Consumer Decision Making: Insights from Behavioral Economics

Session I: Behavioral Measures for Consumer Finance

Catherine Eckel
UT Dallas
Jeff Carpenter
Middlebury College

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Issues in Consumer Finance for Low-Income Consumers

- Limited income, inadequate for expenses
- Savings and (controlling) spending
- Access to credit
  - Availability
  - Use and cost
- Why do consumers make bad decisions?
  - Don't understand (lack of information, financial literacy)
  - Don't do what policy makers think they should (preferences)
- Role for Regulation
  - Access to credit
  - Information transparency (education/financial literacy)
  - Unintended response

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Behavioral Economics and Consumer Finance

- Provide innovative and incentivized measures of critical aspects of preferences
- These preferences govern financial decisions in many domains
- Experiments (incentivized) used to:
  - Illuminate these preferences
  - Identify behavioral regularities that can be addressed with innovative policies
  - Test responses to potential policies (wind-tunnel)

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Measuring Preferences: Why Play Games?

- Theories about how people behave require assumptions about preferences
  - Risk tolerance
  - Time preference
  - Pro-social preferences
- Preferences are often measured using surveys
- Are task-based measures superior to surveys?

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Surveys v. Games

- In surveys, people may misrepresent their true preferences
  - On purpose (image)
  - To make experimenter happy (demand)
  - Inadvertently (wishful thinking?)
  - Note: no cost to misrepresentation!
- Games are designed so that misrepresenting preferences is costly
  - Ex: gambles, present/future tradeoffs, altruism

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Game 1: Risk Tolerance

- How much risk are people willing to take on in order to increase their expected payoff?
- Approach:
  - Show alternative investments
  - Each is a 50/50 chance of winning a low or high amount
  - Let people pick their favorite
  - Play out the lottery
  - Pay in cash, in private

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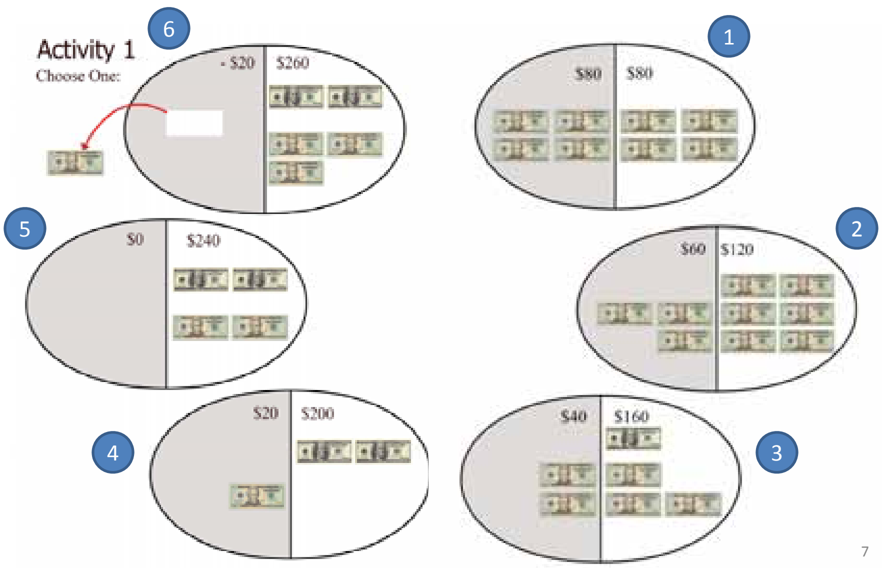
Game 1: Pick your favorite

Each circle is a 50/50 lottery



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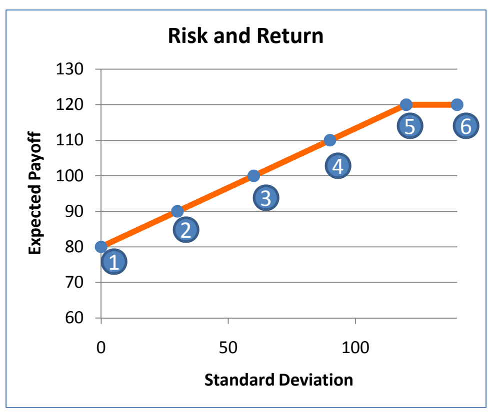
Risk Protocol

Subjects choose most preferred among 6 gambles with 50/50 odds.

Gamble	Low	High
1	80	80
2	60	120
3	40	160
4	20	200
5	0	240
6	-20	260



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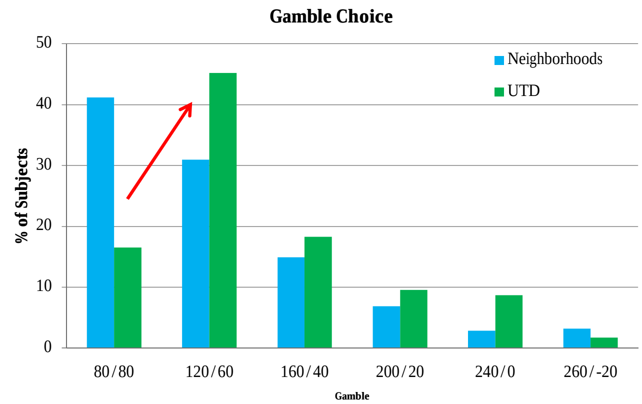
Sample results I

College Student v. Low-Income Adults



Low-income are MORE risk averse, t: p=0.0004, k-s: p=0.0000

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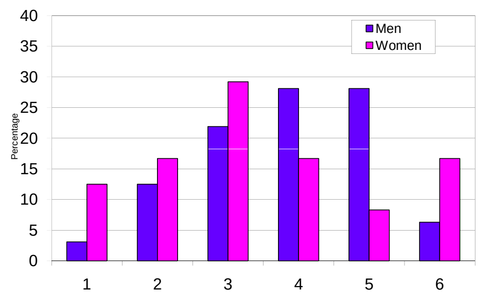
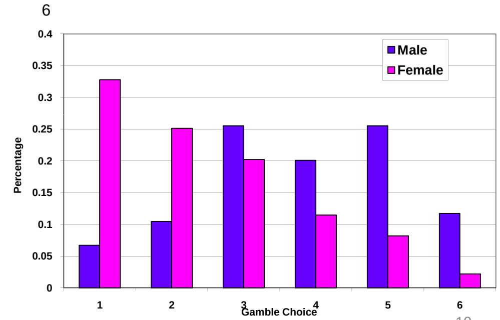
Financial advice exaggerates gender differences



Own Gamble Choices by Men and Women

Advisor's Choices for Men and Women



Lab experiment
Student subjects
Modest stakes ($12-$30)

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Risk Preference Summary

- Risk preferences are related to many behaviors
- Elicited risk preferences of low-income persons are different from non-low-income
- Stereotypes about risk preferences can affect financial transactions
  - Not just gender
- Further work on development of risk preferences is needed
  - Parent-child transmission?
  - Socially learned?
  - Affected by environment (crime)?

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Game 2: Time Preference (Patience)

- How much extra money does it take to get people to defer payment by six months?
- Related to savings, investment, human capital…
- Approach:
  - Show six different decisions
  - Each is a choice between a smaller sooner payment and a larger later payment
    - Later choice = patient
    - Not today
  - Let people make six choices: one is paid
  - Pay in cash, in private
  - Measure = number of patient choices

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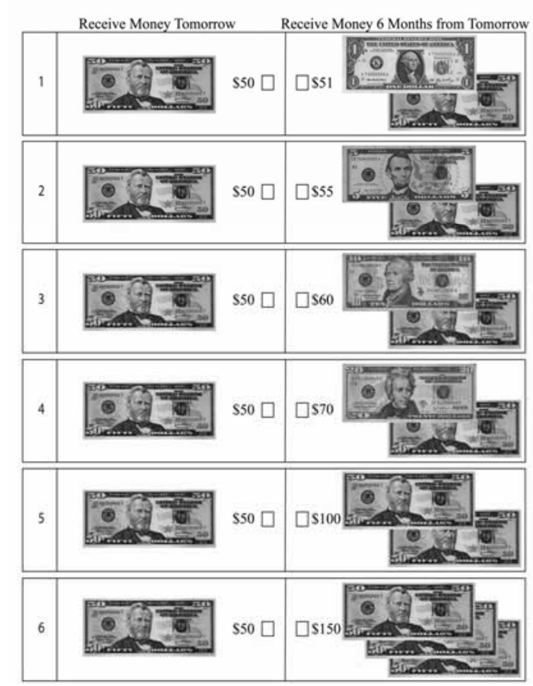
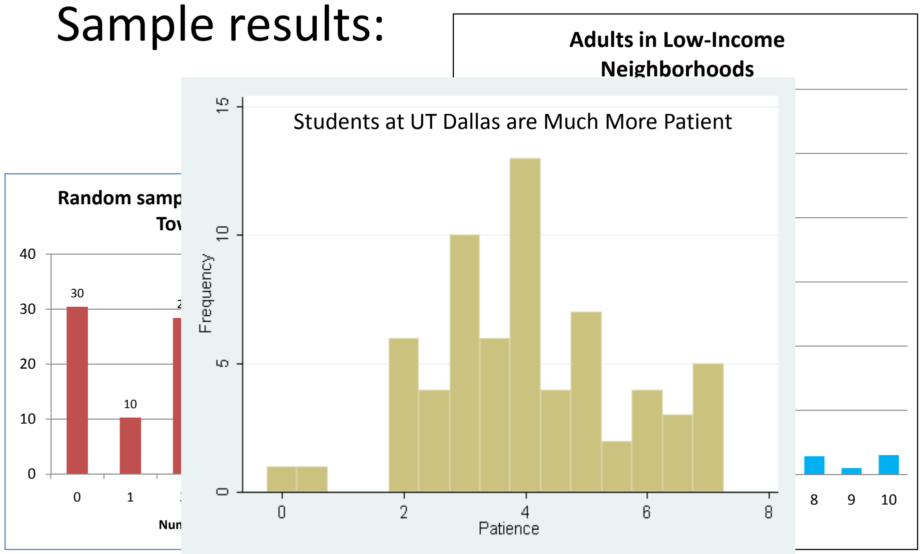
Game 2
Instructions

- For each decision, choose either $50 **tomorrow** or the larger amount in six months.
- When you are done you will have six check marks.
- One decision will be selected randomly for payment.



Sample results:



Low income adults are much less patient.

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Example: Credit score study (pilot, with UT Dallas undergrads and MBAs)

- Why do people have poor credit scores?
- Income, or preferences?
  - Do they take excessive risks?
  - Are they impatient, impulsive?
  - Are they untrustworthy?
- Participants play three games to assess risk preferences, patience and trustworthiness (plus survey measure of impulsiveness)
- Preliminary results:
  - Income is definitely a factor, and explains most of the variation
  - Impulsive have lower credit scores
  - Impatient have lower credit scores
  - Untrustworthy, risk takers have lower credit scores (not signif)

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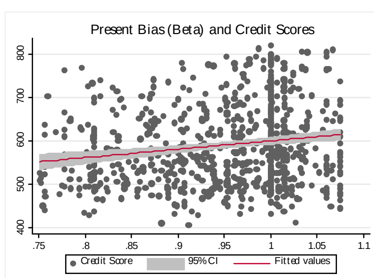
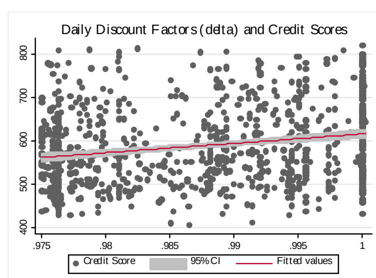
Quasi-hyperbolic discounting and credit scores





- The data comes from 1000 truck driver trainees in Wisconsin.
- On their own, both present bias (beta) and the discount factor (delta) significantly predict credit scores.
- However, when combined only delta survives.

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Time Preference Summary

- Patience is associated with many behaviors
- Elicited patience preferences of low-income persons are different from higher income persons
- Impatient and impulsive preferences are associated with poor credit scores
- As with risk preferences, more work on development of preferences is needed
  - Nature or nurture?
  - Can kids be taught to be patient?

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Changing locations to Latin America

- Start with a broad question: *Do risk preferences correlate with "well-being"?*
  - Joint with Juan Camilo Cardenas (Universidad de los Andes).
  - Illustrates the use of a standard risk experiment and some less standard variations on risk.
- End with a narrow question: *Does peer monitoring attenuate the moral hazard problem inherent in group lending?*
  - Joint with Tyler Williams (MIT).
  - A specific example of why we should also study social preferences.

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Motivation: Risk => Well-being?

- Do people remain poor because they are unwilling to take the risks necessary to increase their income/wealth?
- So far researchers have:
  - inferred preferences from consumption and technology choices (spurious).
  - surveyed preferences (hypothetical).
- But in the end, there is evidence on both sides.

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How is our study different?

- Our participants are incentivized.
- We gather stratified samples of 500 from 6 cities.
- We collect a variety of well-being measures.
- We collect a number of important controls.

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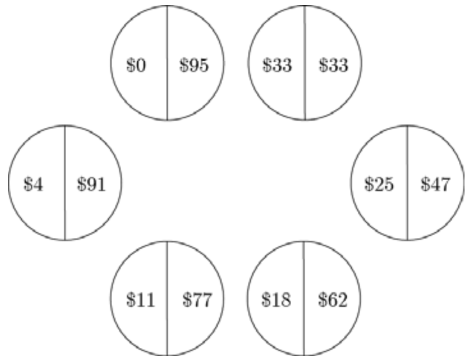
Our measure of risk preferences

- Participants pick the binary lottery that they would like to play:
  - All lotteries are 50|50 so we worry less about probability bias.
  - The dollar payoffs roughly represent the field stakes.
  - The lotteries increase in E[π] and variance as one moves clockwise.



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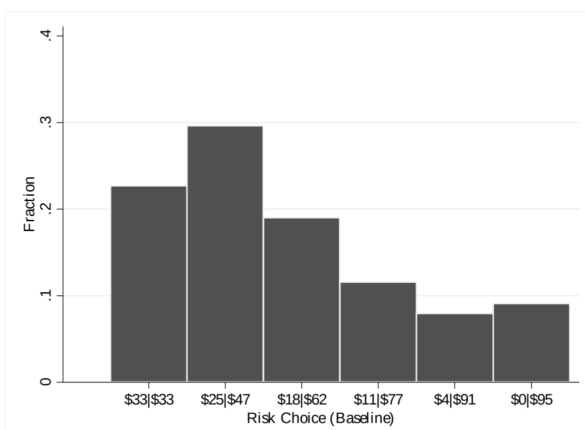
Which lotteries do people choose?



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Experimental risk measures and WB

- To what extent does our baseline measure of risk aversion correlate with well-being?
  - What is the simple correlation between risky lottery choice and an objective measure of WB: economic class?
  - What is the correlation between risky lottery choice and a subjective measure of WB: relative wealth?

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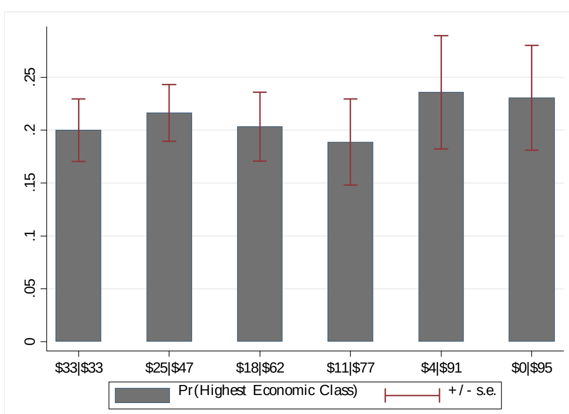
Risk preferences and (objective) class



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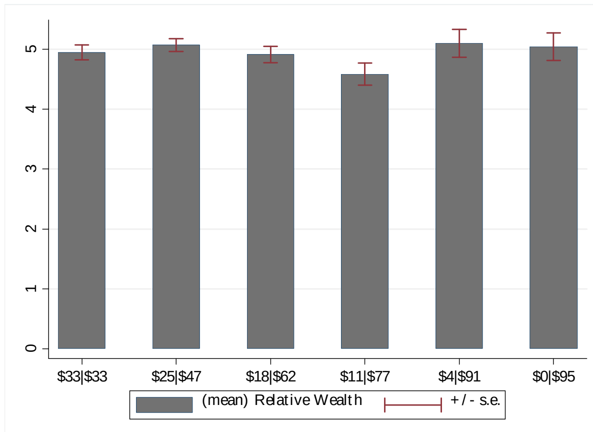
Risk preferences and (subjective) class



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What should we conclude?

- Either there is no relationship between risk attitudes and well-being or we have not measured risk attitudes correctly.
- Why might our standard measure of risk be inadequate?
  - Outside the casino, decisions in the "real" world are uncertain, not risky.
  - Decisions in the real world involve gains and losses.

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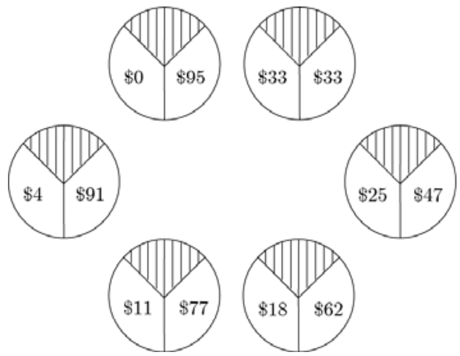
Adding uncertainty

- Instead of bags with 5 low value and 5 high value balls, Ss are only told that there are, for sure, 3 low value balls and 3 high value balls.
- They are told that the other 4 balls may be low or high.
- They are not told the distribution from which the 4 other balls are drawn.



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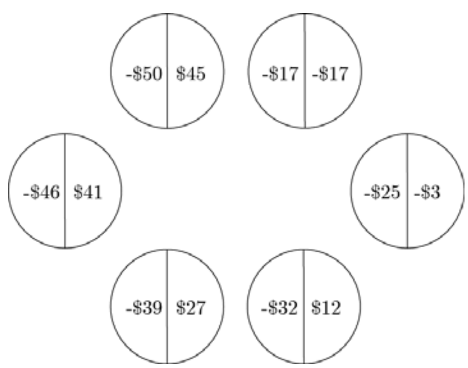
Adding losses

- At the beginning of this treatment, Ss are endowed with $50 and then choose one of the lotteries to the right.
- Adding $50 to all the payoff to the right gets one back to the baseline risk game.



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Reactions to the protocol differences

- We confirm Ellsberg's paradox:
  - On average people accept less risk under ambiguity – the mean falls from 2.8 to 2.6 (t=5.26, p<0.01)
- Confirm Prospect Theory:
  - In the domain of losses people are more risk seeking – the mean lottery chosen with losses increases to 3.23 (t=13, p<0.01).

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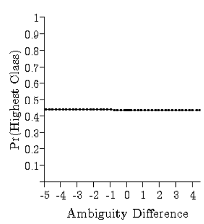
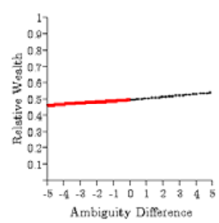
Do the nuanced measures predict?





- Calculating Amb Diff= Amb lottery-Risk lottery and using spline specification we see:
  - Being more (or less) averse to risk under uncertainty also does not predict class.
  - However, the more ambiguity averse one is the less relative wealth one has.

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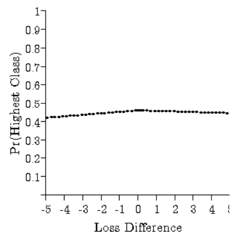
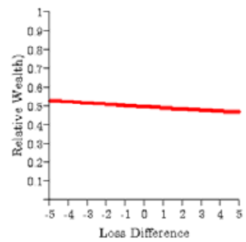
Allowing for loss aversion





- Calculating Loss Diff= Loss lottery-Risk lottery and using spline specification we see:
  - Loss aversion does not predict being in the highest class.
  - However, more loss averse people tend to have lower relative wealth.

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Social preferences and microcredit

- Economists agree that poverty persist partly because the poor lack access to credit.
  - In fact, those who say they had trouble getting credit in the previous data are 5% ($p<0.01$) less likely to be in the top economic class.
- Without collateral, some banks now rely on “group lending” to solve the moral hazard problem.
- Given the amount of money invested in microcredit, it is important to ask whether peer monitoring actually attenuates moral hazard.
  - Does peer monitoring reduce the likelihood of default?

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Our field experiment

- Participants
  - 60 women entering a Paraguayan group lending program.
- Experiment
  - Public goods game with costly monitoring.
- Peer monitoring measures
  - The average propensity to monitor of the other members of one's loan group.
- Administrative data
  - 6 months later we returned to gather loan repayment data from three loan cycles.

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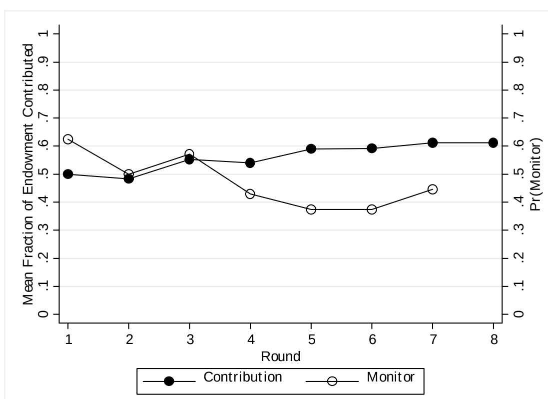
What happened in the experiment?



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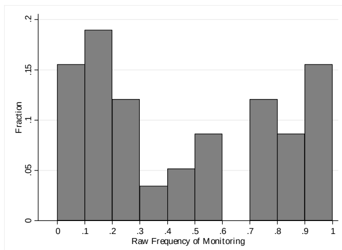
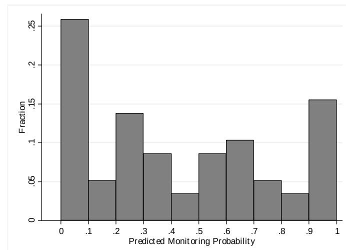
Individual variation in "nosiness"





- The obvious measure of peer monitoring is the fraction of rounds in which one pays to monitor the others.
- But groups contribute at different levels so for an "apples to apples" comparison we predict the probability of monitoring at the average contribution level.

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Information on the loans

TABLE 4: Descriptive Statistics on Loan Activity

Variable	Description	N	Mean	Std. Dev.
Loan Amount	The amount borrowed (in thousand Guarani)	136	379.32	160.86
Business Loan (I)	1 for loans to enhance one's business (versus emergency loans)	136	0.90	0.31
Adverse Shocks	Number of unexpected costly events during the cycle (e.g., illness)	136	0.73	1.07
Informconf (I)	1 for borrowers in Paraguay's national loan default database	136	0.26	0.44
Repayment Problem (I)	1 for borrowers with repayment problems (based on administrative records)	136	0.25	0.43

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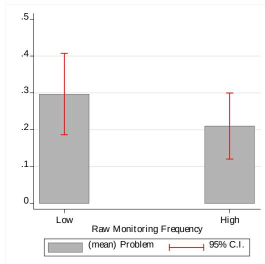
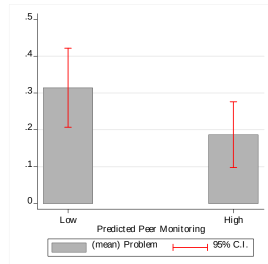
Does peer monitoring reduce default?





- Looking only at the summary statistics, individuals in loan groups with high levels of monitoring by the other group members are 10% less likely to default.
- However, once we control for all the other factors, these estimates rise to over 30%.

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Conclusion

- Incentivized tasks can be used to measure preferences
- Real tasks – more likely to measure real preferences
- Preferences vary by income, education, gender, and other factors
- Preferences are related to important decisions that people make

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