“Grabbing the Opportunity”: Risk Attitudes Among Poor Households in the US

by

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Abstract

Not much is known about the heterogeneity of risk attitudes among poor households in rich countries. This paper provides measurements from a unique data set collected among the urban poor in Atlanta, Georgia. The data set includes lab-in-the-field experiments on the relationship between risk attitudes and several household characteristics. Apart from looking at income, wealth and education, we are particularly interested in household composition as it captures the number and kind of people who are dependant on the income of the household head. This is a largely neglected household characteristic. A larger household may be associated with the head being more risk averse due to the responsibility of caring for others. This may be especially true for households with very few resources, especially relatively fixed resources, like housing. We find that household composition measures are strongly correlated with risk attitudes, and that the housing constraint interacts with the size of the household in interesting ways. The correlation of the risk aversion with adult dependants is positive but the correlation with child dependants is negative, except when the housing constraint becomes more binding. Thus, when formulating or executing policy aimed at supporting poor urban households, it is important to recognize that poverty does not always imply higher risk aversion and responses to new policy will reflect such heterogeneity. Sometimes the poor are willing to take at least some small risks, in order to get a boost in income.

Key words: Poverty, risk attitudes, experiments, behavior, financial decision making.

JEL codes: D14 Household Saving, Personal Finance, D9 Micro-Based Behavioral Economics, G41 Role and Effects of Psychological, Emotional, Social, and Cognitive Factors on Decision Making in Financial Markets, I32 Measurement and Analysis of Poverty

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"There is no security in life, only opportunity"
Mark Twain[1]

1. INTRODUCTION

A new perspective on poverty as it relates to risk in income, resources, and needs has recently emerged. Two pathbreaking studies have highlighted this new perspective : Collins, Morduch, Rutherford, and Ruthven (2009) and Morduch and Schneider (2017). These studies expose the very complex risk management needs that poor households face due to the great variability in both income and spendings that they encounter on a daily basis. Their risk management needs are expressed through a high frequency of micro transactions, such that the total value of transactions during a month greatly exceeds the monthly earnings, often by multiples. Clearly, how well these households manage depend partly on their risk attitudes. Experimenters by now know a lot about the heterogeneity of risk attitudes, but not so much as it pertains to poor households in rich countries. Measurements of risk attitudes of poor and low income households exist primarily for less developed countries, going back to Binswanger (1980) in India.

This paper provides measurements from a unique data set collected among the urban poor in Atlanta, Georgia.[2] This data set includes lab-in-the-field experiments on the relationship between risk attitudes and several household characteristics.[3] We follow in the tradition of Binswanger (1980) and do not make causal claims. Almost all studies that aim to relate risk attitudes to the characteristics of respondents suffer from a lack of clarity about what the underlying causation is, and often relationships are bidirectional. Take income, for example: while it can be argued that a lower income may expose households to more severe consequences of risk, thus perhaps making them more risk averse, it is also the case that risk aversion comes at a cost of foregone expected earnings. Of course,

[1] Quote from azquotes.com.

[2] The data is collected by the Center for Economic Analysis of Risk at Georgia State University under the umbrella of the project Portfolios of Atlanta's Poor. A description of this project can be found in Appendix A, online at http://CEAR.gsu.edu/ https://cear.gsu.edu/category/working-papers/wp-2019/ for working paper WP2019-06.

[3] A lab-in-the-field experiment, also referred as an artefactual field experiment (Harrison and List (2004)), involves implementing a controlled laboratory situation but using field participants rather than students. This gives a broader demographic base with varied work and life experiences compared to laboratory experiments using students.

some demographics, such as gender, are clearly exogenous to risk attitudes, but many others reflect at least partly some choices.

In this study a novel focus is to look at the composition of the household, which at least in some ways reflects choice. When resources are running low some household members that cannot contribute, may have to leave the household, whereas others with resources may move in. In addition to looking at income, wealth and education, we are interested in household composition as it captures the number and kind of people who are dependant on the income of the household head. This is a largely neglected aspect of household characteristics. A larger number of dependants may be associated with the head of the household being more risk averse due to the responsibility of caring for others. There can be many reasons for such an association. For example, it could be due to larger households having more basic, non-discretionary expenses that cannot easily be reduced or eliminated when facing a loss in income. Such constraints make risks more difficult to manage and can thus translate into a higher aversion to risk. Alternatively, income losses may get compounded by psychological effects as a result of household size, thus leading to welfare effects that exceed the loss in income. Several non-linear forms of welfare functions, such as multiplicative ones, imply that the income loss, distributed across the utilities of household members, result in a much higher welfare loss to the household than simple sums. These larger welfare losses may bring the household closer to a lower bound that the head considers unmanageable, and therefore wants to avoid. One important component of basic, non-discretionary expenses that constrain the ability to manage risk is housing. With limited housing resources households are less able to take in renters to substitute for income losses, and less able to move to smaller apartments to lower the rent costs.

Understanding the relationship between risk attitudes and household composition, even in a purely descriptive manner, is informative to the design of public policies and privately provided solutions intended to alleviate poverty. Households that are more risk averse will be less inclined to try out new products, such as new types of insurance or credit and savings options, which may hinder their abilities to improve their lives.

We measure risk attitudes using experimental lottery tasks with real money consequences, and characterize the households of the respondents based on survey responses. Respondents for this data set were recruited from low income neighborhoods in Atlanta. This is a population that has received relatively little attention in the experimental literature: the poor in a rich country. Poor households suffer from the inability to buy a lifestyle that prevails in their society (Shipler (2005)), they live at the margin even if they have one or multiple jobs. Typical jobs are generally volatile by hours and earnings, while past debts and expenses are ever increasing burdens. The poverty line for a household of four, as defined by the US Department of Health and Human Services (HHS), is an annual income of $25,750[4] and several programs base their eligibility criteria on it. Many of the working poor are just above the poverty line when considering their annual earnings, thus ineligible for such program support, although weekly and monthly earnings volatility frequently drag them under the poverty level. Further, a household that loses an income source, thereby falling below the official poverty line, will have to wait for several months for their applications to be processed before receiving any support. While our respondents are all individuals who are heads of households, either sole or shared, we will, for brevity, be referring to their responses as those of the household.

Similar to previous studies we do not see a significant correlation between risk aversion and several income related variables, and when we do the correlation is negative: the poorer you are the more risk averse you are. Specifically, participants with lower hourly earnings tend to be more risk averse. Our most interesting finding is that household composition measures are strongly correlated with risk attitudes. The correlation of the risk aversion with adult dependants is positive but the correlation with child dependants is negative. However, the latter effect disappears when the housing constraint becomes tighter. The somewhat surprising reduction in risk aversion for households with more children but better housing resources may reflect the presence of additional risk management options in the presence of housing resources. In the event of a major income loss the household could either take in additional contributing household members, or move to a smaller house. Under these circumstances, perhaps the household head sees that a small risk, such as the ones offered in the

[4] 2019 HHS poverty guidelines published in the Federal Register https://aspe.hhs.gov/2019-poverty-guidelines

experimental lotteries, is a chance to buy some nice clothing or treats for their children. Such behavior is consistent with the observations made elsewhere that lottery purchases, and certain types of gambling, are more prevalent among the poor.

Section 2 reviews some relevant literature. Section 3 presents the study design. Section 4 gives some descriptive results and Section 5 presents results from our estimation using structural maximum likelihood models . Section 6 concludes.

2. LITERATURE

2.1 Experimental Elicitations of Risk Attitudes

Binswanger (1980) is an early influential study that elicits risk attitudes experimentally from a sample of poor, rural households in India. He finds evidence of moderate risk aversion, but no consistent and significant correlation with wealth or income.[5] He does confirm that early technology adopters are generally less risk averse than others, lending support to the need to pay attention to heterogeneity in risk attitudes when predicting uptake of new financial tools or government programs. Binswanger also conjectured that the size of the household would affect risk aversion, such that a larger household would make the household head more risk averse. However, he finds not evidence for that in his sample. We discuss the household composition further in section 2.2.

Many field experiments that elicit risk attitudes in developed countries include controls for wealth and income, but generally do not include many respondents from the poor population. For example, Andersen, Harrison, Lau, and Rutström (2008), found a negative income effect on a representative sample from the Danish population.[6] Noussair, Trautmann, and van de Kuilen (2014) confirm this effect for a sample representative of the Dutch population. However, these correlations do not particularly inform us about poor households, unless the linear income effect can be assumed to hold for all wealth and income levels. This may not be the case as it is shown in von Gaudecker, van Soest,

[5] Income measures were restricted to salary from secure jobs. Wealth was measured by gross sales value of physical assets.
[6] Income was measured as the self-reported total income before taxes during the year prior to the interview.

and Wengström (2011) who report on an internet experiment using 1,400 CentERpanel participants in the Netherlands and find that those with the second lowest wealth (€10,000-50,000) are significantly more risk averse than both those with lower and higher wealth.[7]

Experiments run in less developed countries usually show either the same negative relationship between risk aversion and income or wealth, or no significant effects. Examples of no significant relationship are Mosley and Verschoor (2005) in Uganda, India and Ethiopia;[8] Tanaka, Camerer, and Nguyen (2010) in Vietnam[9], and Cardenas and Carpenter (2013) in six major cities in Latin America.[10] Negative relations are reported in Bauer and Chytilová (2013) in India[11], Wik, Aragie Kebede, Bergland, and Holden (2004) in Zambia[12], Miyata (2003) in Indonesia[13], and Yesuf and Bluffstone (2009) in Ethiopia[14].

While there have been a few studies eliciting risk attitudes in poor populations in North America, the purpose of those studies have primarily been to explain the role of risk attitudes in financial choices, such as savings, risk sharing, and education and not to correlate household characteristics with risk attitudes directly. For a Canadian low income population, risk aversion is associated with a lower propensity to invest in education (Eckel, Johnson, and Montmarquette (2013)). This result is similar to Binswanger's finding that early technology adopters are less risk averse, and motivates our interest in the heterogeneity of risk attitudes. Further examples of how risk attitudes predict financial behavior among the poor is demonstrated by the finding that less risk averse individuals from a poor population in Texas are less likely to support risk sharing arrangements, i.e. are less likely to offer

[7] The income and wealth variables used by these two studies come from the LISS panel subject pool managed by CentERdata, affiliated with Tilburg University.

[8] How income is measured is not reported.

[9] Income is measured as mean household income in year before interview.

[10] They construct an index of well-being based on home ownership, basic utility access, employment, overall economic status, perceived relative economic status, requiring government assistance, expenditures and having lost a business.

[11] They do not report how income was measured.

[12] They include income per capita, cash liquidity per capita and education in their models. Of these only income per capita was significant and only at 5% level.

[13] The wealth variable is a classification into rich, middle and poor and is done by local village officers.

[14] Wealth is measured using the number of oxen the household has.

conditional cash payments to other experimental group members when experiencing losses (de Oliveira, Eckel, and Croson (2014)).

While this literature seems to indicate that even though there is heterogeneity in risk aversion, the correlation with income and wealth is for the most part insignificant or negative. However, there are some important exceptions to this. Henrich and McElreath (2002) report on risk elicitation experiments where they find that subsistence farmers in both Chile and Tanzania are risk loving rather than risk averse while two wealthier groups, poor urban participants and American undergraduate students, are risk averse. They explain such behavior based on a model where individuals are concerned about the risk of falling below some subsistence minimum. In such a model, those who are above the threshold will act in a risk averse way, while those who are below the threshold will act in a risk loving way.

Further examples of apparent positive correlations between income and risk aversion is the findings from non-experimental research on gambling and lottery purchases. Lang and Omori (2009) show that the least wealthy spend a higher proportion of income purchasing lottery tickets than wealthier individuals. Freund and Morris (2005) show that a significant portion of increase in income inequality during 1976-95 was attributable to the increased prevalence of state lotteries. Barnes, Welte, Hoffman, and Tidwell (2011) report that neighborhood disadvantage measures are significantly correlated with increased lottery gambling intensity.

To the extent that poverty is associated with lower quality schooling and poor health, the literature relating elicited risk attitudes to education, cognition and health may be relevant as further evidence. Dave et al. (2010) conducted experiments with working poor adult Canadians and find that risk aversion is decreasing in math skills. Burks et al. (2009) present experimental tasks and cognitive tests to trainee truckers in the US and confirms that cognition is negatively related to risk aversion. Miyata (2003) reports that risk aversion and education levels in rural Indonesia are negatively related. This pattern is thus similar to that of income and wealth. On the other hand, Andersson, Holm, Tyran, and Wengström (2016) review a wider literature on cognition and risk aversion and report mixed results, indicating the possibility of heterogeneity. Further, if poor health and lack of health-seeking activities are correlated with poverty, findings relating these behaviors to risk aversion may be informative. Leonard et al. (2013) report that more risk averse individuals in the Texas study are less engaged in health-seeking physical activities, but de Oliveira et al. (2016) report that the same respondents are less obese if they are more risk averse. With the exception of obesity, these patterns confirm the negative relation between risk aversion and poverty.

This review of the literature makes it clear that heterogeneity is not only a matter of the degree of correlation but also sometimes of the sign. From this literature we conclude that there may be subsets of poor households who are less risk averse and thus we cannot simply assume that poor people are consistently more risk averse than non-poor others.

2.2 Factors Associated with Poverty

In our analysis we include several variables usually associated with poverty, such as being unemployed or underemployed, having low hourly wages, lacking housing wealth, and lacking education. Based on the effect of income and wealth in many of experimental studies we cite above, we expect these to be associated with higher risk aversion. The surveys we are basing our measures on include several questions associated with unemployment.[15] Combining the responses to these allows us to construct both a short-term and a long-term unemployment variable. The long-term variable captures respondents who have been continuously unemployed for the last year, while the short-term variable captures those who have experienced unemployment but have also had periods of employment during the last year.

We also include household composition, such as household size. We are not the first to show an interest in household size, several experimental elicitations of risk attitudes in less developed countries include measures of household size in their analyses. However, as far as we can tell, we are the first to do so for the poor in a rich country, and the first to make a clearer distinction between household size and the number of dependants. Any household member who either shares the

[15] The survey questions and the construction of our variables are documented in Appendix B and C, online at http://CEAR.gsu.edu/ https://cear.gsu.edu/category/working-papers/wp-2019/ for working paper WP2019-06.

responsibility as a shared head of household, or who is financially independent, is excluded from the number of dependants. Part of the respondent sample was also directly asked which household members that are dependants, and for that part of the sample we use those responses to determine the number of dependants. However, all shared heads and individuals identified as dependants, but not financially independent individuals, are included in the measure of household size. We make this distinction because a larger household can imply either more dependants, making income losses weigh more heavily, or more members that contribute income and other resources, making it easier to share the risk of income losses. If not distinguishing between these type of members, household size may be either positively or negatively related to risk aversion depending on the relative strength of the two effects.

Ward (2016) shows evidence of a negative association between the number of dependants and income per person in China.[16] Thus, any possible efforts households may have engaged in to increase household income to compensate for more dependants appears to have been insufficient. Of course, causation may also be in the opposite direction with low income households more inclined to have more children, perhaps as an insurance for old age. Thus, household size may be related to increased aversion to risk. Some risk elicitation experiments have included measures of household size. Harrison, Humphrey, and Verschoor (2009) find no significant relation to risk aversion in experiments in India, Uganda and Ethiopia. Yesuf and Bluffstone (2009) similarly find no effect from household size in Ethiopia. Wik, Aragie Kebede, Bergland, and Holden (2004) on the other hand find that risk aversion is lower for larger households in Zambia, contrary to the inference one may make from the Ward (2016) study. To control for any money contributions additional household members may be making, we also include a variable capturing money contributions that are not from the household heads and that includes contributions from other household members.

Further, we separate adult members from children, since it is likely that they do not influence household decisions in the same way. For example, adult members may be able to contribute

[16] Ward defines dependants as household members younger than 15 or older than 65, thus assuming that none of those share financial responsibilities and that everybody in the age range 16- 64 do share such responsibilities.

somewhat to household income even if they are generally dependants, while this is less likely for children, at least in rich countries like the US. Some evidence that preferences of parents are associated with the number of children is provided in Bauer and Chytilová (2013). For example, mothers with young children are more patient in their choices, and this is especially strong among the poorest households.[17] While they do not find a significant relation for risk aversion, it does show that household composition can be associated with variations in preferences. Miyata (2003) shows that risk aversion is lower for respondents who live with their parents or parent-in-laws in Indonesia. Dohmen et al. (2011, Table A1) include some measures of the number of children in a household, and find that it has a positive relationship to their measure of risk aversion, which is a self-reported attitude scale response.

As a household gets bigger it puts stress on many resources, but particularly those that are less variable, such as housing. With fixed housing resources a larger household can generate significant crowding with associated negative effects on wellbeing, particularly for children. Citing several studies, Solari and Mare (2012) list many negative outcomes due to crowding: adult psychological withdrawal, loneliness, poor marital relationships, negative parent-child relations, less-responsive parenting, higher rates of being held back a grade in school, and increased child behavioral problems at school. Solari and Mare (2012) analyze the relationship between household crowdedness and several measures of the wellbeing of children, using nationally representative longitudinal data from the Panel Study of Income Dynamics' Child Development Supplement (PSID-CDS) for 1997 and 2001, as well as the Los Angeles Family and Neighborhood Survey for 2000. They find significant effects from crowdedness on childrens' math and reading scores, behavioral problems, and physical health. They also show that crowdedness is correlated with other household characteristics. Single mothers who have never been married live in more crowded houses, as do mothers with poor education and mothers with low income. Stock, Corlyon, Serrano, and Gieve (2014) report that single-parent households tend to be in relatively deeper poverty than two-parent households. Cardenas

[17] The suggested causal link is not proven, but is argued based on theoretical considerations.

and Carpenter (2013) include a measure of home size, but does not directly relate it to the size of the household. They do not find a significant relation between risk aversion and home size.

We conclude that there is heterogeneity in the relationship between risk aversion and household composition and size in this literature. Household size may be associated with an increase or a decrease risk aversion, although measures do not clearly distinguish between members who are dependants and those who contribute to household finances. Crowded homes can lead to many negative psychological effects, but is also a sign that the housing constraint is binding and losses in income cannot be made up by taking in more contributing individuals or moving to a smaller home.

3. STUDY DESIGN

The data used for this study has been made available by a research program called Portfolios of Atlanta's Poor, financed by the Center for Economic Analysis of Risk at the Georgia State University.[18] Volunteer participants who were heads of households (single or shared) were recruited from the membership of several non-profit organizations in the greater Atlanta area that provide services for low-income working families and individuals during 2014-17. Our respondents therefore represent people in poverty, but who are engaged in some sort of self-help. As part of the study all participants were given binary lottery tasks to elicit their risk attitudes and a demographic census and as well as a financial survey.

Participants who were interviewed at the same time were separated for privacy.[19] All task instructions and all questionnaires were read to them privately by the interviewer, and it was also the interviewer who filled in the responses on the record sheets. All participants received $25 as a compensation at the end of each session, and received additional earnings from the experimental tasks. Any task earnings were paid at the end of the task session, but were tracked throughout the

[18] Interviews were done in waves and questionnaires were adjusted somewhat between waves. In particular, additional questions were added for later waves.

[19] Each participant was paired with an interviewer and we tried to keep that pairing the same throughout their participation. Water and snacks were provided to all participants to ensure that they were as alert as possible.

session in a clear and transparent way. Lottery earnings average $61, with a minimum of $39 and a maximum of $79, so that even the smallest amount was larger than the participation compensation.

3.1. *Risk Elicitation Experimental Tasks*

Many restrictions were imposed on the design in order to keep the cognitive load low, given that the participants come from populations where the literacy levels can be expected to be below average and where they have no prior experience with experimental tasks. Prior to conducting the tasks, they were given both instructions and practice. One important difference between the present study and most other risk elicitation experiments is that, instead of picking one task at random to play out and pay, all tasks were paid out. This payment procedure has previously been adopted by Huck and Weizsäcker (1999) and Dixit, Harb, Martinez-Correa, and Rutström (2015) to avoid the impact random payment procedures could have on risk attitudes.[20] Layers of randomness can easily become confusing to participants, particularly in the field, and we expect such confusion to be especially strong among populations with lower literacy rates. Because of our design choice, as demonstrated in Dixit, Harb, Martinez-Correa, and Rutström (2015), there can be an effect on estimated risk aversion due to the cumulative earnings throughout the session. In our analysis we therefore test for any effect from cumulative earnings, but find no significant effect.[21]

Participants were given a series of ten pairwise lottery choices, presented to them using colored balls that were placed in two boxes in front of them. The left box contained balls that were yellow and red and represented the safer lottery. The right box contained balls that were white and blue and represented the riskier lottery. They were also shown a page, illustrated in Figure 1, with a picture of these two boxes where the dollar value of each colored ball was clearly marked. In this example there are 7 yellow balls with the value $1.40, 3 red balls with the value $2.50, 7 white balls with the value $0.10, and 3 blue balls with the value $8.00. The yellow balls always had a lower value than the red balls and the white balls always had a lower value than the blue balls. The probability of the high vs.

[20] Risk attitudes could be affected by random payment procedures if the independence axiom of Expected Utility Theory is violated, or if the additional layer of randomness adds to the cognitive burden on the respondents.

[21] The explanation to how we instrument cumulative earnings and tests showing lack of effects are provided in Appendix D, online at http://CEAR.gsu.edu/ https://cear.gsu.edu/category/working-papers/wp-2019/ for working paper WP2019-06

low value was always the same for the two boxes, but varied across tasks. The participants were asked to choose one of the two boxes and then to put all the balls from that box into a bingo cage. The research assistant then turned the bingo cage 5 times counterclockwise, and then reversed the direction to let one ball fall out. The dollar value of this ball was then recorded on a sheet in front of the participant and the payoff consequence explained.

Table 1 shows the probabilities and the dollar values across the ten tasks. All values and probabilities were selected to allow identification of a wide range of relative risk aversion (RRA) coefficients under Expected Utility Theory (EUT). The first five rows of Table 1 show values for our Low Stake treatment and the last five rows show values for our High Stake treatment. The parameter values for these lotteries were selected such that, for a given risk attitude, the risky option becomes increasingly attractive the higher the probability of getting the high prize. Task 5 in the Low Stake treatment is an instance where all participants should choose the risky option, irrespective of risk attitudes, since there is no risk. To anticipate our results, all of our respondents chose the risky option in this task. Task 1 in the High Stake treatment has a higher expected value for the safe option than for the risky option, and only risk loving participants should choose the risky option. Task 2 in the High Stake treatment has the same expected value for both the safe and the risky option, so again only risk loving participants should choose the risky option. These predictions assume, however, that participants make choices without noise or errors, and we will allow for such errors in our analysis. Allowing for decision errors is a way of making sure our inferences about risk aversion are not confounded by decision biases that occur due to random errors, a possibility pointed out by Andersson, Holm, Tyran, and Wengström (2016).

3.2 Household Characteristics

Table 2 presents our measures of household characteristics, including those reflecting demographics, income and wealth, and education. Care has to be exercised whenever including such characteristics in empirical analyses since they are likely correlated with other household characteristics not included in the model in question. Thus, any significant or insignificant effects are due to the combined effect of the characteristics included and those not included. This is discussed and illustrated in Harrison, Lau and Rutström (2007). This is thus a weakness, not just here, but in all analyses of this kind. An important example of this is the effect of gender: many studies have shown that women may be more risk averse than men. However, in studies that include a wider set of demographics, such as Andersen et al. (2008), Tanaka, Camerer, and Nguyen (2010), Bauer and Chytilová (2013), no such effect is reported.

We include both gender and age since these have been shown to sometimes be associated with risk aversion. We see that the gender distribution is relatively even with 43% being *Male*. With respect to age, 26% are in the *Young* category (younger than 26 years old) and 52% are in the *Old* category (older than 49 years old), implying that 22% are in the middle age range 26 – 49, captured by the variable *Mid*. These are the only covariates that can be claimed to be completely exogenous. All the others may reflect choices, at least partly, and causal claims with respect to the relationship to risk aversion can therefore not be made. This is, of course, also the case in other empirical studies that look at the relationship between various characteristics and risk aversion.

Since being unemployed lowers income and wealth, we include a measure of that called *GeneralUnemployment*. It is a binary variable that takes the value 1 if the individual reports unemployment during the 12 months or 30 days prior to an interview, capturing both long term and short term unemployment. 55% of our respondents are classified as having experienced unemployment by this measure. However, some of these only experienced short term, thus temporary, unemployment, captured by the variable *ShortTermUnemployment*. 22% are classified as only having experienced unemployment temporarily by this measure.[22] This is also a binary variable. It takes the value 1 for those who are classified as unemployed but also had some work during the previous 12 months. We expect unemployment to be negatively associated with risk aversion, if the effect is primarily due to loss of income. Being underemployed may have similar effects on income and wealth, and we capture that with the variable *WorkHours*, which is the response to how many hours the respondent worked during the month preceding the interview. We see underemployment on

[22] Of those who experience long term unemployment (33%) only four respondents still report that they are looking for work. Given their consistent longterm unemployment we still code them as unemployed. We constructed our unemployment measures from a number of different questions.

average with 144 hours, compared to the 160 hours that they would have worked as full-time employed. This average is calculated including both individuals who are underemployed, who are fully employed, and those who work more than one fulltime job. The average calculated only on those with less than full employment is only 90 hours per month.

Apart from how much work a participant has, the earnings for that work also matter for how they manage their poverty. The variable *WorkEarnings* measures the total reported work earnings for the month, divided by the reported number of hours. The average hourly earnings among those who worked is $13.9, thus above the minimum wage of $7.25 but somewhat below what is considered a "living wage" of $15.12 for a family of four, according to the Living Wage Model developed by Amy K. Glasmeier (Nadeau (2017)). Out of those who worked for money during the prior month, 17.5% earned below the minimum wage.

As mentioned earlier we also include the amount of money that is contributed by other individuals or institutions (*OtherIncome*). This variable includes contributions from household members, contributions from other individuals who are not part of the household, contributions and benefits received from non-profit organizations, and government benefits. The monthly average is $1,166, equivalent to 47% of monthly work earnings.[23] Further, we include a proxy for low wealth based on homeownership; *HomeLowEquity* is a dummy variable that takes the value 1 if the participant either rents the home or has a mortgage on the home, and 0 if the participant owns the home without a mortgage. We observe that 85% of our participants have low home equity in this sense.

We also consider lack of education, not only because of its effect on income and finances, but also because of its effect on various forms of literacy and the impact on quality of life that such literacies have. *NoHighSchool* is a dummy variable that takes the value 1 if the participant did not graduate from high school. About a third of our respondents fall into this category. The other

[23] While this variable includes all other money sources apart from working, it is highly correlated (0.87) with contributions from household members for the observations where the dataset has such a breakdown.

education variable, *HighEducation*, measures education levels beyond high school. We observe that 39% of our participants report some education beyond high school.

3.3 Household Composition

Based on the survey responses we identify several measures of household composition related to poverty, presented in Table 2. *SoloResponsible* captures respondents who are the sole head of the household and whose household has at least one other member. Thus, the variable *SoloResponsible* captures those that carry the major financial burden for the household, making all the decisions. They are more vulnerable than households that have several shared heads since their ability to risk pool is more limited (Stock, Corlyon, Serrano, and Gieve (2014)). Slightly less than half of our respondents have the sole responsibility for the household.

The effect on the welfare of the household from any income loss that the household head suffers may be greater the larger is the number of dependants, and, in addition, the management of real life risks, such as job losses or negative health events, may be more difficult, thus decreasing the willingness to take on risk (Ward (2016), Wik, Aragie Kebede, Bergland, and Holden (2004)). These effects can come about because a larger household may have more basic, non-discretionary expenses that cannot easily be reduced or eliminated when facing a loss in income. Alternatively, income losses may get compounded by psychological effects as a result of household size, thus leading to welfare effects that exceed the loss in income. Several non-linear forms of welfare functions, such as multiplicative ones, imply that the income loss, distributed across the utilities of household members, result in a much higher welfare loss to the household than simple sums. These larger welfare losses may bring the household closer to a lower bound that the head considers unmanageable, resulting in an increase in risk aversion.

We distinguish between pure household size (*HHSize*) and the number of dependants (*Dependants*) as discussed earlier. The main difference between these measures is that shared heads are excluded from the count of *Dependants* thus removing any effect of the positive impact such shared heads have on the ability to manage income losses. The average number of additional household members is 3.0 when not including single households. The average number of *Dependants*, not including zero counts, is 3.1. This average is slightly larger since the households who do not have any dependants, i.e. those counted in *HHSize* but not in *Dependants*, are relatively smaller, decreasing the average size.

We include separate measures for adults and children because it is likely that respondents are involved with the care of children in a different way than they are with adults. *NKids* includes both dependant and non-dependant children, while *DependantKids* includes only the former, but they are very similar in magnitude. Both are shown in Table 2 conditional on non-zero values. Following our earlier discussion of the possible psychological effects of crowdedness, we include measures of the number of household members per bedroom (*PersonsPerRoom*) and the number of dependants per bedroom (*DependantsPerRoom*), as well as these measures for children (*KidsPerRoom* and *DependantKidsPerRoom*). The number of bedrooms per dependant can alternatively be viewed as a measure of how thinly the respondent's wealth is stretched: the more crowded the household, the more stretched the resources are and therefore the more vulnerable is the household to financial risks. For example, crowded dependant households are less able to take in renters to substitute for income losses, and less able to move to smaller apartments to lower the rent costs. The average number of people per bedroom (not including the respondent) is 1.2 with 1 child per bedroom. This may not seem large, but Solari and Mare (2012) show that the effect of crowdedness is strongest for relatively small increases in the number of people per room. Further, the maximum number of people per bedroom in the sample is 4, which is not small.

4. DESCRIPTIVE RESULTS

Figure 2 displays the proportion of safe choices by treatment (Low vs. High Stakes), separately for each task number. The proportion of safe choices decreases across tasks throughout both the Low Stake and High Stake tasks. This is consistent with the fact that the expected value of the risky lottery increases by more than the expected value of the safe lottery across tasks as the probability of the high prize increases. We confirm that nobody chooses the safe option in Task 5 Low Stake, where the probability of getting the high prize is one. This finding is contrary to findings in many previous lottery task experiments where some participants still choose the dominated option in the riskless task This is a signal that our participants were paying attention to the details of the tasks. In Tasks 1 and 2 of the High Stake condition we see some participants choosing the risky option, consistent with risk loving behavior (absent noise in their behavior). In Task 1 this is only 4% of our participants, but in Task 2, where the expected value is the same for the safe and the risky option, it is 18%.

Given the parameter values used in the Low vs. High Stake lottery tasks we would expect a higher proportion choosing the safe option in the High Stake vs. the Low Stake treatment, which is what we see. Overall, the proportion choosing the safe option in the High Stake treatment is 47.9% wehereas the proportion is 27.3% in the Low Stake lottery tasks.

We also look at how our covariates are correlated. All household composition characteristics are strongly positively correlated with each other. Thus, if one household composition measure is omitted in an estimated model, the coefficients on the others will reflect the effect of the omitted variable as well. While they are also significantly correlated with some other variables, such as *GeneralUnemployment* and *ShortTermUnemployment*, *WorkEarnings*, *Male*, and *HighEducation*, these correlations are weak.[24] The variables *WorkHours* and *WorkEarnings* are positively correlated with each other, indicating that they both reflect some latent characteristic that is the same. We therefore only include one of them, *WorkEarnings*, in the estimated models.[25]

5. STRUCTURAL ESTIMATION

We perform structural estimations of utility functions using logistic maximum likelihood models, with model parameters as functions of our poverty and control variables. We assume that agents have an expected utility (EU_k^j) of lottery *j* (*Safe* or *Risky*) in task *k* defined as the probability weighted utility of each money outcome ($M_{j,k,t}$) (where *t* indicates low or high dollar outcome) given by

[24] The full correlation table is included in Appendix D (online).

[25] When we include both, WorkHours is never significant.

$u(M_{j,k,t}|r)$, where r is the risk aversion coefficient. For ease of exposition we suppress the agent index i in the expression for Expected Utility:

(3) $EU_k^j = \sum_t [p_{k,t} \times u(M_{j,k,t}|r)]$, where $t = 1{,}2$ and $k = 1 \dots 10$ and $j = S, R$

There is no subscript j on the probability, $p_{k,t}$, since it is the same for the *Safe* and *Risky* lottery in any task k. We employ a Constant Relative Risk Aversion (CRRA) utility specification: $u(M_{j,k,t}|r) = \frac{{M_{j,k,t}}^{(1-r)}}{1-r}$.[26] Risk neutrality is found when r=0. Following Wilcox (2011) we employ contextual normalization by dividing each EU value by the difference between the best and worst outcome in each task. This generates a heteroskedastic model, which allows us to make risk aversion comparisons in the sense of Pratt (1964).

(4) $EU_k^{j,het} = \frac{EU_k^j}{(u(M_{k,max}) - u(M_{k,min}))}$ $where\ j = (S, R)$

The maximum and minimum outcomes $M_{k,max}$ and $M_{k,min}$ are not indexed with the lottery (j) since we identify them across both the *Safe* and *Risky* lotteries within each task. We generate the likelihood function for choosing *Risky* as:

(5) $\mathrm{L}_{j=R} = \frac{\exp\left(\frac{EU_k^{R,het}}{\mu}\right)}{\exp\left(\frac{EU_k^{R,het}}{\mu}\right) + \exp\left(\frac{EU_k^{S,het}}{\mu}\right)}$

where superscript R is *Risky* and S is *Safe,* and *exp* denotes the exponential function. The additional parameter μ in (5) modifies the standard logistic cumulative density function and can be interpreted as a behavioral sensitivity parameter, often referred to as a Fechner error. When the Fechner error is larger than 1, agents' choices are less sensitive to the difference in EU than the standard logistic function would indicate, so the slope of the cumulative density function is flatter. When it is smaller than 1, agents are more sensitive than indicated by the standard logistic function. The choice becomes

[26] This specification has been shown to better fit experimental data than alternatives (Camerer and Ho (1994), Wakker (2008)). As a robustness test we also estimated models based on a CARA utility function, and find very similar results.

non-stochastic as $\mu \rightarrow 0$. In our estimations *r* is defined as a linear function of the variables listed in Table 2[27]:

(6) $r_i = \alpha_0 + \sum_d \alpha_d X_{di}$

X_{di} is the vector of variables from Table 2 and they vary across participants, indexed by *i*. The conditional log-likelihood is

(7) $lnL(r, \mu; y, X) = \sum_{i,k} \left(lnL_{j=R} \middle| y_{i,k} = 1 \right) + \left(1 - lnL_{j=R} \right) | y_{i,k} = 0)$

where $y_{i,k}$=1(0) denotes the choice of the *Risky* (*Safe*) option by participant *i* in task *k*.

5.1. *Structural Estimation Results*

Table 3 presents the results of the structural estimations. We include five models: two that include only household composition covariates and three that include a fuller set of covariates. We focus on effects with a p-value of 0.01 or better, due to the exploratory nature of the study, so as to minimize the chance of rejecting non-effects too casually. The constant term in the *r* equation is significantly different from risk neutrality and hovers around 0.4, perfectly in line with many other experimental elicitations of risk attitudes. The Fechner errors (μ) are around 0.1, implying that there is not much noise in the choices and they are fairly close to being deterministic.[28]

We consistently see very significant associations between risk aversion and our household composition variables across these models, with the exception of *PersonsPerRoom*. *HHSize* and *Dependants* are both associated with higher risk aversion. This finding is contrary to findings reported in Wik, Aragie Kebede, Bergland, and Holden (2004) in Zambia, the only other significant household size effect we have encountered. However, if having a larger household implies higher stakes for real life risks such as job losses or negative health events, managing these risks may be more difficult, and

[27] Since the participants were paid for each of the tasks rather than having one randomly selected for payment we also wanted t make sure that behavior was not affected by the cumulative earnings. In separate models we also include an instrument for cumulative earnings but did not find it significant. Appendix D (online) shows more details on how the instrument was created and the estimation results.

[28] We also estimated model specifications that included covariates on the Fechner errors, as a test of the possibility that effects on risk aversion may simply be effects on decision errors, as demonstrated by Andersson, Holm, Tyran, and Wengström (2016). None of the covariates are significant at a level of p<0.01 and we are therefore confident that our risk aversion effects are not confounded by decision errors.

it is then reasonable to expect a lower willingness to take risks. A larger household may imply that a larger portion of the income goes to basic, non-discretionary expenses that cannot easily be reduced or eliminated when facing a loss in income. Further, depending on the respondent's welfare function for the household, the welfare effects of a larger household may be greater than that evaluated based on the change in income. Of course, since we cannot make any causality claims, the estimates may also be a result of more risk averse respondents chooseing to have more dependants, for less obvious reasons.

Since the difference in the effects due to *HHSize* and *Dependants* is negligible, we infer that any risk pooling possibility that comes with having shared heads, as reflected in *HHSize*, is not associated with risk attitudes. Further support for this inference is found in the insignificant coefficient on *SoloResponsible*.

Contrary to the higher risk aversion when the number of adults in the household is larger, as reflected in *HHSize* and *Dependants*, we find the opposite association for the number of children in the household as reflected in *NKids* and *DependantKids*. However, the effect of the number of children depends also on the housing constraint, as shown by the negative and significant coefficients on *KidsPerRoom* and *DependantKidsPerRoom*. Thus, respondents who are constrained for space for their children are more risk averse than those without children or those with children but no housing constraint. So why would households with children, but no housing constraint, be more willing to take risks in our lotteries than other households? Without a housing constraint the household may have opportunities to manage risk by taking in additional members or by moving to a smaller house. These households may then see a chance to get something special, something they can seldom afford, and the absence of a strict housing constraint facilitates their real life risk management. Perhaps the small chance to buy some nice clothing or treats for their children, which is what the higher reward in the risky lotteries offers, is worth more than what they can get with the smaller, relatively certain reward in the safe lotteries.[29]

Models 3 – 5 in Table 3 include additional covariates. Models 3 and 4 is based on *HHSize* while model 5 uses *Dependants*. Model 3 includes *GeneralUnemployment* while the other two also include *ShortTermUnemployment*. We first notice that the additional covariates do not have any significant effect on the household composition variables. Further, almost all effects are insignificant: there is neither a gender effect nor an age effect; education levels are not associated with risk attitudes, nor is experience with unemployment or having housing equity.[30] The only variable that is significant across all three models is *WorkEarnings*. It is associated with less risk aversion, consistent with previous studies that found negative income effects. In Model 5 we also see a small, but significant effect of *OtherIncome*. Since in this model we base household size on *Dependants*, thus not including shared household heads in the count, this is not surprising since shared heads often contribute to household finances. This positive association is different from the expected negative income effect, but it is quite small. Since *OtherIncome* is measured in thousands of dollars, every additional one thousand dollars is associated with a change in the CRRA coefficient in the third decimal place. On the other hand, the *WorkEarnings* variable is not scaled, thus the coefficient shows that a one dollar change is associated with a change in the CRRA coefficient in the second decimal.

We conclude that poor households are risk averse, and that those who have many adult household members are even more so. On the other hand, households with many children, but who are not constrained by their housing resources, are instead less risk averse. These heterogeneous findings imply that households will not respond in the same way when offered opportunities that they may perceive as risky. Most poor households would choose relatively safe options, when they are presented with a choice. The exception is households that have many children but are not constrained

[29] Appendix D (online) shows a number of model specifications as robustness tests where the the household composition variables are interacted with SoloResponsible. The story does not change. The only specification in which SoloResponsible is significant is when we do not include one of the crowdedness variables.

[30] We conducted a robustness test of the insignificant short term unemployment effect by using an alternative variable that captures only recent, short term unemployment and confirm insignificance. We also conducted a robustness test of the insignificant age effect for Mid, including instead Young and Old, again confirming insignificance.

in their housing resources. Perhaps the available housing resources indicate that they have risk management options available, such as moving to smaller housing or taking in additional contributing household members, and they are therefore open to take some risks since that has a chance of offering them an opportunity to get something special.

6. CONCLUSIONS

We present estimates that associate risk attitudes with several measures of poverty for the urban poor in a rich country, the United States. These individuals were recruited via local non-profit organizations and are therefore representative of a group that is engaged in some sort of self-help. We include several poverty factors, both those related to earnings and those relating to household composition. With the exception of hourly work earnings, we do not find significant effects from earnings variables. Neither unemployment nor the amount of underemployment are significant, and we also do not find education to have much impact. This is consistent with the lack of significance noted by Binswanger (1980), Mosley and Verschoor (2005), Tanaka, Camerer, and Nguyen (2010) and Cardenas and Carpenter (2013) on correlations between risk aversion and income. The negative coefficient on hourly work earnings is consistent with findings from representative, rather than poor, populations, as reported in Andersen, Harrison, Lau and Rutström (2008), Noussair, Trautmann, and Van de Kuilen (2014), Bauer and Chytilová (2013), Wik, Kebede, Bergland and Holden (2004), Miyata (2003), and Yesuf and Bluffstone (2009).

On the other hand, three of our household composition measures are strongly significant: the number of adult household members, the number of children, and how crowded the home is as a function of the number of children. The first and the last are associated with higher risk aversion, which is consistent with what we would expect if these reflect a larger support burden for the household head. These households may find it difficult to manage risk since much of their resources are committed to nondiscretionary spendings leaving them little room to maneuver.

On the other hand, risk aversion is decreasing with the number of children as long as housing is not a constraint. One possibility is that these households see the chance of the risky lottery option providing them with an opportunity to get something special for the children, an explanation that could also be used to explain gambling and lottery purchases outside of the lab. While our lottery prizes are much more modest than those offered in many state lotteries, they are still large enough to result in a significant additional income compared to their earnings outside of the experiment. Our lottery earnings average \$61, with a minimum of \$39 and a maximum of \$79, while the monthly income average is \$1,065, with a minimum of \$65 and a maximum of \$2,800. This implies that the average share of the monthly income that is earned in the lottery tasks is 17%, with a minimum of 4% and a maximum of 127%. Thus, our lottery earnings are not negligible to our participants.

While we confirm the positive association between poverty and risk aversion for most households, which is consistent with the part of the literature that reports significant effects, we find one type of household for which the association is negative. The only other study we are aware of that finds such a negative association is Henrich and McElreath (2002) for subsistence farmers. However, the association is consistent with the literature on gambling and lottery purchases that show an increased tendency to take such risks among poor households. Thus our findings should caution practitioners to not simply assume that households in poverty are more risk averse. Circumstances seem to exist under which they are willing to take somewhat more risks in order to reap higher rewards. This implies that offering these households new programs for managing their risks or for increasing their resources can be accepted even if they appear somewhat risky.

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TABLE 1

Payoffs and Probabilities in the Lottery Tasks

	Safe Option		Risky Option		
Task Number	Yellow value ($)	Red value ($)	White value ($)	Blue value ($)	Probability of red/blue (High prize)
1 Low Stake	1.40	2.50	0.10	8.00	0.3
2 Low Stake	1.40	2.50	0.10	8.00	0.5
3 Low Stake	1.40	2.50	0.10	8.00	0.7
4 Low Stake	1.40	2.50	0.10	8.00	0.9
5 Low Stake	1.40	2.50	0.10	8.00	1.0
1 High Stake	4	6	0	12	0.2
2 High Stake	4	6	0	12	0.4
3 High Stake	4	6	0	12	0.6
4 High Stake	4	6	0	12	0.8
5 High Stake	4	6	0	12	0.9

TABLE 2

Variable Descriptions

Variable name	*Description*	*Mean (stdev) or %*
Male	Percentage	43%
Young	Percentage aged 18-25 years	26%
Mid	Percentage aged 36-49 years	22%
Old	Percentage aged >49 years	52%
GeneralUnemployment	Unemployment (%)	55
ShortTermUnemployment	Only short tem unemployment (%)	22
WorkHours	Hours worked last month conditional on WorkHours>0	143.9 (88.3)
WorkEarnings	Earnings per hour last month (in dollars) conditional on WorkEarnings>0	$13.9 ($10.2)
OtherIncome	Income from other sources than work last month (including $0), in thousands of dollars	$1.17 ($1.94)
HomeLowEquity	Percentage paying rent or having a mortgage on their house	85%
NoHighSchool	Percentage who did not graduate from High School	28%
HighEducation	Percentage who have education beyond high school	39%
SoloResponsible	Percentage of households with a sole head	39%
HHSize	Number of household members, not including the respondent	3.0 (2.0)
Dependants	Dependants in the HH, conditional on Dependants>0	3.1 (2.1)
NKids	Number of children in the household, including non-dependants (conditional on nonzero)	2.8 (1.7)
DependantKids	Number of dependant kids in the HH (conditional on nonzero)	2.7 (1.7)
NumberBedrooms	Number of bedrooms	2.5 (1.1)
PersonsPerRoom	HHSize divided by NumberBedrooms	1.15 (0.7)
KidsPerRoom	NKids divided by NumberBedrooms	1.0 (0.7)
DependantsPerRoom	Dependants divided by NumberBedrooms if DependantsPerRoom>0	1.1 (0.7)
DependantKidsPerRoom	Dependant kids divided by NumberBedrooms if DependantKidsPerRoom>0	1.0 (0.6)

Note: Italics indicates variables included in our EUT model. Other variables are included as they are used to construct some of the variables included

TABLE 3

Structural Estimations of EUT Models

	Model 1	Model 2	Model 3	Model 4	Model 5
r equation					
Constant	0.363****	0.411****	0.411****	0.404****	0.444****
SoloResponsible	-0.054	-0.132*	-0.029	-0.038	-0.101
HHSIZE	0.205***		0.200***	0.200***	
NKids	-0.358****		-0.331***	-0.334***	
PersonsPerRoom	-0.323*		-0.347*	-0.340*	
KidsPerRoom	0.754***		0.718***	0.731***	
Dependants		0.245***			0.242***
KidDependants		-0.399***			-0.379***
DependantsPerRoom		-0.417			-0.431*
KidDependantsPerRoom		0.865***			0.834***
Male			-0.001	0.003	-0.004
Mid			-0.102	-0.097	-0.097
GeneralUnemployment			-0.054	-0.018	-0.064
ShortTermUnemployment				-0.066	-0.017
WorkEarnings			-0.011****	-0.011***	-0.011***
Other Income			0.001*	0.001	0.002***
HomeLowEquity			0.084	0.078	0.077
No High School			0.007	-0.007	0.001
High Education			0.027	0.031	0.049
μ equation					
Constant	0.118****	0.119****	0.112****	0.112****	0.113****
N	800	800	770	770	770

Notes: * pvalue<0.1, ** pvalue<0.05, *** pvalue<0.01, **** pvalue<0.001.
Errors are clustered on the individual respondent due to the panel structure of the data. OtherIncome is scaled to measure thousands of dollars.

FIGURE 1

Sample Image Page for Binary Lottery Choice Task

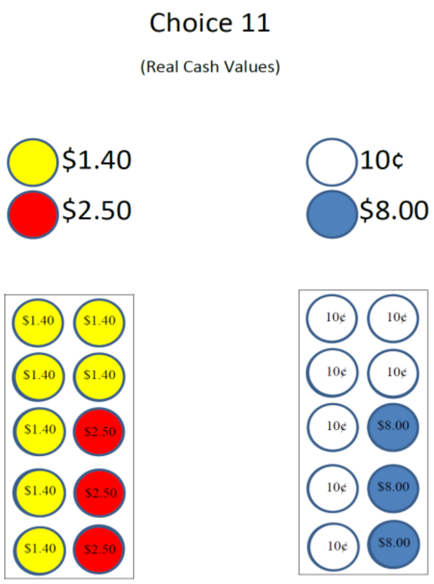

FIGURE 2

Proportion of Safe Choices in Lottery, by Task Number