(2.36)	(2.19)	(2.28)	(2.72)	(2.51)	(2.55)
Black	0.06**	0.06**	0.04	0.04	0.02	0.02
	(2.10)	(2.19)	(1.60)	(1.09)	(0.65)	(0.62)
Lived with both parents	0.01	0.03	0.02	−0.04	−0.02	−0.02
	(0.40)	(0.99)	(0.73)	(−1.09)	(−0.67)	(−0.71)
State dummies/grew up	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.034	0.040	0.037	0.045	0.053	0.053
N	1597	1597	1597	1599	1599	1599

[a]Probit estimates of the probability of being very or extremely risk averse as indicated. Very risk averse is a dummy variable equal to 1 if the respondent's risk aversion is one of the two highest values and is 0 otherwise (roughly a 43–57 split of the sample). Extremely risk averse is a dummy variable equal to 1 if the respondent's risk aversion is the highest value and is 0 otherwise (roughly a 26–74 split of the sample). Robust standard errors in the regressions are clustered by the state where the respondent grew up. t-statistics are given in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

[17]The PSID reports a "risk avoidance" score, which is based on a variety of answers such as whether the parent has medical and auto insurance, wears seat belts, or is a smoker. This measure, which is quite different from our measure of risk aversion, does not explain children's risk aversion.

very risk averse. Combining the parental attitude variables into a principal component, we obtain statistical significance at the 5 percent level for the very risk averse and at the 1 percent level for the extremely risk averse. Including the attitude variables cuts the coefficient to parental schooling from -0.06 to -0.04 (for both categories of risk aversion), which is consistent with attitudes being an important channel of transmission from parental schooling to offspring's risk attitudes.

In the absence of instruments, we cannot make stronger statements, but overall it appears that the impact of parental education is not through parental risk aversion, income, or business ownership, but rather through harder-to-quantify parental attitudes.

3.7 *Robustness*

Previous drafts of this paper reported results using linear probability regressions and ordered logit models. Those results were all qualitatively very similar to the ones reported here. Previous drafts also addressed the potential problem of weak instruments: we calculated p-values for the IV estimates of the effect of parental education using the method proposed by Moreira (2003) (the method only applies to linear models). It appears the potential problem of weak instruments is not important for our results.

Further, we experimented with different specifications for clustering of standard errors. In particular, we clustered by the state where the respondent grew up or by the state where parent or respondent grew up interacted with year of birth. Overall, the particular specification of clustering has little impact on the results. Finally, we experimented with dummies for state where respondent or parent grew up. This also has little effect on the results except in matched samples with small numbers of observations where statistical significance suffers if we include dummies for both parents and respondents.

4. Risk aversion and income volatility

We examine the impact of risk aversion on head of household's income volatility.[18] We do not have instruments for risk aversion that are useful for this purpose, but reverse causality from income volatility to risk aversion might be expected to lead to a positive correlation between these variables. Further, even if potential reverse causality makes the point estimates suspect, we feel it is important to document a negative statistical correlation between risk aversion and income volatility—a lack of correlation would suggest risk aversion had no important economic effects.

The economic literature emphasizes the importance of income volatility for household choices regarding consumption, savings, and wealth (e.g., Caballero (1990), Hubbard, Skinner, and Zeldes (1994)). Households that face relatively high future income risk reduce their current consumption and save more to prepare for possible bad income realizations. This type of savings is known as "precautionary savings." Carroll and Samwick (1997) and Skinner (1988) found substantial precautionary savings, while other researchers found a small precautionary motive (e.g., Guiso, Jappelli, and Terlizzese (1992), Dynan (1993)). The latter finding is often attributed to lacking controls for risk aversion (e.g., Fuchs-Schündeln and Schündeln (2005)).

[18]In this section, we utilize data only for the households whose heads have records on risk aversion.

We analyze the effect of risk aversion on the volatility of the shocks to idiosyncratic head-of-household labor income. Our measure of idiosyncratic head's labor income growth is defined, as is typical in the literature, as the residual from a cross-sectional regression of log head's labor income change on a third degree polynomial in head's age, education dummies, and the interactions of education dummies with the age polynomial. For these regressions, we use data from the 1969–1997 annual family files of the PSID.

Table 11 presents OLS regressions of the volatility of the shocks to idiosyncratic head-of-household labor income on risk aversion and demographic controls.[19] As can be seen from column 1, risk aversion is significantly negatively related to the volatility of head's labor income. Although the risk aversion coefficient may be potentially biased due to reverse causality, the bias would move the coefficient closer toward zero and tend to make it statistically insignificant. Thus, the significance of the OLS coefficient signals an important effect of risk aversion on head's income volatility.

We find that male heads have more volatile incomes, while married, high earnings, and wealthy heads have less volatile income streams. In the PSID, heads are females predominantly when they are unmarried; thus, the result of less volatile income for female heads may reflect the fact that they choose careers by taking into account that they are largely devoid of the type of insurance married couples have—the income of the spouse. In column 2 of Table 11, we present results that instrument parental education with compulsory schooling laws. Risk aversion retains its significance and importance, indicating that it has an effect on the head's income volatility beyond that induced by parental education.[20]

Household income and individual income are typically modeled as the sum of a persistent or permanent component and a transitory component. It has been argued that the volatility of transitory shocks to household income is not as important for household welfare as the volatility of permanent shocks, presumably because transitory shocks can be better insured through credit markets (e.g., Carroll and Samwick (1997), Kazarosian (1997)). Therefore, we analyze the magnitude of the volatility of permanent shocks to idiosyncratic head's labor income for households with heads of different risk aversion levels. To identify the volatility of permanent shocks to log idiosyncratic head's income, we use a procedure proposed by Meghir and Pistaferri (2004) that is described in Appendix C. Essentially, the method uses a moment condition to identify the (unconditional) long-run variance of the first difference in idiosyncratic income under the assumption that the income process contains a random walk and a stationary component modeled as a moving average process.

We estimate the volatility of permanent income shocks for households with very risk averse heads and risk tolerant heads separately. Our first subsample is the very risk averse households (the two highest categories of risk aversion), while the second

[19]Parental education is not a satisfactory instrument in this regression since it may directly affect the head's income volatility through different channels, invalidating the exclusion restriction for instrumental variables regressions. Based on these considerations, we included parental education as a separate control into an OLS regression with head's income volatility as the dependent variable.

[20]This result is unaffected if we exclude endogenous variables in the OLS and IV regressions.

Table 11. Regressions of volatility of shocks to head's idiosyncratic labor income on risk aversion and demographic controls.[a]

	(1) OLS	(2) IV
Log risk aversion/10	−0.10***	−0.10***
	(−3.25)	(−2.78)
Black	0.01	0.01
	(0.82)	(0.50)
Female	−0.11***	−0.11***
	(−6.90)	(−6.76)
Age	0.00	0.00
	(0.08)	(0.42)
Age^2/100	0.00	−0.00
	(0.28)	(−0.16)
Parents' education/HS sum	0.02**	0.02
	(2.32)	(0.46)
One's education (years)/10	0.04*	0.03
	(1.75)	(0.80)
Married	−0.03*	−0.03*
	(−1.74)	(−1.70)
Family size	0.00	0.00
	(0.73)	(0.58)
Log net worth (avg. 1984–1994)/10	−0.03	−0.03
	(−1.37)	(−1.31)
Log income (avg. 1980–1995)	−0.13***	−0.13***
	(−9.45)	(−7.03)
Constant	1.64***	1.62***
	(12.49)	(12.04)
Adj. R^2	0.100	0.102
N	2094	1991

[a]Income and demographic data are drawn from the 1969–1997 annual family files of the PSID. Idiosyncratic head's income growth is the residual from the cross-sectional regression of household head's log labor income change on a third polynomial in age, education dummies (for high school dropouts, high school (but not college) graduates, college graduates), and the interaction of education dummies with the age polynomial. The sample is restricted to households with heads aged 24–65. Female and single heads are included. We drop observations if head's labor income growth is above 700% or below –90%, or with head's real labor income below 1000 1982–1984 dollars. The standard deviation of idiosyncratic head's income growth is calculated for the heads with more than four observations on income growth residuals over the time span of 1968–1996. Average income is the average of the sum of head's and wife's real labor income and their combined real transfer income over the time span of 1980–1995. Average real net worth is the average of the household net worth (exclusive of business net wealth) in 1984, 1989, and 1994. Instruments for parental education: CA and CL dummies (for the respondent's father, when the respondent's father was 15 years old). Robust standard errors in the regressions. t-statistics are given in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

subsample—labeled "risk tolerant"—consists of households with risk aversion below 1. Following Meghir and Pistaferri (2004), we estimate the volatility of permanent shocks to head's income assuming that the transitory component is a moving average process of order 1.[21] The results are presented in columns 1 and 2 of Table 12.

Less risk averse households have higher volatility of permanent shocks to income. In other words, less risk averse individuals choose careers with more volatile income

[21]See Abowd and Card (1989) and Meghir and Pistaferri (2004) for empirical evidence in favor of this specification.

Table 12. Volatility of permanent income shocks.[a]

	Head's Labor Income		Household Income	
	Very RA (1)	Risk Tolerant (2)	Very RA (3)	Risk Tolerant (4)
St. dev. of permanent shocks	0.234 (0.007)	0.267 (0.013)	0.152 (0.009)	0.209 (0.012)
Number of heads	1641	680	820	352
p-Value for H_0 of no difference in perm. vol. in (1) and (2)	3%			
p-Value for H_0 of no difference in perm. vol. in (3) and (4)	0.01%			

[a]The first subsample consists of households whose head's risk aversion is higher than or equal to 5.44 (the highest two categories of the risk aversion distribution); the second subsample consists of households whose values of risk aversion are below 1. We recover the volatility of permanent shocks to head's idiosyncratic income by estimating the following unobserved components income model: $\Delta\tilde{y}_{it} = \varepsilon^P_{it} + (1-L)\theta_q(L)\varepsilon^T_{it}$, where $\Delta\tilde{y}_{it}$ is the first difference in head's log idiosyncratic income, ε^P_{it} is the permanent innovation, ε^T_{it} is the transitory innovation, and q is the order of the autocovariance in the transitory component of log idiosyncratic head's income (we assume that $q = 1$). The model is estimated by the equally weighted minimum distance (EWMD) method, where the weighting matrix is the identity matrix. Data are drawn from the 1969–1997 annual family files of the PSID. Idiosyncratic income growth rates are defined as residuals from cross-sectional regressions of head's log labor income changes on a third polynomial in head's age, education dummies (for high school dropouts, high school (but not college) graduates, college graduates), and the interaction of education dummies with the age polynomial. We restrict the sample to households with heads of ages 24–65. Female and single heads are included. We drop observations if income growth is above 700% or below –90%, or if head's income is below 1000 1982–1984 dollars. Household income is the sum of combined labor incomes of the head and wife, and their combined transfer income. When analyzing the income process for household income, we drop observations if head's or wife's labor income is missing; we keep only households with married male heads, with no changes in family composition. Standard errors are given in parentheses.

paths. The hypothesis that the volatility of permanent shocks is the same for heads with different degrees of risk aversion can be rejected at about 3% for head's idiosyncratic labor income.

Further, we performed the same analysis for *household* idiosyncratic income; see columns 3 and 4 of Table 12. The results are very similar: the hypothesis that permanent idiosyncratic shocks to household income have the same variance for heads with different degrees of risk aversion can be rejected at any conventional level of significance.

We conclude that risk aversion is negatively correlated with the volatility of the shocks to idiosyncratic income and that the self-selection phenomenon emphasized in the precautionary savings literature is empirically relevant.

5. Conclusion

We examined determinants of risk aversion for households in the PSID. Growing up with more educated parents matters: children of educated parents are less risk averse in adulthood. Using compulsory schooling laws as instruments, we showed that the effect of parental education is not just capturing attitudes and abilities of parents: policies that increase schooling will tend to make future generations less risk averse. In particular, they will lower significantly the probability of having extremely risk averse individuals.

We arrived at some other clear conclusions: older individuals and females are more risk averse, and more risk averse parents have more risk averse children. We found that risk aversion matters for observed economic behavior. Individuals with high risk aversion are less likely to choose careers with more volatile income streams.

Appendix A: List of regressors

Age: Age of the respondent at the time of the 1996 interview.

Black: Dummy variable, equal to 1 if the respondent reports being African–American.

Female: Dummy variable, equal to 1 if the respondent is female.

Father high school: Dummy variable, equal to 1 if the respondent's father has a high school degree or more education.

Mother high school: Dummy variable, equal to 1 if the respondent's mother has a high school degree or more education.

Parents' education/HS sum: Sum of the father and mother high school dummies.

Lived with both parents: Dummy variable, equal to 1 if the respondent reports he or she lived with both natural parents most of the time until age 16.

Log county med. income: The log of median income in 1982–1984 dollars in the county where the respondent grew up, when the respondent was 10 years old.

County urb. pop %: Urban population percentage in the county where the respondent grew up, when the respondent was 10 years old.

% County college grads: Percentage of the population 25 or older with college degrees in the county where the respondent grew up, when the respondent was 10 years old.

Log county med. house val.: The log of the median house value in 1982–1984 dollars in the county where the respondent grew up, when the respondent was 10 years old.

County principal component: The principal component of the four previous variables.

CA: The minimum years in school required before leaving school when the respondent's father or mother was 15 years old in the state where the respondent's parent grew up.

CL: The minimum years in school required before work is permitted when the respondent's father or mother was 15 years old in the state where the respondent's parent grew up.

CA8: Dummy variable, equal to 1 if $\mathrm{CA} \leq 8$.

CA9: Dummy variable, equal to 1 if $\mathrm{CA} = 9$.

CA10: Dummy variable, equal to 1 if $\mathrm{CA} = 10$.

CA11: Dummy variable, equal to 1 if $\mathrm{CA} \geq 11$.

CL6: Dummy variable, equal to 1 if $\mathrm{CL} \leq 6$.

CL7: Dummy variable, equal to 1 if $\mathrm{CL} = 7$.

CL8: Dummy variable, equal to 1 if $\mathrm{CL} = 8$.

CL9: Dummy variable, equal to 1 if $\mathrm{CL} \geq 9$.

Own education (years): Number of years of education of the respondent.

Log income (avg. 1984–1996): Mean of the respondent's log of real family income for the years 1984–1996 in 1982–1984 dollars.

Log wealth (avg. 1984–1994): Mean of household log wealth for the periods 1984, 1989, and 1994 (the PSID does not collect wealth annually). The measure includes housing wealth. By "log," we actually mean the following transformation: $\text{sign}(\text{wealth}) \times \log(1 + \text{abs}(\text{wealth}))$. This transformation allows us to keep negative values of wealth.

Parents' risk tolerance: Dummy variable, equal to 1 if either the respondent's father or the respondent's mother had risk aversion smaller than 1.5, and equal to 0 otherwise. Thus, the dummy equals 1 if either parent's risk aversion corresponds to one of the three lowest values for risk aversion: 0.18, 0.43, and 1.46.

Yrs. fam. owned business (7–13): The number of years the respondent's parents report owning a business while the respondent was 7–13 years of age.

Log fam. income (avg. 7–13): Mean of the respondent's log of real family income when the respondent was 7–13 years of age, in 1982–1984 dollars.

Region dummies/grew up: Eight regional dummies identifying the region where the respondent grew up as reported in retrospective questions.

State dummies/grew up: State dummies identifying the state where the respondent grew up as reported in retrospective questions.

Planning score: 1972 reported efficacy and planning. Variable V2939. It is a score from 0 to 6 constructed from the following questions:

- Sure life would work out (V2743 = 1)
- Plans life ahead (V2744 = 1)
- Gets to carry out things (V2745 = 1)
- Finishes things (V2746 = 1)
- Rather save for future (V2748 = 5)
- Thinks about things that might happen in future (V2755 = 1)

Parents' trust/hostility score: Reported trust or hostility in 1972. Variable V2940. Score 0–5. Constructed from the following variables:

- Does not get angry easily (V2751 = 5)
- Matters what others think (V2752 = 1, 2)
- Trusts most other people (V2753 = 1)
- Believes life of average man getting better (V2756 = 1)
- Believes there are not a lot of people who have good things they do not deserve (V2757 = 5)

Leader: Dummy variable, equal to 1 if the parents report they would prefer their child to be a leader versus being popular with classmates. Variable V2760 in the 1972 interview.

Parents hope college for kids: Dummy variable, equal to 1 if the parents report they think all children will go to college in the 1972 interview. Answers 1 and 2 to question V2549, "About how much education do you think the children will have when they stop going to school?"

Appendix B: The effect of schooling laws on parental education and own education

It is important for the interpretation of our results that compulsory attendance and labor laws in a state affected parents but not their children. We provide some evidence on this issue. In Table B-1, we show the results of a regression of own (as opposed to father's) high school graduation indicators on the labor laws in force where (and when) the respondent grew up. If there were substantial variation across states at the time when the PSID respondents grew up and children tend to live in the same state as their fathers, then the instrument might capture a direct effect on the respondents rather than an effect going through the parent. We show results for the full sample and for individuals over 50. The attendance dummies are insignificant in all samples. For the oldest group, the estimated coefficients are positive and CA10 has a t-value of 1.25, indicating that maybe a few individuals in this group were affected directly by attendance laws (although this could itself be an indirect effect). Column 3 reports regressions of own education on the compulsory attendance laws when and where the father grew up; again the attendance dummies are all insignificant. Overall, the results of Table B-1 support the notion that the attendance laws impact the respondents through a schooling effect on the parents.

Our previous results could reflect that individuals from the younger sample are not affected directly nor are their parents. Table B-2 simply verifies that the schooling attendance laws did significantly impact the parents of young respondents. Finally, in Table B-3, we verify that the effect of parental education on risk aversion holds also when restricting the sample to younger individuals (under 50) who are unlikely to be directly affected by the schooling laws. Overall, we believe that it is very unlikely that our results are picking up a direct effect on the respondents.

We try to assess the importance of own education on risk aversion by estimating a sibling fixed-effect model: we regress a dummy for risk aversion on a dummy variable equal to 1 if the respondent has 12 or more years of education and equal to 0 otherwise.[22] We include family fixed effects which control for parental variables and include controls including age, age squared, gender, own income and wealth, as well as birth year dummies and dummies for the region where the respondent grew up. A significant coefficient of education in OLS regressions would indicate an inverse relationship (not necessarily causal) between education and risk aversion after controlling for family background characteristics. Table B-4 summarizes our findings: respondents with 12 or more completed years of education are about 16 percent less likely to be extremely risk averse. This relationship may not be causal, as schooling itself may be affected by the degree of risk aversion (see Belzil and Leonardi (2007), who found that risk aversion acts as a deterrent to higher education investment in Italy). Moreover, schooling could be picking up the effect of omitted variables such as innate cognitive abilities that are not factored out by family fixed effects and cannot be controlled for using PSID data.

[22] We thank an anonymous referee for this suggestion.

TABLE B-1. The effect of schooling laws on own education.[a]

Dependent Var.:	High School Dummy for Respondent		
CA Refers to:	Respondent (1)	Respondent Age > 50 (2)	Father (3)
CA9	−0.02	0.08	0.01
	(−0.70)	(1.44)	(0.51)
CA10	−0.04	0.05	0.03
	(−0.91)	(1.23)	(1.21)
CA11	0.03	0.09	−0.04
	(1.25)	(1.03)	(−1.30)
Age	0.02***	−0.02	0.02***
	(5.21)	(−0.45)	(4.38)
$\text{Age}^2/100$	−0.02***	0.01	−0.02***
	(−5.88)	(0.25)	(−5.07)
Black	−0.05***	−0.14***	−0.05**
	(−3.07)	(−2.85)	(−2.50)
Female	−0.01	−0.01	−0.01
	(−0.79)	(−0.17)	(−0.83)
Lived with both parents	0.03**	0.02	0.03***
	(2.33)	(0.63)	(2.68)
County principal component	0.01	0.02	0.01*
	(1.67)	(1.68)	(1.94)
Constant	0.56***	1.64	0.64***
	(5.71)	(1.66)	(4.79)
States dummies/grew up	Yes	Yes	Yes
Adj. R^2	0.049	0.096	0.049
F (instruments)	0.9	1.29	1.71
N	3348	635	3349

[a]The left-hand side variable is a dummy equal to 1 if the respondent has 12 or more years of education. CA9, CA10, and CA11 are the dummies that capture compulsory schooling laws as proposed by Acemoglu and Angrist (2000) and defined in Appendix A. t-statistics are given in parentheses. Robust standard errors are clustered by the state where the respondent grew up. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Ideally, one would focus on the effect on risk aversion of an exogenous change in schooling as in our previous regressions. Finding a good instrument is not straightforward, and we follow Currie and Moretti (2003), whose instrument for own schooling is the number of (2-year and 4-year) colleges per 1000 college-age persons in the county where the head grew up in the year when the respondent was 17 (college-age defined as being 18–22 years of age).[23] IV results are summarized in the last two columns of Table B-4: more educated respondents are less likely to be very or extremely risk averse. However, our estimates are imprecise, with p-values between 0.3 and 0.4, as our sample is small compared to Currie and Moretti (2003).

[23]Currie and Moretti (2003) constructed a data set that contains the availability of colleges in U.S. counties for 1960–1996 and Janet Currie graciously sent us the data. Our final sample contains only respondents who turned 17 during this period.

TABLE B-2. The effect of schooling laws on parental education for respondents younger than 50 in 1996.[a]

	Parents' Education/HS Sum (1)
CA9	0.11*
	(1.88)
CA10	0.06
	(1.17)
CA11	0.16***
	(2.73)
Age	−0.02
	(−1.06)
$\text{Age}^2/100$	0.00
	(0.15)
Black	−0.37***
	(−5.94)
Female	−0.10***
	(−3.03)
County principal component	0.08***
	(4.90)
Lived with both parents	−0.02
	(−0.35)
Constant	1.87***
	(6.22)
States dummies/father grew up	Yes
Region dummies/grew up	Yes
Adj. R^2	0.25
F	3.33**
N	2773

[a]The left-hand side variable is parents' education (sum of high school dummies). CA9, CA10, and CA11 are the dummies that capture compulsory schooling laws as proposed by Acemoglu and Angrist (2000) and defined in Appendix A for the father. t-statistics are given in parentheses. Robust standard errors are clustered by the state where the respondent's father grew up. Respondents are older than 33 and younger than 50. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

APPENDIX C: ESTIMATING THE VOLATILITY OF PERMANENT SHOCKS

To identify the volatility of permanent shocks to log idiosyncratic head's income, we use a procedure proposed by Meghir and Pistaferri (2004). It can be described as follows. Assume that log idiosyncratic income, $\widetilde{y}_{it}$, consists of a permanent random walk component, τ_{it}, and a transitory moving average component, c_{it} (see Guiso, Pistaferri, and Schivardi (2005), Carroll and Samwick (1997), Hryshko (2008), and Meghir and Pistaferri (2004) for empirical analysis of this income process on microdata and its empirical validation):

$$\widetilde{y}_{it} = \tau_{it} + c_{it} \quad \text{with } \tau_{it} = \tau_{it-1} + \varepsilon^P_{it}, c_{it} = \theta_q(L)\varepsilon^T_{it}. \tag{C-1}$$

Table B-3. Explaining risk aversion: Probit results (marginal effects) for respondents younger than 50 in 1996.[a]

	Very Risk Averse				Extremely Risk Averse			
	(1) Probit	(2) IV–Probit	(3) Probit	(4) IV–Probit	(5) Probit	(6) IV–Probit	(7) Probit	(8) IV–Probit
Parents' education/ HS sum	−0.05***	−0.34	−0.05***	−0.38**	−0.05***	−0.49***	−0.05***	−0.48***
	(−3.36)	(−1.61)	(−3.16)	(−2.00)	(−3.73)	(−6.05)	(−3.86)	(−5.43)
Age	−0.00	−0.01	−0.01	−0.02	−0.01	−0.01	−0.01	−0.02
	(−0.20)	(−0.64)	(−0.87)	(−1.57)	(−0.46)	(−1.03)	(−0.62)	(−1.34)
$\text{Age}^2/100$	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01
	(0.40)	(0.38)	(0.97)	(0.98)	(0.69)	(0.44)	(0.84)	(0.64)
Black	0.03	−0.09	0.04	−0.07	0.02	−0.15***	0.02	−0.12**
	(0.96)	(−0.99)	(1.35)	(−1.07)	(0.77)	(−2.63)	(0.56)	(−2.29)
Female	0.08***	0.04	0.09***	0.06	0.06***	−0.01	0.07***	0.02
	(4.86)	(0.91)	(5.28)	(1.42)	(3.36)	(−0.17)	(3.70)	(0.69)
County principal component	−0.03***	0.00	−0.02**	0.01	−0.02**	0.03***	−0.01	0.02**
	(−2.89)	(0.13)	(−2.32)	(0.36)	(−2.17)	(2.71)	(−1.58)	(2.44)
Lived with both parents	−0.04*	−0.04	−0.04*	−0.04*	−0.05**	−0.04*	−0.05**	−0.05**
	(−1.84)	(−1.57)	(−1.87)	(−1.75)	(−2.44)	(−1.93)	(−2.41)	(−2.18)
One's education (years)			−0.01	0.02			−0.01**	0.03***
			(−1.47)	(1.11)			(−2.10)	(2.77)
Log wealth (avg. 1984–1994)			0.01*	0.01**			0.01	0.01**
			(1.75)	(2.21)			(1.55)	(2.38)
Log income (avg. 1984–1996)			0.02	0.03*			−0.00	0.02
			(1.24)	(1.80)			(−0.26)	(1.15)
State dummies/ father grew up	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2768	2768	2689	2689	2763	2763	2684	2684

[a]Probit and IV–probit estimates of the probability of being very or extremely risk averse as indicated. Instruments: dummies for compulsory attendance laws (when the respondents' father was 15 years old). Very risk averse is 1 if the respondent's risk aversion is one of the two highest values for risk aversion and is 0 otherwise. Extremely risk averse is 1 if the respondent's risk aversion is the highest value and is 0 otherwise. Robust standard errors in the regressions are clustered by the state where the respondent's father grew up. t-statistics are given in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

ε_{it}^P is a permanent shock to log idiosyncratic income for head i at time t; ε_{it}^T is a transitory shock to log idiosyncratic income for head i at time t; $\theta_q(L)$ is a polynomial in L of order q, with $\theta_0 = 1$. We assume that $\varepsilon_{it}^P \sim \text{iid}(0, \sigma_P^2)$ and $\varepsilon_{it}^T \sim \text{iid}(0, \sigma_T^2)$.

The unobserved components model described in equation (C-1) implies that the first difference in log idiosyncratic head's income is $\Delta\tilde{y}_{it} = \varepsilon_{it}^P + (1-L)\theta_q(L)\varepsilon_{it}^T$. Meghir and Pistaferri (2004) proposed the following identifying condition for estimation of the volatility of permanent shocks to log idiosyncratic income:

$$E\left[\Delta\tilde{y}_{it} \sum_{k=-(1+q)}^{(1+q)} \Delta\tilde{y}_{it+k}\right] = \sigma_P^2. \tag{C-2}$$

Essentially, this moment condition identifies the (unconditional) long-run variance of the first difference in income. It can be shown that the long-run variance is equal to the volatility of the permanent shock, σ_P^2, if the income process contains a random walk and a stationary component modeled as a moving average process. We estimate the

Table B-4. The effect of own education on risk aversion: Siblings fixed-effects OLS.[a]

	Fixed Effects		IV Fixed Effects	
	Very Risk Averse	Extremely Risk Averse	Very Risk Averse	Extremely Risk Averse
High school or More	−0.10	−0.16***	−0.76	−0.89
	(−1.38)	(−2.62)	(−0.77)	(−0.99)
Age	−0.24	−0.25	−0.40	−0.43
	(−0.94)	(−1.13)	(−1.10)	(−1.30)
$\text{Age}^2/100$	0.30	0.31	0.49	0.51
	(0.89)	(1.03)	(1.07)	(1.23)
Female	0.06	0.10**	0.11	0.15*
	(1.33)	(2.39)	(1.23)	(1.84)
Log wealth (avg. 1984–1994)	−0.01	0.00	−0.01	0.00
	(−0.72)	(0.68)	(−0.86)	(0.32)
Log income (avg. 1984–1996)	0.04	0.02	0.11	0.10
	(1.45)	(0.75)	(1.05)	(0.98)
N	1752	1752	1752	1752

[a]Linear OLS estimates of the probability of being very or extremely risk averse as indicated. Instruments: the number of colleges (2-year and 4-year) per 1000 college-age persons in the county where the respondent grew up when he or she was 17 as in Currie and Moretti (2003). Controls include year of birth dummies and dummies for the region where the respondent grew up. Very risk averse is 1 if the respondent's risk aversion is one of the two highest values for risk aversion and is 0 otherwise. Extremely risk averse is 1 if the respondent's risk aversion is the highest value and is 0 otherwise. t-statistics are given in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

volatility of permanent shocks to idiosyncratic head's income by the equally weighted minimum distance (EWMD) method, assuming that the transitory component of idiosyncratic income is a moving average process of order 1. The details of our sample selection are as follows. We select households with heads aged 24–65 and drop observations if labor income growth is above 700% or below –90%. Additionally, we drop observations with head's labor income below 1000 (1982–1984) dollars. Households with female and single heads are included in the sample. A household is present in the final sample if it has at least one nonmissing log income difference.

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