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International Center for Public Policy
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Does Education Increase Risk Aversion? Evidence Using Artefactual Experiments in Peru

Alberto Chong and Joan J. Martínez*

September 2019

Abstract

We provide empirical evidence that supports a causal link from education to risk aversion when using representative data from representative surveys and artefactual or lab-in-the field experiments in Lima, Peru. We employ three standard experimental measures of risk aversion and find that each of them is positively correlated with years of education. We suggest that this relationship may be causal as we take advantage of an identification strategy that exploits a national law enacted in order to incentivize the construction of new schools in Lima, which allows us to provide evidence that more education may increase risk aversion. Our findings are further confirmed when applying a broad set of robustness tests.

Keywords: Experiments, Surveys, Risk Aversion, Education, Latin America

JEL classification: D01, O12

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Introduction

Education is usually at the forefront of policymaking in most developing countries, as it is firmly believed that it can be welfare enhancing for it helps individuals make better decisions in an expanded set of choices. Uninformed, uneducated individuals may be less able to distinguish between the costs and benefits of alternative options, which may produce equivocal, welfare decreasing choices. This may range from simple, everyday household decisions, such as comparing nutritional content of foods, to more substantial ones, such as deciding on the optimal business credit line.

While on average there is little doubt that more education will translate into better decisions and thus better choices, it is not uncommon to find cases where more education will not translate into improved choices, but rather puzzling ones, which are not consistent with the paradigm described above. For instance, it is unclear why farmers in developing countries frequently prefer to stick with extremely inefficient methods of farming, even after being taught and demonstrated that simple, modern improvements in their agricultural methods can result in vastly more productive and efficient harvests. Similarly, it is unclear why incipient entrepreneurs in developing countries are so wary about opening formal banking accounts and prefer to keep cash "under the mattress," regardless of the demonstrable benefits and convenience of being part of a commercial banking system.[1]

Although there may be different explanations for these behaviors, in this research we focus on individual risk aversion, which is perhaps as important as other more commonly

[1] This type of examples is not circumscribed to developing countries. For example, in relation to the 2016 presidential democratic primaries in the United States, Blow (2016) argues that the strong preference of black voters towards Hillary Clinton instead of Bernie Sanders, despite the fact that the latter better represents their interests, has endured for decades in spite of "education, a vast, all-purpose term, conjuring up visions of sunlit housing projects, stacks of copybooks and a race of well-soaped, dark-skinned people who never slur their R's…" (Baldwin, 1955).

discussed factors, such as culture and tradition, but is often overlooked in policy considerations. In particular, we study the role that education plays on individual risk aversion and the manner in which the former impacts the latter, if any. We argue that this link may help understand why individuals may be reluctant to make choices consistent with their seemingly best interests, regardless of the education received. In the context of the examples described above, for instance, farmers who learn modern agricultural techniques may also learn that the use of pesticides and other chemicals can put their health at risk and can contaminate their soil and water if they are not careful enough, which may produce the unintended effect of increasing an aversion to the new technique instead of embracing it, especially when compared to their inefficient, but generations-tested agricultural methods. Similarly, in the case of entrepreneurs, when learning about the benefits and convenience of the formal banking system, they may also learn that these benefits may also mean losing physical track of their money, something that they may perceive as risky and thus may be averse to doing.

In this paper, we empirically explore the extent to which education may increase risk aversion as shown by the examples above. This is not a new question, but it is one that is not well understood, which is illustrated by the fact that whereas some studies show a positive correlation between education and risk, other studies find a negative correlation between these two variables. Furthermore, some other empirical studies do not find any link between them. Unlike previous work, we offer three specific contributions to the literature, which we believe are significant to understand the relationship between education and risk. First, we specifically test the causal association that goes from education to risk aversion, which is done by exploiting an exogenous school infrastructure construction shock in Lima, Peru. Second, we employ risk measures based on artefactual, or laboratory-on-the-field

experiments, which are viewed as more reliable than measures based on standard surveys. We use three "tried and true" artefactual measures that have been broadly employed and accepted in the literature as good proxies for risk aversion. Finally, our experimental and survey data are representative of the city, something that was explicitly taken into account and is rather uncommon in this type of empirical work.[2] Given the above, we believe that the contributions of our paper are significant to both the literature on risk aversion and potentially to policymakers, who may be able to better assess the effectiveness of educational promotion as a policy tool.

Overall, our findings are consistent with previous studies that show a positive link between education and risk aversion, with the difference that we also find causal evidence when testing from education to risk. This implies that the extent to which education can shape risk aversion can help provide a better understanding to policymakers who, while clearly understanding the importance of education, tend to significantly discount the importance of risk in policy design.

Our paper is organized as follows. The next section provides a brief review of the literature. The third section describes the data as well as the experimental design including the specific risk games applied. The fourth section presents our identification strategy, and the fifth section presents our main findings. The sixth section offers robustness tests. In the final section, we present a brief summary and conclude.

[2] As Cardenas, et al (2014) explain, the vast majority of experimental data collection from artefactual efforts have been gathered among limited or particular populations, such as small samples of college students (Glaeser et al., 2000; Burks, Carpenter, and Verhoogen, 2003; others).

Brief Review of the Literature

As mentioned above, there is little consensus on the nature of the link between education and risk aversion, if any. Theoretically, some researchers have argued that the link between education and risk aversion may be negative. For instance, Breen et al. (2014) develop a rational choice model of educational decision-making in which the utility of educational choices depends on the risk aversion of individuals as well as on their time discounting preferences. While individuals from advantaged socioeconomic backgrounds may not be affected by risk aversion, those with lower time discounting preferences and low risk aversion may be more likely to opt for more education, which in their model may likely result in higher long-term payoffs. Thus, these researchers find that risk aversion and time discounting preferences may mediate the effect of socioeconomic background on educational choices and the effect of these factors on educational decision-making may vary across socioeconomic groups.[3]

On the other hand, Brodaty et al. (2014) have argued that the link between education and risk aversion may be positive. They propose a model in which an individual's investment in education maximizes expected utility, conditional on public and private information. Their model considers future wage risk and treats the direct and opportunity costs of education as additional sources of risk. They argue for significant and substantial effects of expected returns on individual education choices. The risk affecting education costs and, in particular, the randomness of time-to-degree plays an important role in explaining enrollment in higher education. In fact, they claim that more educated individuals bear more risk and are more risk averse than other groups and yet they will study more

[3] Similarly, related theoretical results stress that earnings uncertainty may depress human capital investment (Lehvari and Weiss, 1974; Olson, White, and Sheffrin, 1979).

because of higher returns and markedly lower expected investment costs. In fact, as described by Outreville (2015), the relationship between risk aversion and the level of education is even more ambiguous. This researcher explains that from a causality point of view, it may be argued that investors with a high level of education are less risk averse, but it may also be argued that less risk-averse individuals choose to pursue a higher level of education.

The ambiguity in theory is also reflected empirically. For instance, Harrison et al. (2007) provide experimental evidence that shows a positive and statistically significant link between higher education and risk aversion. This effect appears to be monotonic given that the sign and significance of the effect remain regardless of the magnitude of the prize of lottery employed.[4] Similarly, Dohmen et al. (2010) use data from a German survey as well as experimental data to study the intergenerational links related to risk taking, and they show a positive causal effect between education level of parents and the risk aversion of the children. Finally, additional studies that find a positive link between education and risk aversion are Hardeweg et.al. (2013) and Jung (2014), among others. However, while there is plenty of research that shows a positive link between education and the different measures of risk aversion, there is also plenty of evidence that shows that such a link may be negative. For instance, Riley and Chow (1992) use data from investment decisions of a sample of U.S. households and show that risk aversion tends to decrease significantly as the years of education increase. Similarly, Caliendo et al. (2009) apply different measures of risk aversion and find a negative and statistically significant effect with higher education, albeit

[4] However, they also find that the more specific the type of degree, major, or faculty does not explain risk aversion.

with a very low marginal effect. Other studies that find a negative link between education and risk aversion are Donkers et al. (2001), Hartog et al. (2002), and Hryshko et al. (2011).

Furthermore, other studies, such as Halek and Eisenhauer (2001) provide evidence showing ambiguous effects between educational level of individuals and risk aversion measures. Hartlaub and Schenider (2012) find that students with a higher social background are less sensitive to their school performance and that individual risk aversion is irrelevant to their educational plans. On the other hand, they find that students with a lower social background are more risk-averse and thus, more likely to opt for a further education. Similarly, Belzil and Leonardi (2007) find that such a link may be non-linear by showing evidence that schooling continuation probabilities decrease with risk aversion at low grade levels but increase with risk aversion at the time when the decision to enter higher education is made, where differences in aversion toward risk account for a modest portion of the probability of entering higher education and differences in parental human capital and abilities are more important.

Data and Experimental Design

The individuals who participated in this study throughout 2007 were recruited in an attempt to fulfill strata quotas for Metropolitan Lima and were selected on the basis of education, gender, age, and average family income in either quartiles or quintiles, depending on data availability. They were invited to the study in a way that the empirical distributions of individuals within these combinations of characteristics resembled those of the population in Lima. That is, the sample collected is representative for the observable characteristics that make the strata. The individuals recruited were living in the different districts of Lima at the time of the interview. This recruitment process was done making sure that they were not

transient individuals, but people that actually lived in the districts from which they were recruited.[5] The recruitment methods in the city included phone calls, door-to-door visits, e-mail invitations, and calls in public workplaces. Once recruited, the people were invited a few days before the experimental session to receive information about the expected gains from participating in the experiments, which included a show-up fee and potential gains as a result of their decisions. At that stage, we gathered information regarding participants' socioeconomic background, which was used as an input in the experimental sessions.

The day before the experimental sessions, participants received a phone call or a visit in order to be reminded about the invitation and to coordinate transportation arrangements. On the day of the sessions—20 in total—the participants were welcomed and the sessions began at the arranged times. Approximately 30 individuals were invited for each session, under the assumption that around one third would not show up, thus allowing each experimental session to have 20–25 participants. The sessions were arranged so that at least three sessions included individuals from high-income strata only, and at least three sessions included individuals from low-income strata only. The rest combined individuals from all strata. The participants met throughout the session in one room where they were able to see each other, although they were not allowed to communicate during the session. During the recruitment process we avoided having two people who knew each other within the same session. However, as the sessions progressed, participants received information about their peers. In particular, social heterogeneity on individuals' decisions in each particular session

[5] This was done through confirmation of identification via their National Identification Card, which all adult citizens (over 18 years old) must possess. The forty-three districts in Metropolitan Lima, a city of almost 9 million inhabitants, are the following: Ancon, Ate, Barranco, Brena, Carabayllo, Chaclacalyo, Chorrillos, Cieneguilla, Comas, El Agustino, Independencia, Jesus Maria, La Molina, La Victoria, Lima, Lince, Los Olivos, Lurigancho, Lurin, Magdalena del Mar, Miraflores, Pachacamac, Pucusana, Pueblo Libre, Puente Piedra, Punta Hermosa, Punta Negra, Rimac, San Bartolo, San Borja, San Isidro, San Juan de Lurigancho, San Juan de Miraflores, San Luis, San Martin de Porres, San Miguel, Santa Anita Santa Maria del Mar, Santa Rosa, Santiago de Surco, Surquillo, Villa El Salvador, and Villa Maria del Triunfo. See the sample participants' distribution by district is available upon request.

was made as salient and clear as possible using the information collected on the socioeconomic composition of the groups.

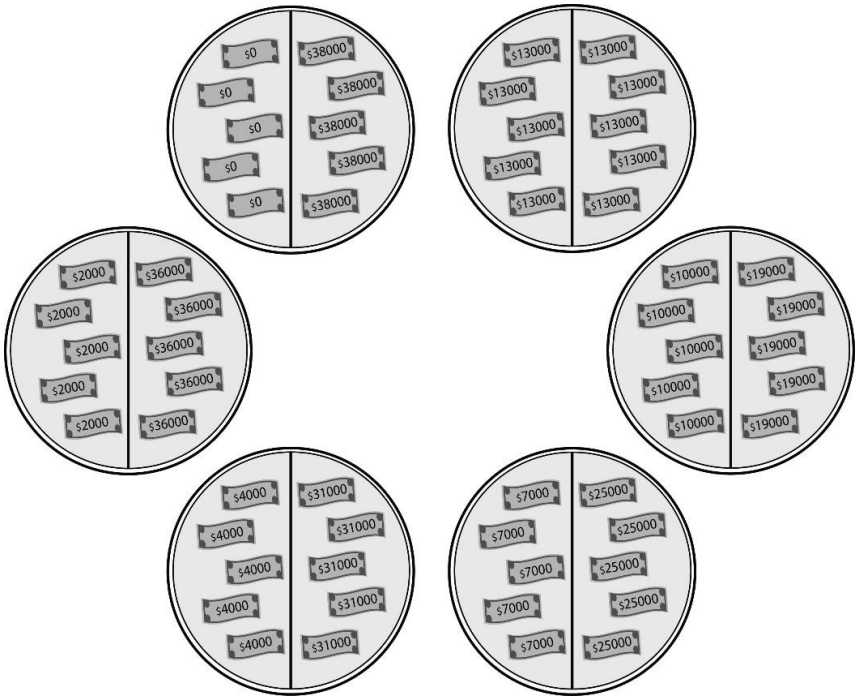
In general, each experimental session followed the exact same protocol, which included the exact same sequence of activities in order to guarantee consistency.[6] Following the battery of experiments, participants completed a post-session survey. To reduce idiosyncratic measurement error, the surveys were administered by the coordinators of the experiments and supported by a group of pollsters especially trained for these purposes. Our full final sample size was 540 individuals in the city of Metropolitan Lima.

The three experimental risk games applied in this research are all "tried and true" activities. The aim was not to create a new risk measure or refine existing ones but to employ broadly accepted experimental risk measures that are believed to adequately capture risk aversion in individuals. In this regard, we follow the well-known tripartite concept by Kahneman and Tversky (2000) and later consolidated in experimental measures using gambling approaches by Binswanger (1980) and more recently Barr (2003). Each player makes three individual decisions that measure aversion towards risk aversion, ambiguity, and losses. In the first activity, which measures risk aversion, there is a distribution of ten tokens within each of six envelopes, so five of the tokens represent low payoffs and the other five represent high payoffs in each envelope. The game consists of six gambles with 50/50 payoffs that go from low to high-expected amounts of money, a scheme that is informed to the participants during the session. An illustration of the gambles that were

[6] The field team participated in a training workshop during the first quarter of 2007, which provided a uniform approach to implementation and related fieldwork details such as sampling procedures, protocol, timing of actions (i.e., invitations, pre-survey, experiments, post-surveys), elements to be included in experimental sessions and the construction of questionnaires. The materials used, such as surveys and protocol delivered to supervisors, are in Spanish (Cárdenas et al. 2013).

presented to the participants of the sessions are staged in **Error! Reference source not found.**. Here, the envelopes are represented as circles and the tokens as bills.

Figure 1. First Experimental Activity – Risk Aversion



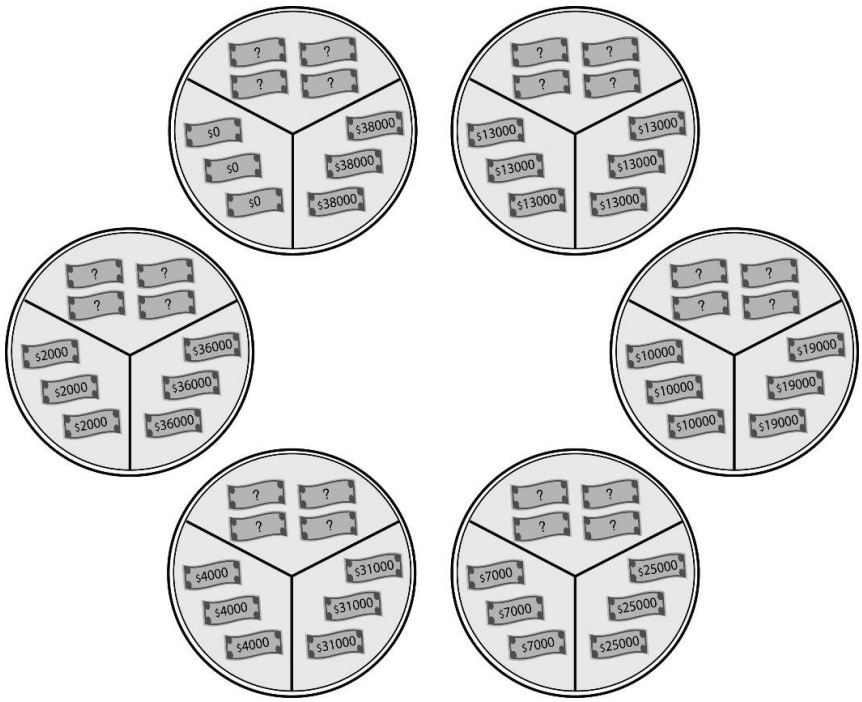
Source: Candelo et al. (2009)

Note that the high and low values marked in the tokens are different in each envelope. As we observe envelopes to the right in clockwise sense, notice that the risk level of the gambles is higher—the gap between high and low payoffs and the overall expected gain increases. This arrangement holds in the three risk activities (Cárdenas et al., 2009, 2013). The player has to decide between one of these six lotteries, which range from a sure low payoff, which is a gamble with relative percentage 0.33/0.33, to an all-or-nothing higher expected payoff with 0/0.95, accompanied with four intermediary combinations.[7] Recall that in this first risk activity the participants know the exact probabilities of the payoffs. The

[7] The other four intermediary lotteries are arranged clockwise. They have relative risk ratios in the following order: 0.25/0.47, 0.18/0.62, 0.11/0.77, and 0.04/0.91. The denominator refers to the low expected pay off and the numerator to the high expected one (Cárdenas et al., 2013).

second activity aims at measuring risk ambiguity by offering the same payoffs for the previous six lotteries, but unlike in the first activity, individuals ignore the exact probabilities for each token to show up. Instead, participants know for certain that three out of 10 tokens correspond to the low payoff and other three correspond to the high payoff. The remaining four tokens were included without telling the participants whether they had low or high payoffs. A representation of this set of gambles is shown in **Error! Reference source not found.**.

Figure 2. Second Experimental Activity – Risk Ambiguity

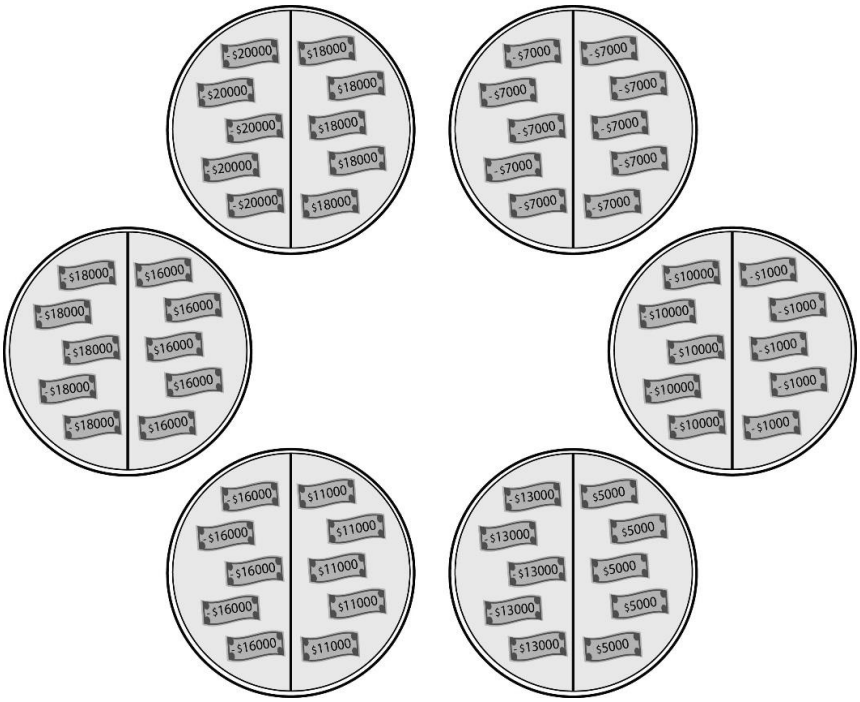


Source: Candelo et al. (2009)

Finally, the third activity measures loss aversion. It also uses six lotteries with 50/50 probabilities but includes the possibility of negative payoffs. In order to avoid negative payments, players are endowed with a fixed amount that is equal to the maximum value he or she could have lost in the maximum-risk envelope. This amount was given regardless of the participant's gains or losses, so that participants who opt for the safer possible choice

(low-payoff token in the first enveloped) would have zero gains. The decision scheme for the loss aversion activity is shown in Figure 3.

Figure 3. Third Experimental Activity – Loss Aversion



Source: Candelo et al. (2009)

In order to ensure that the participants clearly understand the activities, the session coordinator simulates each of the games prior to the participant's decision process, making sure not to bias the election of the participants during the actual game and keeping written records of these events.

Complementary information on the participants is drawn from the pre- and post-game surveys gathered from everyone who attended. **Error! Reference source not found.** presents a description and sources of all the variables we employed, whereas **Error! Reference source not found.** reports their corresponding summary statistics. We observe that half of the sample is female. Similarly, married participants represent about 50 percent of the sample and those who formally own a house is also about 50 percent of the sample. In addition, the average number of years of education is nearly 11, which is the total for an

individual who has completed primary and secondary levels in the mandatory 6 years and 5 years, respectively. Interestingly, the share of participants that are employed at the time of the survey is around 60 percent. National Census values do not differ for 2007 significantly from the values obtained from the expanded sample of participants of the experiment in Lima as seen in the last column of this table.

Table 1. Variables Definitions

Variable	Definition
Individual Characteristics	
Schooling	Years of education of the individual. *Source: Survey and experiments.*
Age	Age of the individual.
Female	Dummy variable that takes the value of 1 when the individual is female, and 0 otherwise.
Married	A dummy variable that takes the value of 1 when the individual is married or cohabitating and 0 otherwise. The base omitted variable was being single.
Homeowner	A dummy variable that takes the value of 1 when the individual is a homeowner, and 0 otherwise.
Employed	A categorical variable that takes the value of 1 when the individual is employed, and 0 otherwise.
Session Characteristics	
Percent women	Share of women per session
Mean age	Mean of the age of individuals per session.
Standard deviation, women	Standard deviation of females per session
Standard deviation, age	Standard deviation of age per session
Participants	Number of participants per session
District Characteristics	
Robbery Victims	Share of district residents of the participant who report being a victim of a robbery in the district
Residents belonging to educational organization	Share of residents who live in the district of the respondent and who report belonging to an educational organization, such as parents association, educational, artistic, musical or cultural associations.

Source: Survey and experiments. In the case of district characteristics, the source is the Study of Perceptions in Metropolitan Lima (2010)

Table 2. Summary Statistics

	Experiment sample, weighted					Census
	N	Mean	S.D.	Min	Max	
Individual characteristics						
Schooling (years)	540	10.72	3.82	0.00	21.00	10.94
Age (years)	540	36.61	13.36	17.00	76.00	30.21
Female (%)	540	0.52	0.50	0.00	1.00	0.51
Married (%)	540	0.51	0.50	0.00	1.00	0.51
Homeowner (%)	540	0.54	0.50	0.00	1.00	0.42
Employed (%)	540	0.64	0.48	0.00	1.00	0.70
Risk aversion						
Risk aversion	540	4.12	1.64	1.00	6.00	
Risk ambiguity	540	4.30	1.62	1.00	6.00	
Loss Aversion	540	3.58	1.86	1.00	6.00	
Session characteristics						
Participants per session	540	22.60	4.64	14.00	32.00	
Percentage of women	540	0.54	0.12	0.23	0.83	
Standard deviation, women	540	0.49	0.03	0.38	0.52	
Mean of age per session	540	35.11	3.44	25.93	41.30	
Standard deviation, age	540	12.56	2.74	6.78	16.35	

Notes: (1) Sample summary statistics were computed using sample weights for Metropolitan Lima city. The National Census from 2007 reports 8,482,619 inhabitants. The census figures were collected with the same question in the experimental survey as in the census.

The outcome values associated to each of the three risk activities described above were employed as dependent variables in our empirical estimations. These are considered objective measures of risk adverse aversion. At the end of the sessions, the envelopes were numbered from 1 to 6.[8] In the first activity, choosing an envelope with higher number—and therefore, lower risk—points out that the participant had very low risk aversion aversion. During the second activity with the presence of ambiguity, risk aversion aversion are more strictly tested. Here, similarly than in the first activity, a higher envelope's number stands for a low risk adverse participant. Lastly, with the possibility of losses, the less risk adverse individuals are tested in the third activity. We can check the consistency of these three

[8] Originally, after the sessions the envelopes were coded with labels 1 (for least risky gamble) to 6 (the riskier gamble). However, for the empirical estimation we inverted this scale; so that the lowest envelope number was associated to the lowest level of risk aversion and the highest number was associated to the highest level of risk aversion.

increasingly strict measures in **Error! Reference source not found.**, where we present simple pairwise correlations between risk aversion, and educational attainments.

Table 3. Correlation Matrix

	Years of School	Risk Aversion	Risk Ambiguity
Risk Aversion	0.184		
	(0.000)		
Risk Ambiguity	0.113	0.550	
	(0.008)	(0.000)	
Loss Aversion	0.205	0.440	0.390
	(0.000)	(0.000)	(0.000)

Notes: Pairwise correlations are reported; p-values in parentheses.

We also employed secondary data sources. In particular, a 2010 perceptions data set gathered by a local university, which contains data on violence and public security and is representative at the district level.[9] We also employed data from the national Census (INEI, 1993, 2007) and data from National Registry of District Municipalities (RENAMU, 2016).[10]

Empirical Approach

As described above, one of the objectives of this research is to better understand whether there is a statistically significant correlation between education and risk aversion as well as the nature of such a link, if any. In order to do this, we employ risk measures from experimental sessions in which agents face risky prospects by making decisions involving money payoffs. Our baseline reduced linear regression form follows the specification:

$$RiskAversion_i = \alpha + \beta_1 Schooling_i + \boldsymbol{X}_i'\beta_2 + \beta_3 W_i + \boldsymbol{S_i'}\beta_4 + \varepsilon_i \quad (1)$$

where $RiskAversion_i$ is the dependent variable i obtained from one of the three risk activities described above, namely risk aversion, risk ambiguity, and loss aversion. The values of the dependent variable range from one to six, where a higher value stands for a higher risk

[9] The data come from Catholic University of Peru (2010). The scope of the survey is Metropolitan Lima only.
[10] Each district in the city is governed by a district municipality, whose highest authority is the mayor. The registry is administrative data reported by municipal authorities about the services provided, planning and other related attributes.

aversion. Our key variable of interest, $Schooling_i$ represents the years of schooling of the participant, and it is obtained directly from surveys applied to the individuals that participated in the experimental games. In addition, the vector $\boldsymbol{X}_i$ reflects a set of individual characteristic such as age, gender, marital status, and type of ownership of the home. W_i is a variable that states the employment status of participant i as an approximate measure of his or her socioeconomic status. Vector $\boldsymbol{S}_i$ contains data collected throughout the experimental sessions, in particular, the percentage of women in the session, average age of participants in the session, the standard deviation of females per session, and the standard deviation of the age of participants. We also control for the number of participants who attended each session, and non-observed factors are clustered at the session level. In addition, all the regressions include fixed effects at the district level. A complete description of every covariate included is shown in **Error! Reference source not found.**. Finally, ε_i is the error term.

As it is well known, a weakness of our empirical approach above is that the relationship between education and risk aversion may be endogenous due to unobservable factors that may be biasing our relationship of interest. Coefficient β_1 in specification (1) may be biased if there is any correlation between education levels and an omitted variable included in the error term, and as such, causal inference may be difficult to establish. In order to deal with this issue, we take advantage of an exogenous government policy in Peru that promoted the construction of new schools. This law was issued in 1996 in order to increase the quality of education in the country by promoting the participation of the private sector in education. As stipulated in the law, its applicability is nationwide. It reduces

entrance barriers of for-profit schools via tax credits, tax exemptions, and others.[11] As a result, rates of private school enrollment rose from 21 percent to 32.6 percent between 1997 and 2007, according to the National School Census. We employ the net change in the number of private schools in Metropolitan Lima after the policy law was enacted as an exogenous source of variation for educational attainment. As this variable is highly correlated with education, we argue that it is not linked with risk aversion aversion, as discussed below.

Main Findings and Causality Issues

We present basic results on Table 4, which include fixed effects at the district level and standard errors clustered at the session level in order to account for session-specific error components. We find a positive and statistically significant link between the schooling variable and our three measures of risk aversion when controlling for a broad set of individual and session-related characteristics.[12] An additional year of education is associated with an increase in the index of risk aversion of about 11 percentage points, an increase in the index of ambiguity of about nine percentage points, and an increase in the index of loss aversion of around 12 percentage points.

Table 4. Education and Risk Aversion
Ordinary Least Squares

	(1)	(2)	(3)	(4)	(5)	(6)
	Risk Aversion		Risk Ambiguity		Loss Aversion	
Individual characteristics						
Years of education	0.104***	0.114***	0.080***	0.097***	0.126***	0.118***
	(0.024)	(0.022)	(0.021)	(0.024)	(0.021)	(0.018)
Age	-0.011	-0.012	-0.005	-0.006	-0.009	-0.010
	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
Female	0.128	0.160	0.328*	0.317	0.225	0.348**
	(0.184)	(0.173)	(0.188)	(0.187)	(0.170)	(0.147)

[11] Article 8, L.D. No. 882
[12] When including a quadratic term for education the sign of the linear term remains positive and statistically significant at one percent while the quadratic term yields a negative and non-statistically significant coefficient.

Married	0.163	0.223	0.008	0.026	0.183	0.208
	(0.170)	(0.157)	(0.195)	(0.192)	(0.182)	(0.181)
Homeowner	0.021	-0.036	-0.078	-0.074	0.413**	0.331*
	(0.207)	(0.182)	(0.202)	(0.181)	(0.186)	(0.173)
Employed	-0.177	-0.082	-0.177	-0.125	-0.151	-0.059
	(0.157)	(0.156)	(0.172)	(0.186)	(0.167)	(0.190)
Session characteristics:						
Percent women		1.434**		1.507**		-1.292***
		(0.657)		(0.589)		(0.444)
Mean age		-0.068*		-0.022		-0.002
		(0.033)		(0.038)		(0.036)
Standard deviation, women		-0.875		4.129		2.374
		(2.280)		(2.425)		(1.811)
Standard deviation, age		0.127***		0.071		0.056
		(0.043)		(0.047)		(0.052)
Participants per session		0.034**		0.008		0.046**
		(0.016)		(0.023)		(0.020)
Constant	3.350***	2.892	3.606***	0.267	2.221***	0.075
	(0.399)	(1.709)	(0.414)	(1.993)	(0.457)	(1.581)
Observations	540	540	540	540	540	540
R-squared	0.0775	0.1207	0.0518	0.0719	0.1029	0.1380

Observations are at the participant level. All regressions include fixed effects at the district level as well as clustered robust standard errors at session level, which are reported in parentheses. Coefficients that are significantly different from zero are denoted by the following nomenclature: *=10%; **=5%; ***=1%

In order to attempt to test for causality, we take advantage of an exogenous policy measure issued by the Peruvian government in 1996, in particular, a law to promote the opening of private schools aimed at increasing the quality of education by reducing barriers to for-profit education enterprises via tax credits, tariff exemptions, and others.[13] We employ the net change in the number of private schools in the districts of Metropolitan Lima after the policy law was enacted as an exogenous source of variation for educational attainment. Our proposed instrument includes all school construction that covers pre-school, primary, and secondary education. In other words, our proposed instrument is the accumulated variation of the number of new private schools across districts in Lima between years 1997

[13] As this law prompted school's private enrollment rates to rise from 23 percent to 32.6 percent between 2000 and 2007, it is rather unclear whether the educational quality also increased (Ministry of Education of Peru, 2016).

and 2007.[14] We define a variable Z_c as the change between the number schools in 2007 located in district c ($school_{c,2007}$) and the number of schools in 2000 ($school_{c,1997}$). The instrument is calculated as follows:

$$Z_c = \left(school_{c,2007} - school_{c,1997}\right)/school_{c,1997} \quad (2)$$

We argue that this is a purely exogenous policy that is uncorrelated to risk aversion, which is consistent with the fact that we do not find any discernable pattern that may be linked to any observable, as several overlapping factors were at play in the process, such as educational demand, district purchasing power, entrepreneurship, vacant infrastructure, and several others.[15] We calculate the net change in private primary schools in 2007 compared to 1997 from each of the 43 Metropolitan Lima districts. The expansion in educational institutions for this period is consistent with the process of deregulation in the provision of basic educational services in the country, and in particular, we find no discernable pattern along the lines that relatively rich districts may have opened more schools after the law was enacted (Balarin, 2013, 2015; Arregui, 2000; Du Bois, 2004).

The standard educational system in Peru is composed of four levels. It has basic education, which caters to kids ages 3 to 5 years old, primary education, which is geared toward children aged 6 to 11 years of age, secondary education, geared toward children aged 12 to 17 years of age, and tertiary education, which is geared towards young adults 18 or older. The public system is free and is mandatory for primary and secondary school, but not for basic and tertiary education. It should be noted that there are some misconceptions regarding to the educational system in Peru. While education is mandatory and enrollment is

[14] The data come from the National School Registry at the Ministry of Education of Peru, which provides basic information regarding the schools' principal (i.e., name, genre, and contact phone number), its district location, and the availability of basic services within the school (i.e., water, electricity, sanitation).
[15] They were matched with information from the National School Census, which also come from the Ministry of Education of Peru.

thus unsurprisingly high, typically reaching more than 90 percent of eligible children in the case of primary education and around 70 percent in the case of secondary education, actual attendance is substantially lower as monitoring by the corresponding authorities is non-existent (Guadalupe et al., 2017). This issue is compounded by the fact that the opportunity cost of keeping children in school, even though it is free, may be relatively high, which is reflected by the fact that more than one third of children ages 5 to 17 are in the labor force and by the fact that the quality of public education in the country both urban and rural is widely perceived and accepted to be of extremely low quality (Guadalupe et al., 2017). In the context above, it is not surprising to find that the Peruvian government has tried to promote different policy measures in order to increase attendance at all educational levels. In fact, ever since the law to promote the opening of private schools mentioned above was implemented, education enrollment and attendance in Peru has increased significantly (Guadalupe et al., 2017).

An admitted weakness of using our instrument is that since the average age of our respondents is almost 37 years of age when the data were collected, a significant group of them was not directly impacted by this policy. When using the sub-sample that were directly impacted by the policy, our sample is reduced to 230 observations, and in particular, we focus on the sample of respondents that were of school age (18 years of age or less) in 2007 or earlier, which is the year when the intervention was performed. This subsample does not show any bias among observables as t-tests show not statistically significance differences between observables when comparing the selected subsample with the remaining one or when comparing the selected subsample and the full sample.

We classify the increases in private school construction categories by quintiles and use this variable as an instrument in order to test for the relationship between years of

education and risk aversion. Table 5 provides our findings. Overall, we find a positive and statistically significant link between education and our risk indexes, which gives support to the idea that additional years of education increase risk aversion, on average. In every specification, the Anderson-Rubin F-statistic largely passes the Staiger and Stock's (1997) threshold as defined by rule of thumb by Stock and Yogo (2005). We are able to reject that the maximum IV size distortion is larger than 10 percent, which renders our instrument as a reasonably strong one. Notice that once corrected for endogeneity in schooling, our coefficients become substantially larger, which highlights the importance of addressing these issues in order to overcome a possible downward bias in the ordinary least squares results.[16]

Table 5. Education and Risk Aversion
Instrumental Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Risk Aversion		Risk Ambiguity		Loss Aversion	
Individual characteristics						
Years of education	0.447**	0.492**	0.395**	0.389**	0.482*	0.464*
	(0.208)	(0.216)	(0.201)	(0.199)	(0.276)	(0.257)
Age	0.006	0.005	0.008	0.08	0.001	0.000
	(0.008)	(0.011)	(0.011)	(0.011)	(0.009)	(0.008)
Female	0.228	0.274	0.236	0.297	0.271	0.318
	(0.202)	(0.182)	(0.292)	(0.324)	(0.284)	(0.326)
Married	0.124	0.183	0.247	0.138	0.262	0.268
	(0.155)	(0.182)	(0.191)	(0.133)	(0.193)	(0.237)
Homeowner	-0.126	-0.167	-0.739	-0.663	-0.687	-0.235
	(0.335)	(0.338)	(0.374)	(0.327)	(0.368)	(0.342)
Employed	-0.392	-0.135	-0.245	-0.251	-0.193	-0.286
	(0.143)	(0.147)	(0.147)	(0.164)	(0.147)	(0.170)
Session characteristics						
Percent women		2.254*		1.835*		0.816
		(1.325)		(1.034)		(0.952)
Age mean		-0.022		-0.021		0.029
		(0.018)		(0.020)		(0.19)
Standard deviation,		1.285		2.335		2.911
women		(1.440)		(1.979)		(2.132)
Standard deviation, age		0.183		0.125		0.243
		(0.085)		(0.089)		(0.137)

[16] First-stages are available upon request. Also, We also employed ordered probits and IV ordered probits as an alternative method. Our findings are analogous—basic probits are shown in the Appendix.

Participants per session		0.0826		0.0285		0.091
		(0.068)		(0.024)		(0.056)
Constant	3.425	4.285	4.465	5.463	2.356	3.534
	(2.235)	(2.994)	(2.453)	(4.473)	(2.287)	(3.184)
Observations	230	230	230	230	230	230
Wald Test, F-Stat	6.43	6.78	11.93	13.27	9.62	5.78
P-Value	0.0036	0.101	0.0011	0.184	0.0222	0.062

Notes: The method of estimation is two-stage least squares. The observations are at the participant level, but instrument is at the district level. All regressions include fixed effects at district level and clusters at session level. Instrument is the accumulated growth (%) of number of private primary schools 1997–07, by participant's district of residence. Coefficients that are significantly different from zero are denoted by the following nomenclature: *=10%; **=5%; ***=1%

Robustness

Our identification strategy bears on the assumption that any variation in the number of schools that occurs in the district in which the participant lives has a systematic effect on their risk adverse aversion only through their education attainments. While we believe that this is a reasonable assumption as we simply exploit an exogenous policy shock, it may be true that households whose risk aversion preferences may be linked to unobservable factors may attempt to systematically move to districts with new schools resulting of the new law. Thus, we need to examine whether households systematically seek to move to districts with lower risks, as reflected by having more schools. In fact, it is reasonable to expect that other analogous "pull factors" would also play a significant role in attracting households to other districts. Households would not only seek to live in areas with more schools, but they would also be more likely to move to districts that offered more health services, more public safety, more public sanitation services, more road conditioning, and overall increased urban development. We employ data from the Peruvian National Registry of District Municipalities to test this idea.[17] When using ordinary least squares, we find that there is no

[17] For the sake of consistency with our experimental and survey data, we use information for 2007. However, the use of data for different years and even year averages for reasonable years do not change our findings.

statistically significant correlation between risk aversion and any measure of the quality of life indicators in the case of health services, which includes hospitals, health establishments, health centers and doctors' offices; public safety services, which includes civil urban organizations, neighborhood committee and self-defense committees against crime; sanitation services, which include centers of growth and development of children, control of acute respiratory infections and diarrheal diseases; roads conditioning, which includes repair and construction of roadways and pavement roads, as well as the presence of strategic local economic strategic development plan in the district. All regressions control for schooling, population, gender, age, type of household, and a household index of assets.

Table 6. Risk Aversion and Pull Factors

Dependent variable:	Health Services	Public Safety	Sanitation	Road Maintenance	Urban Planning
			Risk aversion		
Coefficient	0.1814	0.1005	-0.0107	0.2382	-0.0991
Standard Error	(0.4020)	(0.2495)	(0.2776)	(0.2767)	(0.2899)
			Risk ambiguity		
Coefficient	-0.0618	0.1586	-0.1293	0.0989	-0.0988
Standard Error	(0.2818)	(0.1761)	(0.2098)	(0.2010)	(0.2022)
			Loss aversion		
Coefficient	0.3135	0.2234	-0.1642	-0.2357	0.0885
Standard Error	(0.4559)	(0.3387)	(0.3426)	(0.3241)	(0.3175)

Notes: Number of observations for all regressions is 540. The method of estimation is ordinary least squares. The observations are at the district level of Metropolitan Lima districts. Robust standard are reported in parentheses. All regressions include district fixed effects and clusters as well as a set of district-level controls including schooling, population, gender, age, type of household, and index of assets. The municipality district services are listed as follows. (i) Health services: hospitals, health establishments, health centers and doctors' offices. (ii) Public safety services: civil urban organizations, neighborhood committee and self-defense committee against crime. (iii) Sanitation services: centers of growth and development of children, control of acute respiratory infections and diarrheal diseases. (iv) Road maintenance: repair and construction of roadways and pavement roads. (v) Has strategic local economic strategic development plan. Coefficients that are significantly different from zero are denoted by the following nomenclature: *=10%; **=5%; ***=1%

Just like "pull factors" may play a significant role in any potential relocation of households, there are also "push factors" that are important to consider. As the literature points out, community-related factors, such as crime and social cohesion, appear to be

relevant determinants of risky aversion (Gould et al., 2002; Lochner and Moretti, 2001; Huang et al., 2009; Huang et al., 2012; others). We augment the instrumental variables version of our main risk aversion specification of Table 5 and now include both a crime and social capital proxies.[18] When controlling for the rate of street robbery victims in the district of residence and the share of participants in organizations with education purposes in the district of residence, we find that the coefficient of years of education keeps the expected sign and remains statistically significant at conventional levels.[19] These findings are shown in Table 7.[20]

Table 7. Risk Aversion and Push Factors

Dependent Variable	Risk Aversion	Risk Ambiguity	Loss Aversion
	(1)	(2)	(3)
Years of education	0.314**	0.434***	0.271*
	(0.136)	(0.152)	(0.153)
Street robbery victims that reside in district (%)	-0.007	0.007	0.008
	(0.014)	(0.016)	(0.019)
District residents in organizations w educational aims (%)	-0.023	-0.021	-0.007
	(0.029)	(0.025)	(0.028)
Constant	-2.440	-9.842**	-4.720
	(4.179)	(4.860)	(5.789)
Observations	540	540	540
Anderson-Rubin Wald test, F statistic	4.85	9.22	2.39
Anderson-Rubin Wald test p-value	0.1375	0.157	0.1352

Notes: The method of estimation is two-stage least squares. The observations are at the participant level. Robust standard errors clustered by session are reported in parentheses. Regressions include the same controls as in the most complete specifications in Table 5 namely, age, female, married, homeowner, employed, share of women in session, mean age in session, female standard deviation of session, age standard deviation of session, participants per session. Similar to Table 5, the instrument is the accumulated growth (%) of number of private primary schools 2000-2007, by participant's district of residence. Coefficients that are significantly different from zero are denoted by the following nomenclature: *=10%; **=5%; ***=1%

[18] We obtain analogous findings when using ordinary least squares.
[19] Street robbery is the most prevalent form of crime in the Lima, according to the Study of Perceptions in Metropolitan Lima. Table 1 shows definitions and sources.
[20] A complementary approach is to look at mobility among adult citizens. When using census data from 2007 (www.inei.gob.pe), which is the year of the experimental sessions, we find that the share of adults who had moved from out of the city into Lima during the previous five years is less than 10 percent of total number of adults, which equals to less than 2 percent of total households. When focusing on within-city movements only, we find that this is even less common, as just 1.3 percent of total households moved within districts in the previous five years. When focusing on school-aged children instead of adults we find analogous results. Detailed findings are available upon request.

We also conduct a set falsification tests using instruments based on upcoming schools variations and not prior to when the experiments were conducted. In theory, doing this should result in findings that do not have effects on risk aversion as the latter have been reported in a prior year to such schools openings, which occurred in 2007 as described above. In particular, we use the school variation between 2008 and 2009 and the school variation between 2008 and 2014. When regressing the years of education on our three risk measures by using a two stage least squares method analogous to the one employed above with the alternative instruments, we find results fully consistent with our expectations as the corresponding coefficient of our years of education variable is not statistically significant at conventional levels in any case considered. Findings are shown in Table 8.

Table 8. Falsified Instrumental Variables

	Risk Aversion			Risk Ambiguity			Loss Aversion		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Variation 2008/2009					
Years of Education	0.045	0.111	0.199	0.111	0.924	0.111	0.033	0.032	0.044
	(0.076)	(0.119)	(0.252)	(0.242)	(0.535)	(0.222)	(0.368)	(0.254)	(0.357)
Constant	3.999***	2.353	2.261	3.746*	-1.425	-3.426	2.252	1.3644	2.226
	(1.21)	(2.253)	(2.958)	(1.963)	(3.225)	(4.330)	(1.569)	(2.992)	(2.722)
R-squared	0.0933	0.1563	0.1055	0.1252	0.1524	0.1252	0.0833	0.0795	0.094
				Variation 2008/2014					
Years of Education	0.192	0.195	0.211	0.088	0.095	0.139	-0.062	-0.084	-0.252
	(0.251)	(0.232)	(0.352)	(0.122)	(0.132)	(0.242)	(0.263)	(0.644)	(0.524)
Constant	2.644**	2.011	2.946	1.957	-1.333	-1.235	2.444	3.294	2.269
	(1.012)	(2.555)	(2.264)	(2.260)	(3.596)	(3.52u)	(2.620)	(3.964)	(3.763)
R-squared	0.066	0.0619	0.065	0.114	0.115	0.064	0.022	0.025	0.045
Observations	230	230	230	230	230	230	230	230	230

Notes: All regressions include the same controls as in Table 4 and Table 5. The method of estimation is two-stage least squares. The observations are at the participant level. Regressions include fixed effects at the district level and standard errors are clustered at the session level. Instrument is the accumulated change (%) in the number of private primary schools from 2000 to 2009 and from 2000 to 2014 by participant's district of residence. Coefficients that are significantly different from zero are denoted by the following nomenclature: *=10%; **=5%; ***=1%

Summary and Conclusions

In this paper, provide empirical evidence on the link between risk aversion and education when using representative data from surveys and artefactual experiments in Lima, Peru. We find that the relationship between years of education and measures of risk aversion

is positive and statistically significant at conventional levels when employing ordinary least squares. Furthermore, we employ an exogenous government policy as part of our identification strategy, which is orthogonal to the dependent variable, and find evidence that, with one exception, there is support to claim a causal link that goes from years, education to risk aversion. We apply a broad number of robustness tests, which further confirm our results.

In general, our results are closer in line to the studies that show a positive link, rather than a negative or non-monotonic one. This means that from a policy perspective, our findings support the idea that more education may sometimes end up translating in unexpected decisions by individuals, which may help explain the apparent paradox of people failing to take advantage of new learned technologies, methods, or processes, regardless of capital or related resources. The fact that these unexpected behaviors are more prominent in more traditional, rural areas in developing countries is consistent with an increase in risk aversion due to more education. In future research, we expect to further study these issues.

References

Arregui, P. (2000) "Las Políticas Educativas Durante los Noventa en el Perú: Resultados y Pendientes" *Tarea: Revista de Educación y Cultura* 46:7-11.

Balarin, M. (2013) "Mapping and Exploring the Consequence of the Rise of Private Education in Peru". Working Paper UKFIET.

Baldwin, J. (1955) "Notes of a Native Son", Beacon Press, First Edition, New York, NY.

Barr, A. (2003) "Risk Pooling, Commitment, and Information: An Experimental Test of Two Fundamental Assumptions, Working Paper 187, Oxford University.

Belzil, C. and M. Leonardi (2007) "Can Risk Aversion Explain Schooling Attainments? Evidence From Italy", Labour Economics, 14, 6: 957-970.

Binswanger, H. (1980), "Attitudes Towards Risk: Experimental Evidence from Rural India", American Journal of Agricultural Economics 62: 395-407.

Blow, C. (2016) "Stop Bernie-Splaining to Black Voters", New York Times, February 10th, B21.

Breen, R., H. van de Werfhorst, and M. Meier Jaeger (2014) "Deciding Under Doubt: A Theory of Risk Aversion, Time Discounting Preferences, and Educational Decision Making", European Sociological Review, 30, 2: 258-270

Brodaty, T., R. Gary-Bobo, and A. Prieto (2014) "Do Risk Aversion and Wages Explain Occupational Choices?", Journal of Public Economics, 117: 125-148

Caliendo, M., F. Fossen and A. Kritikos, (2009). Risk Attitudes of Nascent Entrepreneurs–New Evidence from an Experimentally Validated Survey, Small Business Economics, 32(2), 153-167.

Candelo, N., S. Polania, (2009). "Methodological Steps and Experimental Design to Measure Social Capital and Collective Action in Six Latin American Cities" Serie Documentos Cede, Universidad de los Andes, Bogotá.

Cardenas, J., A. Chong, and H. Nopo (2013) "Stated Social Behavior and Revealed Actions: Evidence from Six Latin American Countries Using Representative Samples" Journal of Development Economics, 104: 16-33

Dohmen, T., A. Falk, D. Huffman, and U. Sunde (2010) "Are Risk Aversion and Impatience Related to Cognitive Ability?" American Economic Review 100:1238-60.

Donkers, B., B. Melenberg and A. Van Soest, "Estimating Risk Attitudes using Lotteries: A Large Sample Approach," Journal of Risk and Uncertainty 22 (2001), 165–95.

Du Bois, F., (2004) "Programas Sociales, Salud y Educación en el Perú: Un Balance de las Políticas Sociales" Lima: Instituto Peruano de Economía Social de Mercado, Fundación Konrad Adenauer.

Gould, E., B. Weinberg and D. Mustard (2002) "Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997", Review of Economics and Statistics, 84(1), 45-61.

Guadalupe, C., J. Leon, J. Rodriguez, and S. Vargas (2017) Estado de la Educación en el Perú: Análisis y Perspectivas de la Educación Básica, Proyecto Fortalecimiento de la Gestión de la Educación en el Perú, GRADE, Lima.

Halek, M., and J. Eisenhauer (2001) "Demography of Risk Aversion", Journal of Risk and Insurance, 1-24.

Hardeweg, B., L. Menkhoff and H. Waibel (2013) "Experimentally Validated Survey: Evidence on Individual Risk Attitudes in Rural Thailand", Economic Development and Cultural Change, 61(4), 859-888.

Harrison, G., M. Lau, and E. Rutström (2007) "Estimating Risk Attitudes in Denmark: A Field Experiment", Scandinavian Journal of Economics, 109:341-68.

Hartlaub, V. and T. Schneider (2012) "Educational Choice and Risk Aversion: How Important is Structural Vs. Individual Risk Aversion?" Working Paper, DIW Berlin.

Hartog, J., A. Ferrer-i-Carbonell and N. Jonker (2002) "Linking Measured risk Aversion to Individual Characteristics", Kyklos, 55: 3–26.

Hryshko, D., M. Luengo-Prado, and B. Sørensen (2011) "Childhood Determinants of Risk Aversion: Long Shadow of Compulsory Education", Quantitative Economics, 2: 37-72

Huang, J., H. van den Brink, and W. Groot (2009) "A Meta-Analysis of the Effect of Education on Social Capital", Economics of Education Review, 28(4), 454-464.

Huang, J., H. van den Brink and W. Groot (2012) "Does Education Promote Social Capital? Evidence from IV Analysis and Nonparametric-Bound Analysis", Empirical Economics, 42(3), 1011-1034.

Jung, S. (2014) "Does Education Affect Risk Aversion? Evidence From the British Education Reform", Working Paper, Université de Cergy Pontoise.

Kahneman, D. and A. Tversky (eds.) (2000) Choices, values, and frames. Cambridge University Press, United Kingdom.

Lehvari, D., Y. Weiss (1974) "The Effect of Risk on the Investment in Human Capital", American Economic Review, 64: 950–963.

Lochner, L., and E. Moretti (2001) "The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports", NBER Working Paper 8605.

Ministry of Education of Peru (2017) National School Census, 2008-2013

Olson, L., H. White and H. Shefrin (1979) “Optimal Investment in Schooling When Incomes Are Risky” Journal of Political Economy, 87, 3: 522-539

Outreville, J. (2015) “The Relationship Between Relative Risk Aversion and the Level of Education: A Survey and Implications for the Demand for Life Insurance”, Journal of Economic Surveys, 29(1), 97-111.

Riley Jr., W., and K. Chow (1992) “Asset Allocation and Individual Risk Aversion”, Financial Analysts Journal, 48(6), 32-37.

Appendix

Education and Risk Aversion
Ordered Probits

	Risk aversion	Risk ambiguity	Loss aversion
Individual characteristics			
Years of education	0.110***	0.112***	0.118***
	(0.0268)	(0.0383)	(0.0236)
Age	-0.0136*	-0.00615	-0.0119***
	(0.00825)	(0.00865)	(0.00457)
Female	0.185	0.392**	0.425***
	(0.226)	(0.177)	(0.161)
Married	0.227	-0.0733	0.151
	(0.168)	(0.246)	(0.159)
Homeowner	-0.235	-0.0182	0.320
	(0.229)	(0.273)	(0.237)
Employed	0.0249	-0.0279	0.105
	(0.192)	(0.177)	(0.134)
Session characteristics:			
Percent women	-0.0431	-0.0544	-0.0785
	(0.101)	(0.0700)	(0.0537)
Mean age	-0.0194	-0.167*	0.0105
	(0.134)	(0.0955)	(0.119)
Standard deviation, women	-16.54	-21.26	-14.11
	(28.63)	(21.25)	(17.29)
Standard deviation, age	-0.0256	0.000998	-0.124
	(0.195)	(0.136)	(0.113)
Constant	-13.12	-20.23	-12.64
	(25.05)	(17.66)	(15.51)
Observations	540	540	540
Pseudo R-squared	0.0921	0.1321	0.1321
Wald chi2	20.66	43.52	179.5
Prob > chi2	5.48e-06	4.01e-06	0

All regressions include session fixed effects, district fixed effects and the standard errors are clustered at the district level. The method of estimation is maximum likelihood. The observations are at the participant level. Robust standard errors are reported in parenthesis. Coefficients that are significantly different from zero are denoted by the following nomenclature: * = 10%; ** = 5%; *** = 1%.