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Risk attitudes and economic well-being in Latin America ☆

Juan Camilo Cardenas [a], Jeffrey Carpenter [a,b,c,*]

[a] Facultad de Economía & CEDE, Universidad de los Andes, Colombia
[b] Department of Economics, Middlebury College, United States
[c] IZA, Germany

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ABSTRACT

A common conjecture in both the theoretical and policy literatures on development is that people remain poor because they are too impatient and risk averse to accumulate the resources needed to improve their well-being. The empirical literature, however, suggests that this conjecture is far from proven. We sample more than 3000 participants drawn representatively from six Latin American cities and find little correlation between baseline risk aversion and well-being, measured as an index of eight outcomes. We do, however, find that measures of ambiguity aversion, loss aversion and the willingness to take advantage of a risk pooling scheme all correlate with well-being. Participants who are ambiguity averse, loss averse, and who react conservatively in the risk pooling condition all have significantly lower scores on our well-being index. These results are robust to the inclusion of a variety of important controls like human capital accumulation and access to credit.

1. Introduction

In 1930, Irving Fisher made a bold claim that has often been taken as a matter of fact in the policy and academic literatures on economic development ever since. He claimed that, to paraphrase, people remain poor because their inherent preferences are incompatible with growth (Fisher, 1930; Thaler, 1997). Since then discussions about attitudes towards risk (Arrow, 1965; Pratt, 1964) have caused the conjecture to transform into a statement often associated with the "culture of poverty" (Lewis, 1959): people remain poor because they are too impatient to save and too risk averse to take the sort of chances needed to accumulate resources and advance their well-being.

Despite early economic experiments that found no significant link between the risk preferences of farmers and wealth (Binswanger, 1980; Sillers, 1980; Walker, 1980) and, that "poor" rats tended to actually have lower discount rates in an innovative animal study that exhibited the sort of internal validity not attainable in human studies (Kagel et al., 1995), this conjecture continues to be the basis of economic models (Azariadis et al., 2005; Banerjee, 2000; Katz and Stark, 1986; Lipton, 1968; Netting, 1993) and policy (Adubi, 1996; Holzmann and Jorgensen, 1999; Knight et al., 2003; Sinha and Lipton, 1999).

The importance of this conjecture about the characteristics of the poor has caused it to gather considerable empirical attention. In the economics literature, empirical tests can be divided into two broad categories. In one category, researchers begin by inferring preferences from observed choices and then correlate these preferences with wealth or other measures of well-being. The results of this literature are mixed: some researchers find the poor to be more impatient (Lawrance, 1991) and risk averse (Moscardi and de Janvry, 1977; Rosenzweig and Wolpin, 1993) but others find no link between wealth and discount rates (Ogaki and Atkeson, 1997) and that the self-employed are actually more risk averse (Halek and Eisenhauer, 2001). Further, this method has been criticized because wealth or its correlates enter both stages of the analysis and this might lead to spurious correlation (Lybbert and Just, 2007).

The spurious correlation problem is mitigated to a large extent in studies that rely on direct measures of preferences from surveys. Using hypothetical questions, researchers report that people with

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* Corresponding author.
E-mail addresses: jccarden@uniandes.edu.co (J.C. Cardenas), jpc@middlebury.edu (J. Carpenter).

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higher incomes are less risk averse (Donkers et al., 2001; Hartog et al., 2002) and more patient (Ashraf et al., 2006; Holden et al., 1998). Because there is some evidence that incentivizing participants reduces the noise seen in hypothetical preference measures (Camerer and Hogarth, 1999), other researchers have used questions involving real monetary stakes to measure preferences. With these methods, researchers in India and Canada find the poor to be more impatient (Eckel et al., 2005; Pender, 1996) but this does not appear to be true in Denmark (Harrison et al., 2002). In Ethiopia, one study reports the poor to be more risk averse (Yesuf and Bluffstone, 2007) but the opposite holds in Spain (Bosch-Domenech and Silvestre, 2006) and among poor farmers in Chile and Tanzania (Henrich and McElreath, 2002).

A number of empirical concerns remain, regardless of whether direct measures of preferences are incentivized or not. Most would agree, for example, that it is no longer appropriate to gather just the standard measures. Instead of being risk averse, it might be, for example, that the variation in attitudes towards potential losses (Kahneman and Tversky, 1979) or the aversion to ambiguous situations (Ellsberg, 1961) matters. Concerning patience, the hyperbolic discounting model suggests that people appear to be much more impatient about decisions with immediate consequences than they are when they think about similar decisions scheduled to take place in the future (Angeletos et al., 2001). In terms of inference, because samples from the field tend to be targeted and small, the data often lacks variation in the important socio-economic characteristics and this may hinder the representativeness of the analysis. In terms of identification, reverse causality and omitted variables like the availability of credit (Stiglitz, 1989) are also perennial issues.

Like the other important contributions to this literature, we are unable to completely settle all the identification issues (the possibility of reverse causation, in particular); however, we advance the literature by using incentivized tasks in the field, by gathering a large and representative sample, and by collecting a number of important controls. Our focus is on the relationship between incentivized risk attitudes and an index of poverty constructed from a number of outcome measures (home ownership, basic utility access, employment, overall economic status, perceived relative economic status, requiring government assistance, expenditures and having lost a business). To supplement the standard analysis we broaden our risk preference measures by introducing new measures of one's aversions to losses, ambiguity, and the willingness to pool risks with others. Our participants faced monetary incentives equivalent to two days pay, on average, in 159 sessions. Our sample is the most extensive and complete assessment of risk attitudes in Latin America gathered to date; it includes more than 3000 participants who were drawn representatively from six Latin American capital cities: Bogotá, Buenos Aires, Caracas, Lima, Montevideo, San José. In addition to the incentivized tasks, participants completed an extensive survey that provides a number of important controls for our analysis including demographics and their access to credit.

As a preview, we first show that our procedures replicate many of the stylized facts in the related experimental literature: risk attitudes are varied but most people react more conservatively when the lotteries become ambiguous and less conservatively when losses are involved.

Considering the link between preferences and well-being, we do not find an association between baseline risk attitudes and our index of well-being. While it is tempting to consider this an indictment of the “Fisher hypothesis”, we show that interesting associations do appear when we consider our new preference measures. In fact, some of our results dovetail nicely with the extensive literature on decision-making biases: when the task is changed so that the decision problem is more ambiguous, we find that people classified as “ambiguity averse” (i.e., those that shy away from risk even more when the odds are ambiguous) tend to have lower well-being scores. Similarly, those people who accept more risk when losses are possible and are therefore classically “loss averse” also tend to have lower scores on the well-being index. The risk pooling choices of our participants correlate with well-being too. Here we see that those participants who do not take advantage of the opportunity to pool risk (i.e., they tend to choose less risky lotteries in the pooling treatment) also have significantly lower well-being scores.

We proceed by describing the incentivized preference tasks, our well-being measures, and our sampling strategy in the next section. In Section 3, we summarize the data from our incentivized tasks and examine the extent to which demographics predict preference task choices. In Section 4, we analyze whether baseline risk attitudes correlate with our index of well-being. We expand our analysis in Section 5 by considering the links between the additional preference measures we collected and well-being. We end the paper in Section 6 with a summary and a discussion of the relevance and limitations of our work.

2. Methods

We discuss four components of a larger set of experiments that took place in six Latin American capital cities during the spring of 2007. Other components are discussed in Calonico et al. (2007). Representative samples of individuals from heterogeneous urban societies in Bogotá, Buenos Aires, Caracas, Lima, Montevideo and San José were recruited to participate voluntarily in a set of economic experiments with salient economic incentives that averaged about what a worker could get for $1\frac{1}{2}$–2 days of work at the minimum wage, or US$10–12 per participant.

Four lottery choices gave us the information necessary to assess participant attitudes towards risk, ambiguity, losses and risk-pooling. In each case, a participant was shown a ring of six possible binary lotteries and asked to pick one to play. To minimize any problems that the participants might have with understanding and assessing probabilities (Kahneman et al., 1982), the likelihood of good and bad outcomes were equal in each task. Fig. 1 displays a version of the baseline graphic used in the field that has been redrawn with dollar payoffs proportional to the field payoffs. The payoffs for each 50–50 lottery were chosen so that the expected payoff of each lottery increases as one moves clockwise (from $33 to $47.5), but so does the variance of the payoffs. This pattern is only violated as one moves from the $4|$91 lottery to the $0|$95 lottery. Here the expected value does not change but the variance continues to increase. Using the constant relative risk aversion utility function, $U(x) = \frac{x^{1-r}}{1-r}$ to evaluate the risk attitudes at which people should be indifferent between any two neighboring lotteries we find that the coefficient of relative risk aversion r that would make one

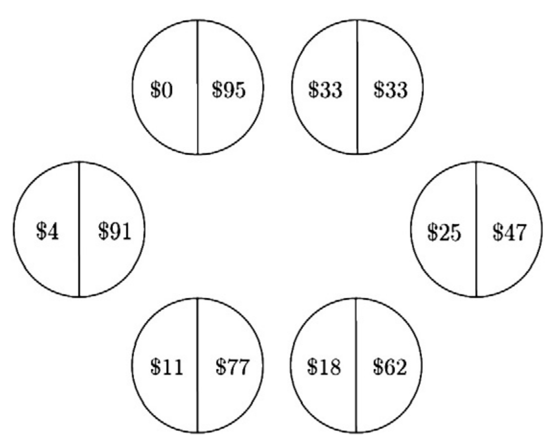

Fig. 1. The decision task (with representative U.S. dollar payoffs) used to assess baseline attitudes towards risk. Participants are asked to choose one of six 50–50 lotteries in which the odds of a high payment are the same as the odds of a low payment. As one moves clock-wise around the ring, the lotteries increase in risk and expected payoff except for the last lottery, which has the same expected payoff as the fifth but is riskier. The participant's risk attitude can be bound by the chosen lottery. To determine payouts for the task, the experimenter uses a bag of five low value balls and five high value balls where the ball values are determined by the chosen lottery and the participant blindly picks a ball from the bag.

indifferent between the first and second lotteries, for example, will solve:

$$U(33) = \frac{1}{2}U(25) + \frac{1}{2}U(47)$$

$$\frac{33^{1-r}}{1-r} = \frac{1}{2}\left(\frac{25^{1-r}}{1-r}\right) + \frac{1}{2}\left(\frac{47^{1-r}}{1-r}\right)$$

The cutoffs, therefore, are the following: picking \$33|\$33 indicates extreme risk aversion, $r > 1.77$. Picking \$25|\$47 indicates $0.82 \leq r \leq 1.77$, \$18|\$62 indicates $0.48 \leq r \leq 0.82$, \$11|\$77 indicates $0.28 \leq r \leq 0.48$, \$4|\$91 indicates $0 \leq r \leq 0.28$, and picking \$0|\$95 indicates $r \leq 0$ or possible risk seeking.

The lotteries were implemented in the field using bags of balls. The participants were told that they were to choose a lottery from the ring and that each lottery represented a bag with ten balls inside. Each of the six bags was comprised of five high value balls and five low value balls. Once the participant chose a lottery, she then blindly picked a ball from the corresponding bag and earned the payoff from this choice.

Participants then made choices from three rings where the setup is slightly altered. In the ambiguity condition, the possible outcomes of the lotteries are the same but the chances of either the good or bad outcome are uncertain. Instead of six bags with five high and five low value balls for sure, participants were told that each bag had three high value balls and three low value balls for sure, but they were not told the distribution of the remaining four balls. This meant that the probability of the good outcome was uncertain; it was somewhere between 3/10 and 7/10. This choice was presented to the participants using the graphic in Fig. 2.

In the loss condition, motivated by prospect theory (Kahneman and Tversky, 1979), participants began with an endowment of \$50 and then chose from the six lotteries in Fig. 3. As one can see, if you add \$50 to each payoff, you get back to the baseline, Fig. 1. This means that the only thing that has changed is the framing of the decision problem. The purpose is to investigate whether participants react differently when losses are possible compared to the baseline.

In the pooling condition, participants reconsidered the decision task in Fig. 1 only this time they were asked if they wanted to pool their risk. Specifically, participants were told that they could join a pooling group in which all the payoffs from the poolers would be combined and each pooler would get a $1/n$ share of the total earnings. If they decided to not pool, the game was identical to a replay of the baseline. The order of decisions was as follows: decide to pool or not, learn the number of poolers in the group, decide on a lottery from Fig. 1 without communicating with each other. In this case, we examine if people are willing to join an insurance program and if they respond optimally to the fact that risks are now pooled when they make their lottery choices.

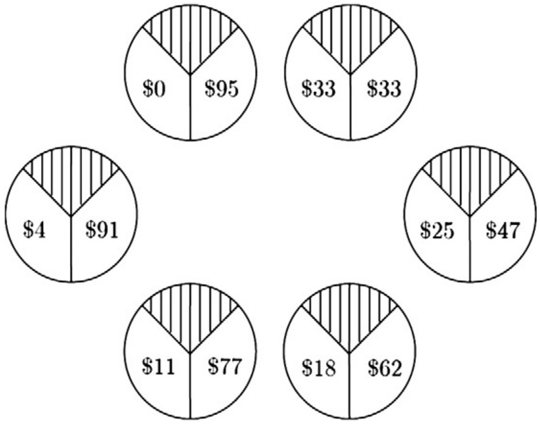

Fig. 2. The decision task (with representative U.S. dollar payoffs) used to assess attitudes towards ambiguity. Participants were asked to choose one of six lotteries in which the odds of a high or low payment are bound between 3/10 and 7/10 but are unknown. To determine payouts for the task, the experimenter uses a bag of ten balls. The participant knows that there are at least three low value balls and three high value balls in the bag but does not know the distribution of the remaining four balls which could be either low or high value. The participant blindly picks a ball from the bag.

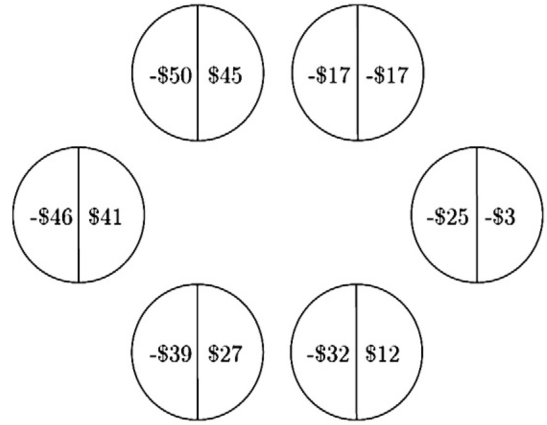

Fig. 3. The decision task (with representative U.S. dollar payoffs) used to assess attitudes towards losses. Participants were asked to choose one of six lotteries in which the odds of a high or low payment are equal but some payoffs are negative. The only difference between this task and the risky task in Fig. 1 is the frame: adding the \$50 endowment for this task to all the payoffs results in the same lotteries depicted in Fig. 1.

In many instances participants should decide to pool, although their final choices will surely depend to some extent on the expected choices of the people that they pool with. Given the outcomes of the lotteries are completely independent, the probabilities of really good and really bad outcomes fall, even in groups of two. In other words, even though the expected payoff will not change, risk will fall for some poolers. Consider two-person groups as an illustration. Going it alone, the moderately risk averse person who picks the \$18|\$62 in the baseline and must have $0.48 \leq r \leq 0.82$ earns expected utility of $\frac{1}{2}\left[\left(18^{1-r}\right)/(1-r)\right] + \frac{1}{2}\left[\left(62^{1-r}\right)/(1-r)\right]$ which will be lower than what she plans on receiving in a two-person group, $\frac{1}{4}\left[\left(18^{1-r}\right)/(1-r)\right] + \frac{1}{2}\left[\left(40^{1-r}\right)/(1-r)\right] + \frac{1}{4}\left[\left(62^{1-r}\right)/(1-r)\right]$, for any allowable r.

The harder decision problem is which lottery to pick once one has joined a pooling group. Notice, however, that because the pooling arrangement equalizes payoffs in the group, strategic motivations are moot and the problem is the same as the one a social planner would face. If we maintain the same two-person group example and assume common knowledge of symmetric underlying risk attitudes, the predictions of what choices participants should make is relatively straightforward. Given our parameterization, a simple heuristic arises: compared to your first risky choice, if you pool, pick the next riskiest lottery. A group of two players who chose \$11|\$77 in the baseline, for example, would do best to pick \$4|\$91 in the pooling task and the logic is simple. If pooling reduces our risk a little, our preferences should cause us to compensate by picking a lottery with slightly more risk and higher expected value.

At the end of the last activity one of the four activities was randomly selected to be paid.[1] While one monitor calculated individual earnings and called each of the participants for payment (privately), the rest of the monitors interviewed the participants for detailed information about their background and opinions towards various dimensions of social exclusion.

One advantage of our sample, other than size, is that we strove to make the city subsamples representative. Other studies have looked

[1] Not only is it common in economic experiments of this sort to pay for one choice randomly, there are a number of papers that validate the procedure. See both the results and the other studies discussed in Hey and Lee (2005).

cross-culturally (Henrich et al., 2001; Henrich et al., 2006) at samples from mostly isolated small-scale societies, or samples of college educated people in urban settings (Herrman et al., 2008). We went to great lengths to stratify our sample based on initial vetting questions about economic position, education, gender and age in large urban Latin American cities.

To reduce errors that might result from variation in the participants' ability to read, the post-experiment surveys were administered by a group of hired pollsters trained for this purpose. Each city team agreed to sample more than 500 participants from their cities and conduct more than 25 sessions. The local team in each city designed a stratified sample from the population of their cities, based on socio-economic class, education, gender and age as criteria. In the end, 3106 people participated in the six cities providing a unique data set that combines detailed data from their socio-economic and demographic background with behavioral data from their decisions during the incentivized tasks. This is, as far as we know, the most comprehensive experimental data set gathered for Latin America given the number of countries included, the completeness of the demographics, the sample sizes and the replicability of the designs in each city.

Each of the city teams conducted sessions of various group sizes from 9 to 38 people with a mean size of 22 people in each session. All of the sessions followed a common protocol with the same sequence of activities.

The outcome measures that we collected to build an index of well-being are summarized in the first eight rows of Table 1 along with other information about our participants. We use factor analysis to create the index from these eight outcome variables. The resulting index possesses the desired characteristics: the first principal factor has an eigenvalue greater than one, indicating some index consistency and all the factor loadings make sense (i.e., they are all positive indicating that higher values of each of our outcome measures contribute positively to the index).[2]

While most of the index components are intuitive, some require more description. For example, because incomes, wealth and instances of poverty differ by city, we normalized each participant's socio-economic class into one of three economic classes: low, middle, and high class. This categorization was based on the social stratification used by each city for classifying neighborhoods by income. These stratifications are used when assigning utility rates (e.g., electricity), for example with the goal of charging higher rates to higher income neighborhoods thus subsidizing low income neighborhoods. However, some cities have more categories than others: Buenos Aires and San José have three categories, Caracas and Montevideo have four, Lima has five and Bogotá has six. To make these comparable across cities, we grouped levels for cities that had more than three levels into the respective low, middle and high socio-economic classes.

Our relative status measure is novel in that we asked each participant to imagine where she stood on an economic ladder with ten rungs (so that those at the top of the economy were on the tenth rung). In other words, what was the participant's evaluation of her relative economic position in society?

To economic class and relative status, we add a variety of measures that broaden the analysis from wealth to well-being, more generally. The inclusions are an indicator for home ownership (56% affirmative in our sample), an indicator for participants who report having all three basic services: electricity, piped water, trash collection, an indicator for being employed (58% affirmative), the level of family expenditures measured as multiples (1–7) of the local minimum wage, an indicator for receiving any government assistance (50% affirmative) and an indicator for having lost a business to bankruptcy (7% affirmative). For the analysis, the last two measures were transformed to have the same, positive, frame as the others.

Table 1
Summary statistics of participant characteristics.

	Mean	s.d.	min	max
Law economic class (indicator)	0.26	0.44	0	1
Relative status (number)	4.95	1.71	1	10
Own home (indicator)	0.56	0.50	0	1
Basic services (number)	2.89	0.43	0	3
Employed (indicator)	0.58	0.49	0	1
Expenditures (number)	2.58	1.15	0	7
Receiving assistance (indicator)	0.50	0.50	0	1
Suffered bankruptcy (indicator)	0.07	0.24	0	1
Female (indicator)	0.56	0.50	0	1
Age (years)	37.26	14.57	17	80
College (indicator)	0.02	0.14	0	1
Married (indicator)	0.31	0.46	0	1
Children (number)	1.10	1.22	0	8
Indigenous heritage (indicator)	0.02	0.14	0	1
African heritage (indicator)	0.03	0.16	0	1
Home size (bedrooms)	2.62	1.18	0	10
Income earners (number)	2.06	1.10	0	10
No access credit (indicator)	0.23	0.42	0	1
No access politics (indicator)	0.04	0.19	0	1

Notes: 3106 people participated in 159 sessions. The sessions were distributed as (sessions|participants): Bogota (31|567), Buenos Aires (25|497), Caracas (25|488), Lima (28|541), Montevideo (28|578), San Jose (22|435). The eight items in the top panel are used to create a well-being index. The remaining items are used as controls.

The other control variables that we gathered include college which is an indicator for whether the participant has achieved a college degree or more education. The two heritage indicators are 1 if the participant self-reports indigenous or African ancestry. We measure two characteristics of the participant's home. Home size is measured by the number of bedrooms and we measure the earning power of the household by asking for the number of income earners in the home. Lastly, to capture a standard alternative explanation for poverty (McKenzie and Woodruff, 2008; Stiglitz, 1989) we ask two questions about socio-economic exclusion. No access to credit is an indicator which is 1 if the participant has not been able to get a loan in the past five years and no access to politics takes the value 1 if the participant has been excluded from participating in the political process in the past five years.[3]

With the help of Table 1, we can summarize our participants. Overall our participants were 56% female, 31% were married, only 2% had been to college, 2% revealed indigenous heritage and another 3% claimed African heritage. In addition, 23% said that they had no access to credit, if needed, but only 4% said they had absolutely no access to the political process; in other words, surprisingly few felt completely disenfranchised. On average, our participants were 37 years old, they had slightly more than one child and they lived in homes with about two and a half bedrooms and two income earners.

3. An overview of the behavioral data

Considering the lottery choices, our results appear to be consistent with previous field studies (e.g., Binswanger, 1980 or Barr and Genicot, 2008).[4] In the risky baseline, the modal choice is \$25|\$47 which demonstrates considerable risk aversion. Numbering the lotteries clockwise from one to six in order of increasing riskiness, the average choice in the baseline is 2.80 which puts the average closest to the \$18|\$62 gamble.

[2] Our approach is similar, in spirit, to both the poverty scorecard approach, especially in terms of the outcomes we consider, and the multidimensional poverty measurement approach developed by Alkire and Foster (2011).

[3] The exact phrasing (back-translated from Spanish) was: "Please tell me if in the past five years, you have ever wanted to participate in these activities and were unable to." The respondent could indicate getting a loan and participating in an election as options.

[4] As hoped we found considerable variation in the lotteries chosen in the baseline risk task: 23% of participants "played it safe" and chose \$33 for sure, 30% picked the \$25|\$47 lottery, 19% picked \$18|\$62, 11% picked \$11|\$77, 8% picked \$4|\$91 and the remaining 9% picked \$0|\$95.

Table 2
The demographic determinants of preferences.

	Risk choice	Ambiguous choice	Loss choice	Pooling choice	Pool?
Female	0.034***	0.056***	0.059***	0.047***	0.035*
	(0.012)	(0.013)	(0.011)	(0.018)	(0.020)
Age	−0.002***	−0.002***	−0.003***	−0.001**	0.004***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
College	−0.021	−0.001	−0.019	−0.064	0.068
	(0.044)	(0.053)	(0.035)	(0.042)	(0.074)
Married	0.020	0.037**	0.048***	0.031	0.050**
	(0.016)	(0.016)	(0.016)	(0.022)	(0.021)
Children	−0.004	−0.004	−0.001	0.002	−0.012
	(0.005)	(0.006)	(0.005)	(0.008)	(0.009)
Indian heritage	−0.021	−0.034	−0.060*	0.004	−0.077
	(0.037)	(0.041)	(0.035)	(0.067)	(0.064)
African heritage	−0.018	−0.016	−0.036	0.017	−0.054
	(0.032)	(0.032)	(0.039)	(0.044)	(0.061)
Home size	−0.006	−0.006	0.002	−0.011	−0.015
	(0.007)	(0.006)	(0.006)	(0.008)	(0.010)
Income earners	0.003	0.002	0.001	0.003	0.017*
	(0.007)	(0.007)	(0.006)	(0.009)	(0.010)
No access to credit	−0.013	−0.029*	−0.013	−0.049***	−0.041*
	(0.015)	(0.017)	(0.014)	(0.019)	(0.022)
No access to politics	0.009	−0.037	0.065*	0.014	−0.044
	(0.034)	(0.035)	(0.037)	(0.046)	(0.050)
Observations	3085	3086	3086	1480	3087
Experimental sessions	159	159	159	159	159
Psuedo R-squared	0.005	0.008	0.008	0.006	0.032

Notes: The dependent variable is the lottery chosen (numbered 1–6 in order of increasing risk) in each lottery choice task. Because the differences in risk are ordinal, columns 1–4 report ordered probit marginal effects on the probability of choosing the safe $33|$33 lottery in each task. Column 5 reports probit marginal effects on the probability of pooling risk in the last game. City fixed effects are included. (Standard errors) have been clustered at the session level. *** indicates significant at the 1%, ** 5% and * 10% levels.

Based on the pseudo-experiment conducted by Ellsberg (1961) and the subsequent work, we expected that participants would react, on average, more conservatively (i.e., risk aversely) in the ambiguous choice condition. Indeed, there is some shift from the more risky lotteries to the less risky ones under ambiguity. Although the shape of the distribution does not change dramatically, the average choice does fall to 2.66 which is statistically significant ($t = 5.26$, $p < 0.01$) because of the large size of our sample. Indeed, ambiguity causes the average participant to choose safer lotteries.

Prospect theory (Kahneman and Tversky, 1979) posits that losses are treated differently than gains. In particular, anchored at some reference point people tend to be more risk seeking in the loss domain than in the gain domain. We see that our loss manipulation triggers substantial movement towards riskier lotteries. The average choice climbs to 3.23 which is again highly significant ($t = 12.99$, $p < 0.01$) compared to the baseline. The distribution of choices also changes substantially. There appears to be more bifurcation in the loss choice distribution: the mode is the safe $33|$33 lottery but there is now, compared to the baseline, more than twice as many people choosing the $0|$95 lottery.

As suggested above, pooling should cause people to choose more risky lotteries because the reduced risk associated with the insurance can be offset by choosing lotteries with higher expected values. Indeed, the average choice is 2.86 which is higher (more risk seeking) than the baseline but the difference is only significant at the 5% level ($t = 2.14$, $p = 0.03$). At the same time, if we consider only those participants who chose to pool, the average choice is 2.94 and the difference is highly significant ($t = 3.60$, $p < 0.01$).

We can also assess the extent to which these lottery choices are influenced by demographics. As seen in other samples (c.f., Croson and Gneezy, 2009) we find in Table 2 that women are significantly more risk averse than men. What is more noticeable perhaps, is that we find this to be true in all four domains. Women are 3.4% more likely than men to choose the safe $33|$33 lottery in the baseline risk task, they are 5.6% more likely in the ambiguous choice task, 5.9% more likely in the loss task and 4.7% more likely in the risk pooling task. Married participants also seem more likely to "play it safe". At the same time, older participants take more risks in each of the conditions as do participants with limited access to credit.

Returning to the risk pooling task, we can also ask who chooses to join pooling groups? In other words, who is willing to engage in social risk-sharing? As the final column of Table 2 indicates, gender, age, marital status and access to credit are important factors in this context too. Women are significantly more likely to pool risk, as are older and married participants. In addition, families with more than one income earner are more likely to pool but those with no perceived access to credit choose to pool significantly less.

4. simple risk and economic well-being

The first step in our analysis is to replicate what others have done: does our measure of risk aversion correlate with well-being? In Fig. 4 we ask whether there is any relationship between our well-being index and the baseline lottery choices made by our participants.[5] The bar heights indicate the average index score for the participants that choose each of the six lotteries in the first, baseline, risky task. According to the conjecture that motivates our work, the bar heights in Fig. 4 should increase from left to right because the gambles are arrayed from extremely risk averse ($33|$33) to risk neutral or risk seeking ($0|$95) and more risk tolerant people should be better off. Contrary to this conjecture, as one can see, the participants who choose risk aversely (i.e., the $25|$47 lottery) have the highest well-being scores and those that choose a moderately risky lottery (i.e., the $11|$77) have the lowest scores, on average. Although treating the lottery choice differences as cardinal increments and plotting the resulting bivariate regression does indicate a slightly negative (as opposed to the hypothesized positive) slope, the effect is small. At first blush, there does not appear to be a strong relationship between baseline risk preferences and well-being.

In Table 3 we present more of the details of this replication exercise. As column 1 confirms, there is a slight negative slope to the linear fit pictured in Fig. 4, however, the standardized coefficient is far from significant ($p = 0.60$). Furthermore, the point estimate becomes

[5] In the on-line appendix we present results detailing each of the possible correlations between the eight well-being measures we collected and the observed risk attitudes.

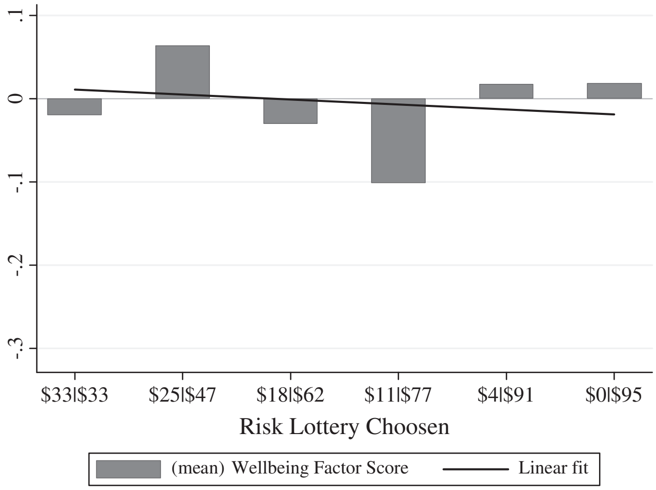

Fig. 4. Simple measures of risk tolerance and economic well-being. Bar heights represent the mean well-being index (a factor score of eight outcomes) for each of the possible risky lotteries that could be chosen in the baseline experiment. The linear fit controls for all the variables summarized in Table 1 and indicates the relationship between simple risk preference measures and well-being is weak.

only slightly larger when we control for observables in column 2 and it remains negative (and insignificant). In sum, with a very large sample and a lot of important controls we find no evidence for the conjecture that greater risk tolerance corresponds to enhanced economic well-being.

At the same time, a closer inspection of the second column of Table 3 reveals interesting associations between some of our controls and the well-being index. Of most interest, perhaps, is that financial exclusion, measured in our case as not having access to credit, is associated with lower well-being. The strong effect of credit is particularly interesting because it is a factor that we deemed important to control for and is often absent from tests of the relationship between preferences and outcomes. Additionally, it is not surprising (but confirming of our survey) to find that having a college education or more, being married, having a larger home with more income earners are all associated with greater well-being scores (and being older, having more children and being of minority status are associated with lower well-being scores).

5. Ambiguity, losses, risk pooling and well-being

As hinted at in the Introduction, our protocol allows us to take a second step in our analysis, one that exploits the additional measures that we collected to identify several biases that now regularly appear in the empirical and theoretical decision-making literatures. Perhaps it is not simple risk aversion that correlates with well-being. Instead, biases that arise as the decision environment becomes closer to the conditions encountered in real life might be more closely associated with outcomes. Few real world decisions, for example, apart from those encountered in the casino, involve pure risk. Rather than knowing all the possible payoffs and the probabilities associated with those payoffs, many decisions are made under uncertainty when the important parameters are ambiguous — you often do not know what the chances of an outcome occurring are for sure (e.g., Bryan, 2010). In addition, real world lotteries usually involve both gains and losses and it is now reasonable to expect that people treat losses differently from gains. Lastly, people in the real world occasionally make risky choices as part

Table 3
Simple risk preferences and economic well-being.

	(1)	(2)
Risk choice	−0.012	−0.015
	(0.021)	(0.017)
Female		0.006
		(0.017)
Age		−0.073***
		(0.018)
College		0.138***
		(0.013)
Married		0.141***
		(0.021)
Children		−0.238***
		(0.023)
Indian heritage		−0.029*
		(0.016)
African heritage		−0.049***
		(0.016)
Home size		0.240***
		(0.031)
Income earners		0.098***
		(0.022)
No access to credit		−0.073***
		(0.017)
No access to politics		0.001
		(0.017)
Pool risk		−0.019
		(0.016)
Observations	2866	2864
Sessions	159	159
R-squared	0.01	0.30

Notes: Standardized OLS. The dependent variable is an individual's well-being index generated from a factor analysis of economic class, relative economic status, home ownership, basic utility service, employment, expenditures, government assistance and bankruptcy. Higher index scores indicate greater well-being. Risk choice is the numbered lottery, in increasing order of riskiness, chosen in the baseline risk task. City fixed effects included. (Standard errors) have been clustered at the session level. *** indicates significant at the 1%, ** 5% and * 10% levels.

Table 4
Ambiguity, loss and pooling choices and economic well-being.

	(1)	(2)	(3)	(4)
Ambiguity choice	0.042**			0.059*
	(0.021)			(0.034)
Loss choice		−0.033*		−0.063**
		(0.020)		(0.029)
Pooling choice			0.027	0.027
			(0.025)	(0.025)
Risk choice	−0.037*	−0.004	−0.044*	−0.054*
	(0.021)	(0.019)	(0.027)	(0.029)
Female	0.008	0.003	0.011	0.008
	(0.017)	(0.017)	(0.025)	(0.025)
Age	−0.073***	−0.073***	−0.073**	−0.073**
	(0.036)	(0.018)	(0.036)	(0.036)
College	0.138***	0.139***	0.155***	0.156***
	(0.013)	(0.013)	(0.016)	(0.016)
Married	0.149***	0.140***	0.129***	0.127***
	(0.021)	(0.021)	(0.025)	(0.025)
Children	−0.238***	−0.239***	−0.214***	−0.215***
	(0.023)	(0.023)	(0.031)	(0.031)
Indian heritage	−0.029*	−0.028*	−0.036	−0.037
	(0.016)	(0.016)	(0.027)	(0.027)
African heritage	−0.048***	−0.048***	−0.040	−0.038
	(0.016)	(0.016)	(0.026)	(0.026)
Home size	0.240***	0.240***	0.205***	0.204***
	(0.030)	(0.031)	(0.032)	(0.032)
Income earners	0.098***	0.098***	0.081***	0.081***
	(0.022)	(0.022)	(0.027)	(0.027)
No access to credit	−0.074***	−0.073***	−0.071***	−0.072***
	(0.017)	(0.017)	(0.024)	(0.024)
No access to politics	0.001	0.001	−0.014	0.016
	(0.017)	(0.017)	(0.033)	(0.033)
Observations	2864	2864	1373	1373
Sessions	159	159	159	159
R-squared	0.30	0.30	0.26	0.27

Notes: The dependent variable is an individual's well-being index generated from the factor analysis of eight outcome variables. Higher index scores indicate greater well-being. Standardized OLS. The behavioral variables are measured as the numbered lottery, in increasing order of risk, chosen under each condition. First two columns include an unreported control for whether one pooled risk or not. The third and fourth columns are limited to the sample of people who chose to pool risk in the third task. City fixed effects included. (Standard errors) have been clustered at the session level. *** indicates significant at the 1%, ** 5% and * 10% levels.

Table 5
Reactions to ambiguity, losses and pooling and well-being.

	(1)	(2)	(3)	(4)
Ambiguity aversion	0.065**			0.090*
	(0.025)			(0.045)
Ambiguity seeking	−0.001			0.009
	(0.015)			(0.027)
Loss aversion		−0.053**		−0.062*
		(0.025)		(0.037)
Loss seeking		0.023		−0.039
		(0.023)		(0.037)
Risk averse (when pool)			0.083***	0.060*
			(0.031)	(0.033)
Risk seeking (when pool)			0.005	0.003
			(0.021)	(0.022)
Female	0.008	0.006	0.012	0.009
	(0.016)	(0.017)	(0.025)	(0.025)
Age	−0.073***	−0.073***	−0.073***	−0.073***
	(0.018)	(0.018)	(0.036)	(0.036)
College	0.138***	0.137***	0.156***	0.157***
	(0.013)	(0.014)	(0.016)	(0.016)
Married	0.142***	0.140***	0.127***	0.125***
	(0.021)	(0.021)	(0.025)	(0.025)
Children	−0.238***	−0.238***	−0.214***	−0.214***
	(0.023)	(0.024)	(0.031)	(0.031)
Indian Heritage	−0.030*	−0.028*	−0.036	−0.038
	(0.015)	(0.017)	(0.028)	(0.028)
African Heritage	−0.048***	−0.047***	−0.041	−0.038
	(0.016)	(0.015)	(0.026)	(0.025)
Home Size	0.240***	0.240***	0.204***	0.201***
	(0.030)	(0.031)	(0.033)	(0.033)
Income Earners	0.098***	0.097***	0.081***	0.083***
	(0.022)	(0.022)	(0.028)	(0.028)
No Access To Credit	−0.074***	−0.073***	−0.070***	−0.072***
	(0.016)	(0.016)	(0.024)	(0.023)
No Access To Politics	0.001	0.001	−0.007	−0.007
	(0.017)	(0.017)	(0.017)	(0.017)
Observations	2864	2864	1373	1373
Sessions	159	159	159	159
R-squared	0.30	0.30	0.27	0.27

Notes: The dependent variable is an individual's well-being index generated from a factor analysis of eight outcome variables. Higher index scores indicate greater well-being. Reactions are measured as deviations from the baseline risk task. Lottery choices in each task are numbered 1–6 in order of increasing riskiness. Where A is the ambiguous lottery choice, L is the loss choice, P is the pooling choice and R is the choice in the risky baseline, Ambiguity Aversion is the value A-R, conditional on A-R<0; Ambiguity seeking is A-R>0, Loss Aversion is L-R>0; Loss Seeking is L-R<0, Risk Averse (when pooling) is P-R<0 and Risk Seeking (when pooling) is P-R>0. Standardized OLS. City fixed effects included and the first two columns include an additional control for whether one pooled risk or not. (Standard errors) have been clustered at the session level. *** indicates significant at the 1%, ** 5% and * 10% levels.

of a group instead of alone. Having set up insurance schemes, individuals should reconsider their lottery choices.

If there is no clear relationship between simple, more traditional, measures of risk aversion and economic well-being, do the supplementary measures correlate better? In Tables 4 and 5 and Figs. 5–7 we report the results of testing the extent to which these additional preference measures are associated with well-being. The results are conservative in that we continue to control for a number of other factors, we have included city fixed effects, we cluster standard errors at the session level to account for the idiosyncrasies that may occur during individual sessions and, despite the resulting inflated standard errors due to possible multicollinearity, we force the three measures to compete “head-to-head” to explain the variation in well-being.

To begin, Table 4 reports the results of adding our supplementary preference measures, one-by-one, to the framework established in Table 3. An obvious place to start is to continue to number the lotteries clockwise in increasing order of riskiness (as in Sections 3 and 4), however, we will consider a more flexible specification below. The initial results are encouraging. In the first column we see that participants who pick riskier lotteries in the ambiguous task have significantly higher well-being scores (and therefore, those who shy away from risk in the ambiguous task, i.e. those who could be more ambiguity averse, have lower well-being scores). Specifically, a standard deviation increase in the amount of risk taken on in the ambiguous task is associated with a 0.042 standard deviation increase in the well-being index. In the second column we see that participants who accept more risk in the loss task (perhaps indicating loss aversion) have significantly lower index scores. Here a standard deviation increase in the riskiness of the loss choice is associated with a 0.033 reduction in economic well-being. Finally, within the restricted sample of poolers, we see that those who take on more risk in the pooling task are better off but the point estimate is not significant. Finally, in column four we allow all three measures to compete head-to-head and see that, if anything, the ambiguity and loss choice coefficients grow and remain significant.

Two other aspects of Table 4 are worth commenting on. First, once we control for our participants' separate reactions to ambiguity, losses and the prospect of pooling risk, the coefficient on the baseline risk measure increases. In three of the four columns, the baseline risk measure is now significant and in each case the point estimate is negative indicating that the relationship between risk and economic well-being is exactly the opposite of what has traditionally been assumed. Second, a number of our controls continue to be strong predictors of well-being — a point we return to below.

To consider an alternative, more flexible specification we follow Klibanoff et al. (2005) who argue that ambiguity aversion can only be understood in reference to one's risk aversion. As such, we take the difference in behavior between the additional measures and the risky baseline as a second specification of the preference measures. We also allow for the relationship between preferences and well-being to be kinked by using a spline specification. Instead of assuming that the relationship between preferences and well-being will be the same regardless of whether people act more or less conservatively to the different conditions, we allow the slope to change at the origin. This specification also allows us to look for well-being differences that might arise between classically ambiguity and loss averse participants and their compatriots. As a result, there are six independent variables of interest reported in Table 5: accepting less or more risk in the manipulation compared to the baseline for each of the three conditions. Specifically, where WB_i is the well-being index for participant i, we use the following specification:

$$\begin{aligned} WB_i = {} & \beta_0 + \beta_1(Ambiguity_i - Risk_i) + \beta_2 max\{Ambiguity_i - Risk_i, 0\} \\ & + \beta_3(Loss_i - Risk_i) + \beta_4 max\{Loss_i - Risk_i, 0\} + \beta_5(Pool_i - Risk_i) \\ & + \beta_6 max\{Pool_i - Risk_i, 0\} + \beta_7 X_i + \epsilon_i \end{aligned}$$

where X_i is a vector of controls and ϵ_i is an error term. *Risk*, *Ambiguity*, *Loss*, and *Pool* are the lottery choices ordered from no risk to possible risk seeking (i.e., clockwise from one to six) and the difference is the effect of the design manipulation. *Ambiguity-Risk* is our measure of one's reaction to ambiguity, *Loss-Risk* is our measure of the reaction to possible losses and *Pool-Risk* is our measure of the net effect of pooling on behavior. Because these measures can be positive or negative, the max portions of the specification allow those who are more conservative in the treatments (i.e., those for whom the difference is negative) to have different outcomes than those who behave more risk seeking in the treatments. Calculating the marginal effects illustrates the usefulness of the spline. For someone who demonstrates ambiguity aversion and chooses more conservatively in the ambiguity condition than in the baseline, the difference will be negative and the effect of this difference on well-being will be captured by β_1 alone because β_2 will be multiplied by zero. A person with a positive difference (who sought more risk under ambiguity) will have the effect $\beta_1+\beta_2$. Similarly, loss averse participants who choose riskier lotteries when losses are possible have positive differences and the effect of this aversion will be picked up by the sum $\beta_3+\beta_4$. Lastly, the effect of choosing riskier lotteries in the pooling condition will be embedded in $\beta_5+\beta_6$.[6]

[6] We also control for whether one chooses to pool or not in the first two columns of Table 5.

For convenience, the relationship between ambiguity aversion and well-being is graphed in Fig. 5 where the horizontal axis measures the relative tolerance towards ambiguity against the baseline risk aversion measure (i.e., Ambiguity-Risk). The bar heights indicate the average economic well-being index score for the participants whose choices resulted in each of the possible differences. As the figure suggests, those people who react extremely, in the classical sense of being averse to ambiguity (i.e., Ambiguity-Risk<0), have lower index scores but those who either ignore ambiguity or appear to embrace it do relatively well. Fig. 5 also plots the estimated relationship between ambiguity aversion and the well-being index. The estimates come from the first column of Table 5. Here the standardized estimate of β_1 is 0.065 (i.e., a standard deviation reduction in the difference Ambiguity-Risk leads to a reduction of 0.065 standard deviations in the well-being index) and we estimate $\beta_1+\beta_2$, the effect of being ambiguity seeking to be -0.001 which is not significantly different from zero ($p=0.97$), indicating that only those who are ambiguity averse in the traditional sense have lower index scores.

Reactions to losses, graphed in Fig. 6, are also significantly correlated with well-being, despite the graph not being quite as clean as Fig. 5. Although it appears that participants with extremely low values of the loss difference have lower well-being scores, there are only 19 (of 3106) observations in this tail of the distribution. This fact is accounted for in the spline fit also represented in Fig. 6. Here, the spline reveals another interesting fact that jibes very nicely with the results of Fig. 5: those people who are categorized as classically loss averse in our tasks (i.e., those who accept more risk when losses are possible — so the difference is positive) also have significantly lower well-being scores. Considering the details of the spline estimated in column 2 of Table 5, we see first that the standardized estimate of β_3, loss seeking, although positive as seen in Fig. 6, is not significantly greater than zero. At the same time, our estimate of $\beta_3+\beta_4$, the effect of loss aversion, is significant at the 5% level and negative.

Although not part of the standard literature on decision-making biases, we also get strong results from our pooling manipulation. In Fig. 7, where the sample is limited to those participants who chose to pool, one can see very clearly that although there is not a strong relationship between taking more risks in the pooling condition and well-being, people who tend to shy away from risk in the pooling task (compared to the baseline), have lower index scores. This pattern is confirmed by the estimates listed in column 3 of Table 5 and by the spline graphed in Fig. 7. Our estimate of β_5 suggests that a standard deviation increase in our measure of "pooling aversion" results in a reduction in one's well-being index score of almost one-tenth of a standard deviation (i.e., $\beta_5=0.083$, $p<0.01$). Further, our estimate of the sum $\beta_5+\beta_6$ — those who seek additional risk in the pooling task — is indistinguishable from zero ($p=0.82$).

As a final check on our results, in the last column of Table 5 we allow all six preference measures to compete "head-to-head" for variation in the well-being index. Given the intercorrelations among the measures are high ($p<0.01$ for each pair-wise comparison), it is surprising that multicollinearity does not claim all the previous results,

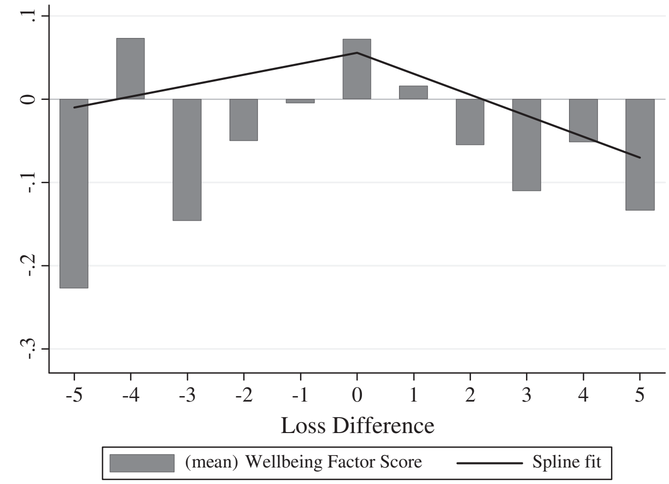

Fig. 6. Loss aversion and economic well-being. Numbering the lotteries in Figs. 1 and 3 clockwise 1–6 and then taking the choice difference (Loss choice — Risk choice) provides a measure of loss aversion along the horizontal axis. Bar heights are calculated as the mean well-being index (a factor score of eight outcomes) for each possible difference. The regression fit is from a spline specification that allows for differences on either side of zero and controls for all the variables summarized in Table 1 and suggests that loss averse participants i.e., those with positive Loss Differences, have lower well-being.

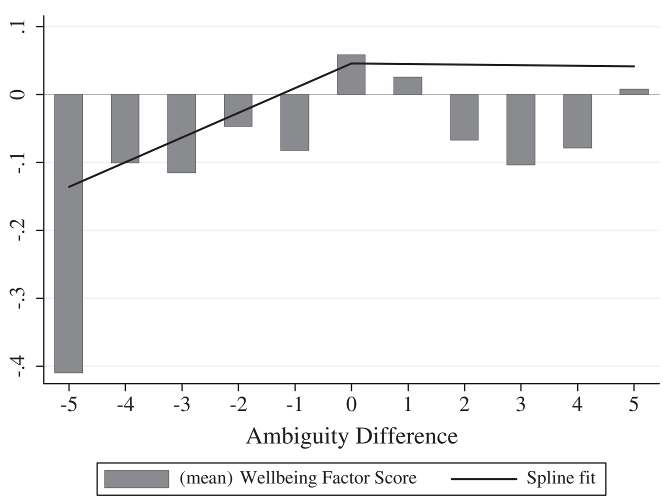

Fig. 5. Ambiguity aversion and economic well-being. Numbering the lotteries in Figs. 1 and 2 clockwise 1–6 and then taking the choice difference (Ambiguous choice — Risk choice) provides a measure of ambiguity aversion along the horizontal axis. Bar heights are calculated as the mean well-being index (a factor score of eight outcomes) for each possible difference. The regression fit is from a spline specification that allows for differences on either side of zero and controls for all the variables summarized in Table 1 and indicates that ambiguity averse participants i.e., those with negative Ambiguity Differences, have lower well-being.

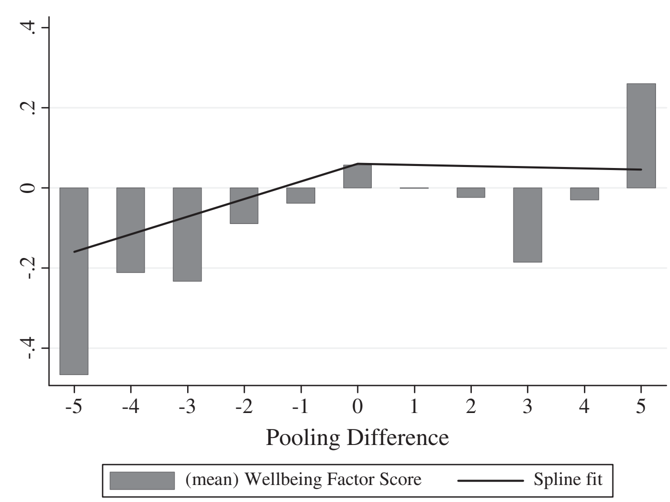

Fig. 7. Risk pooling and economic well-being. Numbering the lotteries in Fig. 1 clockwise 1–6 and then taking the choice difference (Pooling choice — Risk choice) provides a measure of risk tolerance when players choose to pool risk along the horizontal axis. Bar heights are calculated as the mean well-being (a factor score of eight outcomes) for each possible difference. The regression fit is from a spline specification that allows for differences on either side of zero and controls for all the variables summarized in Table 1. The fit suggests that participants who do not take advantage of the risk pooling mechanism i.e., those with negative Pooling Differences, have lower well-being.

but it doesn't and, we see estimates of the effects of ambiguity, loss and "pooling aversion" that are very similar to those in the previous columns. Additionally, we see in the final column of Table 5 that many of our controls are important determinants of well-being: older participants, those with a lot of children and minorities tend to have lower well-being scores and college graduates, married participants, people who live in larger houses and those with more than one income earner in the family all tend to have higher index scores. Perhaps most importantly, we also find that credit-constrained participants have robustly lower well-being as measured by our index, and as a basis for comparison, the effect can cancel many of the benefits one receives from post-secondary education.

6. Discussion

There is a long tradition in economics and public policy of assuming that people are poor because they have attitudes and preferences that keep them from saving and investing in projects that can improve their situations. Our field research tests the link between preferences and well-being.

Our first step is to compile the most comprehensive sample of incentivized risk attitudes in Latin America gathered to this point. Looking at summary behavior from this sample suggests that our procedures are valid in that we replicate a number of standard biases found in the related behavioral literature (e.g., ambiguity and loss aversion).

Our second step is to use this large sample of incentivized participants and a broader set of well-being measures to try to replicate previous results that have used standard risk aversion instruments. We find little evidence of robust links between risk aversion and well-being, a conclusion that is similar to a number of previous studies mentioned in our Introduction.

Anticipating a possible null result from a standard risk protocol, we also gathered more finely tuned instruments, ones designed to allow for the fact that risk exposure may take different forms for people living near poverty (e.g., exposure to losses, spontaneous pooling arrangements or the lack of information about the true probability distribution of outcomes). In our third step we analyze the links between these new risk measures and well-being to see if our results improve. Indeed they do, even after controlling for a variety of other important factors like human capital accumulation and access to credit. In addition, our new measures perform in ways that reflect the extensive lab and field literature on decision-making biases. Not only do we see classic instances of ambiguity and loss averting behavior in the field, we can show that these particular biases also predict well-being in ways that have yet to be documented in a large sample. We find that ambiguity averse and loss averse participants have significantly lower well-being and the magnitudes of the effects are not negligible.

Surveying the existing literature suggests there are a number of possible mechanisms to explain our results (but discovering new ones is likely to be a fruitful topic for future research). For example, Engle-Warnick et al., 2008 show that ambiguity averse farmers in Peru are less likely to adopt new technology and Alpizar et al., 2011, in a similar study in Costa Rica, show ambiguity aversion explains how farmers are likely to adapt to environmental uncertainty. In both cases the bias can lead to worse outcomes. Broadening the context slightly, there is also some evidence that entrepreneurs have a greater tolerance for ambiguity (Begley and Boyd, 1987). Considering loss aversion, much of the existing evidence focuses on labor supply in the context of reference dependent preferences. When workers become acclimated to some reference income, loss aversion implies that they are more sensitive to negative than to positive shocks and will therefore work harder to achieve their targets than to surpass them. As a result, the extensive evidence, summarized in Goette et al., 2004, indicates that loss averse workers are likely to target some reference income level and stop working once the target has been achieved. Clearly this could be bad for pecuniary outcomes, especially if income targets are not very ambitious.

Even though the experimental literature on risk pooling is not as well developed, there is plenty of evidence from the broader empirical literature on the benefits of noticing, and optimally taking advantage of risk pooling opportunities. For example, in recent work on risk sharing among households, Fafchamps, 2011 surveys the empirical literature that assesses the importance of, and the extent to which, groups pool risk effectively and finds both that a lot of risk pooling occurs in the developing world to smooth consumption and that it is often very fragile.

While the primary goal of this project was to test the extent to which risk preferences and their more contextually relevant variants correlate with economic well-being, we also wanted to control for social exclusion, particularly one's access to credit. As it turns out, perceived credit hindrances appear to matter robustly and have effects that are (roughly) of the same magnitude as our behavioral results. Given preferences and credit access compete in our analysis, these results go a long way to inform one standard critique of what we are calling the "Fisher hypothesis": that preferences do not matter, it is malfunctioning credit markets that may keep people poor. Indeed, in our data both preferences (albeit not simple risk preferences alone) and access to credit correlate with well-being. This is particularly relevant for developing countries where access to the formal banking sector remains limited and the promises of microfinance programs are yet to be fully realized. In this regard, our results suggest lessons about the use of financial mechanisms that seem to create Pareto enhancing behavior such as moderate increases in risk tolerance when risk can be pooled, behavior that might have implications for the design of microfinance programs.

While our results are substantial because of the quality and variety of our incentivized risk measures, the size and representativeness of our sample and the number of controls that we have gathered, there are still important issues that cannot be completely resolved by our study and will need to be addressed in future research. The limitations of our work are of two basic types: alternative interpretations of our measures and causality.

Considering alternative interpretations, one might worry that our risk aversion task is confounded by liquidity, for example. As one reviewer suggested, what if participants choose the safe option simply because they have a pressing need for cash? Considering the results of Table 4, it is hard to imagine that these participants would tend to also have higher well-being; however, it will be important to gather more data on the cash flow position of future participants to more directly address this concern.

Another valid concern is that the well-being differences picked up by the ambiguity and loss tasks could be driven by a deeper cause such as numeracy or more general cognitive skills (e.g., Burks et al., 2009). If this was the case then the biases we estimate might just be symptomatic of these root causes. At the same time, our spline specifications indicate that the reductions we find in economic well-being are one-sided and these decrements overlap exactly with the biases found in numerous lab studies, facts that weaken the case for misunderstanding. If deviations from the risky baseline were driven by misunderstanding or cognitive ability and the deviating participants also scored lower on the well-being index, then we would expect the well-being decrements would be significant on both sides. Nonetheless, we took advantage of the covariates we could gather during the sessions to control, as best as possible, for educational achievement (the college indicator) as a proxy for cognitive ability.

For risk pooling we are much more circumspect about the interpretation of our results. At present there are few behavioral studies of the motivations for risk pooling and an obvious hypothesis is that social preferences (e.g., conditional cooperation or a broader sense of communitarianism) could cause people to enter the risk pooling agreement and behave more conservatively, assuring payoffs for all. For this reason, measures of social preferences should also be gathered in the future.

We have been able to establish correlations between various measures of behavior in risky situations and an index of well-being, but we cannot, with this sample, definitively determine the direction of causality. Do preferences cause well-being as is assumed by much of the existing theoretical literature or do the preferences of people change with their economic circumstances? To untangle these relationships will require econometric instruments that can be used to predict preferences but are only correlated with well-being because of their causal effect on preferences. Clearly, this will be a "hard nut to crack" and more work will be required to develop convincing instruments or experimental manipulations.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jdeveco.2013.01.008.

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