“Nothing Left to Lose”:
Risk Attitudes Among Vulnerable Households

by

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Abstract

In this paper we investigate how experiences with poverty, and the vulnerabilities that are induced by it, affect risk attitudes. We do this for a population that has received relatively little interest in the experimental literature: the working poor in a rich country. Our conception of vulnerability is broader than the familiar one of financial vulnerability. Apart from including financial variables that are associated with vulnerability, we also include a number of household characteristics that have been identified as adding to vulnerability in the poverty literature. We collect behavioral data using lab in field experiments coupled with detailed questionnaires. The main lesson from the analysis is that we can find circumstances in poor communities, where the aversion to risk is decreasing in some household vulnerability factors. This is consistent with the relationship between income and risk taking as expressed in the literature on gambling and lottery purchases. Specifically, we find that risk aversion is decreasing with the number of kids, as long as this does not lead to a stretching of the housing resources so that the home becomes crowded. Risk aversion is also decreasing as homes become more crowded with adult dependants. Other vulnerability factors lead to increasing risk aversion. This heterogeneity in risk attitudes has implications for public policy as well as for the design of insurance and credit instruments for this population. The individuals’ choices to either self-insure through savings, to rely on credit, to purchase formal insurance products, or to depend on publicly provided safety nets will vary with what type of vulnerabilities that characterizes them.

Key words: Poverty, vulnerability, risk attitudes, experiments, 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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1. Introduction

Risk attitudes vary across individuals, contexts, and time, and depend partly on the environment and experiences of the individual. While there is a justified interest in explaining how unusual events, such as disasters, wars or recessions, affect risk attitudes, there is also a need to look at how more stationary environmental factors play a role. In this paper we investigate how experiences with poverty, and the vulnerabilities that are induced by it, affect risk attitudes. Evidence of how poverty affects psychological and emotional factors are presented in DeCarlo Santiago, Wadsworth and Stump (2011), and we believe that risk attitudes may be affected in similar ways.[1] We do this for a population that has received relatively little interest in the experimental literature: the working poor in a rich country. Our conception of vulnerability is broader than the familiar one of financial vulnerability. We are not primarily looking at the relationship between risk attitudes and the risk of falling below some poverty threshold. Instead, we identify several factors in the environment of a decision maker that are associated with vulnerability more broadly conceived, as suggested in the poverty literature. These factors include the decision maker being the sole head of household with no risk sharing partner, the size of the household, the number of dependant children in the household, how crowded the home is, and the education level of the household head, in addition to several financial variables such as unemployment, underemployment, and low hourly wages. We measure these factors, as well as risk attitudes, in a lab-in-field experiment using respondents from a low income African American neighborhood in Atlanta.[2]

Financial vulnerability due to poverty is usually seen as the risk of falling below some poverty threshold. Morduch and Schneider (2017) show that this risk has increased during the last several decades as volatility in income and expenses has increased for both poor and near-poor households. However, poverty also affects other dimensions of vulnerability. For example, it lowers a person's access to health and medical resources and therefore increases health vulnerability. Poverty also lowers a person's access to educational resources, thus reducing many types of literacy and cognitive abilities, making individuals vulnerable to informational influences and problems in information processing and judgment. Poverty induces intergenerational vulnerabilities as well, since the poverty of parents increases their children's risk of poverty. These vulnerabilities are even greater when individuals in poverty have many dependants, particularly children. The ability of a person in poverty to manage such multi-dimensional risk depends not only on cognitive characteristics and culturally transmitted habits, but also on the perception of these risks and, importantly, on the attitude to such risks. The higher a person's aversion to risk, the less likely that person is to adopt new ways of thinking and new solutions to managing these risks. This can result in lower longterm welfare. On the other hand, a high aversion to risk also means that they are less exposed to risks of hardship in the shortrun since they are more likely to avoid severe negative outcomes, strengthening their longterm situation. Understanding the relationship between vulnerability broadly conceived and risk attitudes is important for public and private institutions to design effective tools and solutions that can assist in managing risk in vulnerable communities.

Evidence on the relationship between some types of vulnerability and risk attitudes using lab-in-field experiments exists, many of them pointing to higher risk aversion for more vulnerable individuals, but some find the opposite.[3] Few of these focus primarily, or entirely, on generally vulnerable populations,

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[1] There is also evidence of other psychological and cognitive factors, such as self-control and financial literacy, being related to risky choices including the use of costly, but easily accessible, store cards and payday loans (Gathergood (2012)).

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

[3] There is also evidence based on responses to attitudinal questions, but since our focus is on lab-in-field experiments we do not review them here. Examples include Donkers and van Soest (1999), and Dohmen et al. (2011).

however. Using a representative sample from the Danish population Andersen, Harrison, Lau and Rutström (2008) show that income is negatively correlated with risk aversion. Such a negative relation would imply, for those in their sample who already have low income, that increasing financial vulnerability is related to increased risk aversion. In a famous forerunning to many modern day field experiments Binswanger (1980) presented poor farmers in India with a series of risky choice options. He found significant negative income effects for two of the risk elicitation tasks (but not for others), and no effect from the amount of land owned, the most important asset. Von Gaudecker, van Soest and Wengström (2011) report on an internet based experiment using 1,400 CentERpanel participants in the Netherlands and find that those with the lowest wealth (<€10,000) have significantly lower risk aversion than those in the next lowest wealth category (€10,000 – 50,000). Such evidence that financial vulnerability may be associated with a decrease, rather than an increase, in risk aversion is corroborated by 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, Tidwell and Hoffman (2011) report that neighborhood disadvantage measures are significantly correlated with increased lottery gambling intensity. Of the experimental studies referenced here, only Binswanger (1980) is based on a sample from a vulnerable population.

Apart from evidence on financial vulnerability there is also some evidence on how cognitive vulnerability is related to risk aversion. Dave, Eckel, Johnson and Rojas (2010) conducted experiments with 881 working poor adult Canadians and find that risk attitudes elicited using a cognitively less demanding method due to Eckel and Grossman (2002) and Binswanger (1980) are lower than those elicited using a Holt and Laury (2002) style multiple price list. [4] They also measure math skills and find that low math skills are associated with higher risk aversion. Burks, Carpenter, Goette and Rustichini (2009) present experimental tasks and cognitive tests to 1,000 trainee truckers in the US and find that cognition is negatively related to risk aversion. On the other hand, Andersson, Holm, Tyran, and Wengström (2016) review a wider literature on cognition and risk aversion and find mixed results. More importantly they demonstrate that significant effects between cognition and risk aversion may be confounded by unobserved effects between cognition and decision errors. Decision errors can lead to biases that are mistakenly inferred to be effects due to risk aversion.[5] Of these studies only Dave, Eckel, Johnson and Rojas (2010) is based on a sample from a vulnerable population.

There has also been some interest in how vulnerability in the health dimension relates to risk aversion. Leonard et al. (2013) find a significant negative relation between stated intentions regarding physical activity, and risk aversion for a sample of 169 adults from a low-income African-American community in Texas using a lab-in-field experiment. The intention scale includes as higher values both actively engaging in physical activities and having a habit of doing so.[6] If such intentions are correlated with being healthier the inference would be that risk aversion increases with health vulnerability. Further support for risk aversion increasing in health vulnerability is found in Harrison, Lau and Rutström (2010). They investigate the relationship between risk attitudes and smoking, using the same sample as Andersen, Harrison, Lau and Rütstrom (2008) and report significantly higher risk aversion among smoking than

[4] Similar evidence but for German highschool students is demonstrated in Huck and Weizsäcker (1999).

[5] Using two different elicitation instruments in an experiment on 1,422 adults from the Dutch CentERpanel, where two instruments are used that vary in how they generate biases from decision errors, they find that the effect of cognitive ability on risk aversion is positive for one and negative for the other. This significantly weakens the earlier inferences on associations between risk aversion and cognition.

[6] The scale is “pre-contemplation”, “contemplation”, “preparation”, “action”, and “maintenance”. This scale is validated in the public health literature.

among non-smoking women, but no significant effect for men. However, using the same respondents as Leonard et al. (2013), de Oliveira et al. (2016) report a negative relationship between directly measured obesity and risk aversion, which is evidence that risk aversion can decrease with health vulnerability. Such a negative relationship is also reported in Anderson and Mellor (2008) and Sutter, Kocher, Glätzle-Rützler andTrautmann (2013). The former finds a negative relationship between self reported BMI (i.e. obesity) and risk aversion using a lab-in-field experiment with a sample of 1,000 individuals, representative of the adult population in Williamsburg, Virginia, while the latter finds a negative relationship among Austrian children and adolescents. Of these studies, only the sample used in Leonard et al. (2013) and de Oliveira et al. (2016) is from a vulnerable population.

In this study we focus on a vulnerable population and explore the extent to which the degree of vulnerability increases or decreases risk aversion. Our participants are working poor individuals in the Atlanta metropolitan area who are in need of financial support from government or non-profit organizations but who, for the most part, are generally seeking job opportunities and working at least intermittantly. We intentionally focus only on this narrow part of the socio-economic spectrum since this is a population that is very vulnerable in all possible dimensions, while actively trying to leave poverty through work effort. We present participants with experimental lottery tasks that elicit risk preferences and that have actual money consequences. We also interview these same individuals in detail regarding their financial and family circumstances, allowing us to relate risk attitudes to various measures of vulnerability.

We include several measures of vulnerability induced by poverty. Since single heads of households with many dependants are more vulnerable, we include several variables that capture such circumstances in addition to variables relating to income, wealth, and education. We create variables that capture vulnerability based on the respondent being the sole head of household, being underemployed, having low hourly wages, having little education, heading a household that is larger and that has more children, and that is crowded. Using survey data from China, Ward (2016) demonstrates that the number of dependants, i.e. household size, is negatively related to income per person, thus financial vulnerability is increasing in household size. We suspect that the same is true for poor working populations in the US, given that access to fulltime employment is limited for this population, increasing the likelihood that additional adult household members add more expenses than income. We include measures both of the number of adults and children in the household. Stock, Corlyon, Castellanos and Gieve (2014) show evidence that poverty is also more likely in single-parent households than in two-parent households, motivating us to focus on respondents who are sole head of the household. There is also evidence that the crowdedness of households has a negative effect of wellbeing, particularly for children. Citing several studies Solari and Mare (2012) list many negative vulnerability outcomes due to crowded homes: 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) analyse the relationship between household crowdedness and several measures of child wellbeing, using both nationally representative longitudinal data from the Panel Study of Income Dynamics' Child Development Supplement (PSID-CDS) 1997 and 2001 as well as Los Angeles Family and Neighborhood Survey 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 poverty characteristics. Single mothers who have never been married live in more crowded houses, as do mothers' with poor education and mothers' with low income. They also demonstrate that the negative effect of crowding may be diminishing, indicating that even relatively mild crowding can have significant negative effects on wellbeing. We include both a measure of the overall crowdedness of the household, but also of the crowdedness due to children.

In the next section we describe our study design, both the risk elicitation task and the vulnerability measures. Section 3 gives some descriptive results and Section 4 presents results from logit regressions. Section 5 disusses the results from our estimation using structural maximum likelihood models. Section 6 concludes.

2. Study Design

The data used for this study is collected as part of a larger research program called Portfolios of Atlanta's Poor, financed by the Center for Economic Analysis of Risk at the Georgia State University. Volunteer participants were recruited from the membership of several non-profit organizations in the greater Atlanta area that provide services for low-income families and individuals in the fall of 2014, the spring of 2015, and the spring of 2017. We refer to these three periods as Wave 1, Wave 2, and Wave 3. In Wave 1 and 2, interested volunteers were asked to come to a series of three sessions, separated by one to three weeks. We only include data from the first two sessions in the analysis presented here. The risk preference elicitation task was conducted in the first session, and various surveys were given in the second session. In Wave 3, the risk preference task was not conducted in the first session so that, instead, all questionnaires could be completed in just two sessions. Following these two sessions the respondents in Wave 3 participated in a longitudinal survey study conducted over 6 months. We only include data from the first session and from the risk preference task, which was conducted about halfway through this longitudinal survey.

All sessions took place either in our own facility on the university campus, in the participant's home, or in the non-profit locations; each participant could choose which location they preferred. Very few selected their own home, most selected the non-profit location. A lot of staffing resources were required in scheduling sessions. Many participants were distracted by their financial and social circumstances, were limited in their phone access for financial reasons, and were thus prone to cancel or not show up and be difficult to get hold of for rescheduling. This lead to some attrition: In Waves 1 and 2 50 individuals were interviewed in session 1, and only 47 in session 2. In Wave 3 we had 59 individuals who started in session 1, but only 32 who stayed in the study long enough to complete the risk preference elicitation task. We thus have 106 participants who completed the survey questions that we use to construct our covariates, but only 82 who completed the risk preference task, and 79 who did both. This limits the complexity of our model specifications, but still allows us to investigate our main hypotheses.

Participants who were interviewed at the same time were separated for privacy. Each participant was paired with an interviewer. Water and snacks were provided to all participants. During the sessions they responded to questionnaires and performed experimental tasks. 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 recordsheets. We used paper and pen recordings in Waves 1 and 2, but electronic recording using Qualtrics software in Wave 3. 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 session in a clear and transparent way. Lottery earnings average $61 with a minimum of $39 and a maximum of $79, thus even the smallest amount was larger than the participation compensation.

During the first session of Waves 1 and 2 the respondents were given a demographic questionnaire and several experimental lottery tasks for eliciting risk preferences. During the second session of Waves 1 and 2 they were given other experimental tasks (that we are not analyzing here), and a questionnaire that covered work and earnings history, plus some other questions and tasks that we are also not analyzing here. In Wave 3 all the questionnaires from sessions 1 and 2 of Waves 1 and 2 were given in the first of the two sessions.[7]

2.1. *Risk Elicitation Experimental Tasks*

Many restrictions were imposed on the design in order to keep the cognitive load low, as the participants come from populations where the average 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 pay for, all tasks were paid out. This payment procedure was adopted by Huck and Weizsäcker (1999) to avoid the impact random payment procedures have on risk attitudes. Layers of randomness can easily become confusing to participants, 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 the estimated risk aversion due to the cumulative earnings throughout the session. In our analysis we therefore control for cumulative earnings.

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 with a picture of these two boxes where the dollar value of each colored ball was clearly marked. An example of such a page is shown in Figure 1. 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. low value was always the same for both of 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 record sheet in front of the participant and the payoff consequence explained. Table 1 shows the probabilities and the dollar values across the ten tasks.[8] The first five rows 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 is 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 that both in our regression analysis and in our structural estimations of utility functions. Allowing for decision errors is a way of making sure our inferences about risk aversion is not confounded by decision biases that occur due to random errors, a possibility pointed out by Andersson, Holm, Tyran, and Wengström (2016).

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[7] Appendix A shows the demographic questionnaire and the income and earnings questions used to construct the covariates of the models. Appendix A is available as CEAR working paper 2018-05 at https://cear.gsu.edu/category/working-papers/wp-2018/.

[8] All values and probabilities were selected to allow identification of a wide range of relative risk aversion (RRA) coefficients under Expected Utility Theory (EUT).

2.2 Vulnerability Measures

Based on the questionnaires that participants responded to in the first and second session we identify a number of variables as measures of vulnerability, defined in the broader sense discussed earlier. Our vulnerability variables are presented in Table 2. *SoloResponsible* captures respondents who are the sole head of the household, who are not married[9], but whose household has at least one other member. Thus, the variable *SoloResponsible* captures those that carry the entire, or at least major, financial burden, both the responsibility of bringing in money and the responsibility of paying bills. They are likely to be more vulnerable to economic shocks than are households with a shared responsibility, since shared responsibility allows them to pool both resources and risk. Supporting this assumption is the finding in Stock, Corlyon, Castellanos and Gieve (2014) that single-parent households tend to be in relatively deeper poverty than two-parent households, thus exposing them to more poverty-induced vulnerabilities. Slightly less than half of our respondents fall into this category.

The vulnerability of *SoloResponsible* households is exacerbated by the size of the household since more people are affected. Ward (2016) show that in China the number of dependants, i.e. household size, is negatively related to income per person, thus financial vulnerability is increasing in household size. We expect that the same is true among low income households in the US, especially due to a high degree of underemployment that makes it unlikely that many adult household members contribute more to the finances than they add to expenses. While some adult household members may be contributing some money, we control for this with the variable *OtherIncomeTotalMonth*, which is included in Table 3.[10] *SoloLargeHH* is an interaction between *SoloResponsible* and the size of the household, *HHSIZE* (excluding the respondent and those that are only renters). Vulnerability should increase when the household, i.e. the number of dependants, is larger, since any given income risk affects more dependant individuals. The size of the household headed by a *SoloResponsible* individual (3.2) is larger than the average household in our study (2.3), with a significance level of p=.03 for the difference. These size differences imply that in a single headed household there are on average 3.2 dependants, but in a shared household, there are only 1.3, since at least one of the additional members is a shared head.

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. *SoloManyKids* interacts *SoloResponsible* with the number of children (*NKids*) in the household. The households of the *SoloResponsible* have more children (2.1) than the average study household (1.3), and the difference has a p-value of .02. This is mainly due to the smaller proportion of *SoloResponsible* households who have no children, compared to the average study household (29% and 55%, respectively). Caring for more children makes these *SoloResponsible* heads of households more vulnerable.

Since we recruited participants via different NGOs in the different waves, we are also interested in investigating what differences in household characteristics we may see across waves. We see some differences in the average household size between Waves 1 and 2 on the one hand (2.8), and Wave 3 on the other (1.4). The average household size is significantly smaller in Wave 3, partly due to the larger number of single households (34% vs. 18% in Waves 1 and 2), but we also see smaller household sizes for non-single households (2.1 vs. 3.4). This is due to differences in the number of adults only. There is no significant difference across waves in the number of kids (*NKids* has a p-value of .08 for the

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[9] One respondent reported not being married but being in a domestic partnership and we treat this respondent as married for the purposes of defining *SoloResponsible*.

[10] While this variable includes all other money sources apart from working, in Wave 3 it is highly correlated (0.87) with contributions from household members. In Waves 1 and 2 we did not ask for a breakdown of the source of such other money.

unconditional difference, and even higher p-values for the difference in both the proportions of no kids and the conditional difference in *NKids*).

We also include measures of how crowded the *SoloResponsible* home is, captured by the variables *SoloPersonsPerRoom* and *SoloKidsPerRoom*. The two variables exclude the respondent, so they are directly comparable. The number of bedrooms per person can 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 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. Importantly, Solari and Mare (2012) site many studies that demonstrate negative effects on well-being and vulnerability from living in crowded households, and provide new evidence on the negative effects on childrens' wellbeing. The average number of persons per bedroom (not including the respondent) among our *SoloResponsible* households is 1.2 with 0.8 kids 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.

Since being unemployed lowers income and wealth we include a measure of that called *Unemployed*. It is a binary variable that takes the value 1 if the individual reports unemployment during the 30 days before the interview.[11] We see a fairly large portion of the respondents (45%) who are unemployed by this measure. Being underemployed has a similar effect and we capture that with the variable *HrsWorkTotalMonth*, which is the response to how many hours the respondent worked during the month preceeding the interview. We see underemployment with an average of 144 hours, compared to the 160 hours that they would have worked as fulltime employed. Interestingly, we see that underemployment among those who work is only present during Waves 1 and 2, since in Wave 3 we have more than full employment with 205.5 hours.

Apart from how much work a participant has, the earnings for that work also matters for vulnerability. The variable *WorkEarningsPerHour* 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 at MIT (Nadeau, 2017). As is the case with hours worked, we see that hourly earnings are below the "living wage" only in Waves 1 and 2.

Finally, we also consider lack of education as contributing to vulnerability, not only through its effect on income and finances, but also through its effect on various forms of literacy and its impact on quality of life. *EducNHS* 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.

We will refer to all vulnerability measures that are based on household size as household vulnerability measures (*SoloResponsible* and its interactions: *SoloLargeHH, SoloManyKids, SoloPersonsPerRoom, and SoloKidsPerRoom*), and to the the others as non-household vulnerability measures (*Unemployed, HrsWorkTotalMonth, WorkEarningsPerHour, EducNHS, FatherEducNHS,* and *MotherEducNHS).*

2.3. *Other Control Variables*

We include three types of control variables: demographic, income, and wealth. Notice that none of these are interacted with *SoloResponsible*. We display these variables in Table 3. We see that the gender

[11] This is a measure of short run unemployment.

distribution is relatively even with 43% being *Male*. 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*. We include only one income variable in addition to the financial vulnerability measures and that is the amount of money that is contributed by other individuals or institutions (*OtherMoneyTotalMonth*). Here we see another difference between the waves with 23% of the responses in Waves 1 and 2 reporting no such additional income. The amount of other income is more than 3 times higher in Wave 3 than in the earlier waves, consistent with the later wave including participants that are better off than those in the earlier wave. We include four variables that proxy the wealth of the individual. *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. 85% of our participants have a low home equity in this sense. *PersonsPerRoom* and *KidsPerRoom* measure crowdedness across all households, not just those that are not run by a *SoloResponsible*. There does not appear to be a big difference in crowdedness between our *SoloResponsible* households and others. Finally, we also include a measure of education levels beyond highschool, *EducMHS*. 39% of our participants report some education beyond highschool.

In our analyses, we also include a control for the cumulative earnings a participant makes throughout the incentivized lottery tasks, (*CumW*).[12] This is necessary since risk attitudes may change as earnings accumulate, but it is also the case that earnings depend on the risk attitude of the participant. On average, at least if the number of tasks is large, earnings should decrease with risk aversion since risk averse participants give up expected earnings in order to avoid risk. Because of this endogeneity we create an instrument for these earnings that depends only on exogenously given variables, such as task characteristics.

3. Descriptive Results

Figure 2 displays the proportion of safe choices by treatment (Low vs. High Stakes and Waves 1 and 2 vs. Wave 3), 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 that include a riskless task and where some participants still choose the dominated option, signaling 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%.

Table 4 shows the proportion of safe choices across the two conditions, pooling across periods. 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 treatment, which is what we see. This also confirms the general pattern by task number in Figure 2. The waves are similar with the exception of a small, but significant, difference across the waves in the Low Stake condition (p-value=0.02).

We also look at how our covariates are correlated. All the household vulnerability measures are strongly positively correlated with each other, but not with the other non-household vulnerability

[12] Since some parrticipants did another paid task before the lottery tasks analysed here, cumulative earnings include the earnings from that prior task.

measures, with the exception of *unemployed*, that is negatively correlated with all household vulnerability measures. [13] Thus, if one household measure is omitted in an estimated model, the coefficients on the others will reflect the effect of the omitted variable as well. *HrsWorkedTotalMonth* and *WorkEarningsPerHour* are negatively correlated with *EducNHS*, which seems intuitive. *WorkEarningsPerHour* and *HrsWorkedTotalMonth* are also negatively correlated with *OtherMoneyTotalMonth* in Waves 1 and 2, indicating some substitutability between these income sources. In Wave 3 the correlation is not significant.

4. Regression Analysis of Binary Lottery Choices

Table 5 shows several logit regression models of the binary lottery choices as functions of the vulnerability variables from Table 2, the other control variables from Table 3, cumulative earnings and lottery characteristics.[14] The propensity to choose the safe option can be expressed as

$$(1)\ P_i^k = \frac{1}{(1+e^{-I_i^k})}$$

for task *k* and participant *i*, and where the indicator variable is

$$(2)\ I_i^k = \beta_0 + \sum_v \beta_v F_{vi} + \sum_d \beta_d X_{di} + \sum_z \beta_z L_{zk} + \beta_w W_{ik}.$$

F_{vi} is the vector of vulnerability variables and X_{di} is the vector of control variables, and both vary across participants, *i*. L_{zk} is the vector of lottery characteristics that vary across tasks, *k*, and W_{ik} is the instrument for cumulative earnings that varies across participants and tasks.

Models 1-3 do not include any of the control variables from Table 3, Model 4 has some (only Male and Mid) and Model 5 is the full model including all variables. All models cluster the errors on the participant id. We first verify that as the probability of the high payoff is increasing (*ProbHigh*) the propensity to choose the safe option decreases. Further, as the stakes increase (*HighStake*) the propensity to choose the safe option increases. Both of these are strongly significant (p-values<.001).

We see some robustness across the model specifications for the effects of the household vulnerability measures. We focus on effects with a p-value of 0.01 or better, due to the relatively small sample size and the exploratory nature of the study. In these regressions we include both *SoloLargeHH* and *SoloManyKids*, and the coefficient on *SoloLargeHH* therefore measures the marginal effect on choices from being in a large adult household and *SoloManyKids* the additional effect on choices from having many kids. We find a positive relationship between the propensity to choose the safe lottery option and *SoloLargeHH* and *SoloKidsPerRoom*. However, we find a negative relationship for *SoloManyKids,* and also for *SoloPersonsPerRoom* in the full Model 5. We therefore infer that individuals who are sole heads of larger households, are more averse to risk. However, when the household is large due to many kids they are less averse to risk instead, but only as long as additional kids do not make the home more crowded, i.e. do not stretch the housing resources too thinly. In Model 5, the full model, the marginal effect of a *SoloLargeHH* is +.29 and the change in that if the household size is due to kids (*SoloManyKids*) is -0.41. If the larger number of kids creates crowdedness, the marginal effect on choosing the safe option is positive (+1.27). Figure 3 illustrates the net effect of varying the number of kids from 1 to 4 on the propensity to choose the safe option based on the coefficient estimates in Table 5. Each upward sloping line shows the relationship between number of kids and the aversion to risk, keeping

[13] Appendix B includes the full correlation tables and is available as a CEAR working paper 2018-05 at https://cear.gsu.edu/category/working-papers/wp-2018/.

[14] All marginal effects are evaluated at the means of the variables using the Stata margins command.

the number of bedrooms constant (thus allowing crowdedness to increase). The upper dashed line shows the effect for a household with 1 bedroom (the most crowded case), the line below that for 2 bedrooms, and then for 3 and 4 bedrooms, respectively. The figure makes it clear that the aversion to risk is increasing across all the bedroom configurations as the household has more kids, but less so for the larger homes with less crowdedness. The downward sloping dotted grey line shows the relationship between the number of kids and the aversion to risk keeping crowdedness constant at one kid per bedroom. While this is downward sloping, reflecting the fact that the coefficient for *SoloManyKids* is negative and larger than the coefficient for *SoloLargeHH* in absolute terms, the slope is small in absolute terms compared to the other lines where the crowdedness is varying. Thus, while the underlying preference structure imply that having more kids makes the head of the household less averse to risk, the fact that the extra children puts pressure on the housing resources leads to a net increase in the aversion to risk.

Figure 4 shows that the opposite holds for adult dependants. For these households the sign of the net effect of the number of household members and the crowdedness depends on exactly how crowded the home is. The respondents with the smaller homes, i.e. the more crowded ones, display decreasing risk aversion with additional adult dependants. These respondents therefore break the otherwise consistent pattern with risk aversion increasing with vulnerability. The upward sloping dotted grey line holds crowdedness constant at one person per room, reflecting the positive coefficient on *SoloLargeHH*.

We find no separate influence on risk aversion from the financial vulnerability variables: *Unemployed*, *HrsWorkTotalMonth*, or *WorkEarningsPerHour*. The lack of significance for *EducNHS* implies that we are not adding further support for a relationship between cognitive abilities and risk aversion, as reported in Burks, Carpenter, Goette and Rustichini (2009), and Dave, Eckel, Johnson and Rojas (2010). A potentially important confound is how the aversion to choosing risk changes with the cumulative earnings across the tasks, captured by the variable *CumW*. Dixit, Harb, Martinez-Correa and Rutström (2015) report that risk aversion decreases with cumulative earnings. We do not see a significant effect from cumulative earnings here.

To sum up, we see that most significant vulnerability measures are related to increased risk aversion, but we also find that there are some household heads that are less averse to risk as they become more vulnerable. In particular, vulnerability associated with crowded households with adult dependants are associated with less risk aversion. We speculate that this may be due to a selection effect where less risk averse heads of households surround themselves with friends and adult children who are unable to be financially independent. We also see a pattern where risk aversion decreases with the number of dependants that are kids, but since this usually implies increased crowdedness and stretched resources, the net effect is a positive.

The main lesson from this analysis is that *we can find circumstances in poor communities, where the aversion to risk is decreasing in some household vulnerability factors*. This is consistent with decreasing risk aversion as expressed in the literature on gambling and lottery purchases, as well as decreasing risk aversion due to wealth effects reported in von Gaudecker, van Soest and Wengström (2011) and due to health effects in Anderson and Mellor (2008), Sutter, Kocher, Glätzle-Rützler andTrautmann (2013), and de Oliveira et al. (2016).

5. Structural Estimation

We perform structural estimations of utility functions using logistic maximum likelihood models, with model parameters as functions of our vulnerability and control variables. This allows us to estimate risk aversion coefficients as preference parameters, rather than to rely on explaining choices as in the previous section. We assume that agents have an expected utility (EU_k^j) of lottery *j* 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 $u(M_{j,k,t}|r)$, where *r* is the risk aversion coefficient. For ease of exposition we suppress the agent index *i* in the following.

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

where *t* denotes outcomes in task *k* and lottery *Safe* or *Risky*. 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: $u(M_{j,k,t}|r) = \frac{{M_{j,k,t}}^{(1-r)}}{1-r}$. Risk neutrality is found when r=0. Due to its popularity in some literatures we also include a Constant Absolute Risk Aversion (CARA) utility specifications: $u(M_{j,k,t}|r) = 1 - \exp(-r\mathrm{M}_{j,k,t})$. Risk neutrality is found at the limit when r→0. In the lotteries participants were provided with two choice options. We denote EU_k^S as the valuation of the safer option in lottery task *k* (with yellow-red balls), and EU_k^R as the valuation of the riskier option, the one with white and blue balls. 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 a Pratt (1964)sense.

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

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:

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

The additional parameter μ 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 non-stochastic as $\mu \to 0$. In our estimations *r* is defined as a function of the vulnerability variables in Table 2 and the control variables in Table 3, plus the instrument for cumulative earnings:

(4) $r_i = \alpha_0 + \sum_v \alpha_v F_{vi} + \sum_d \alpha_d X_{di} + \alpha_w W_{ik}$

The conditional log-likelihood is

(5) $lnL(r, \mu; y, F, X, W) = \sum_{i,k}(lnL_{j=R}|y_{i,k} = 1) + (1 - lnL_{j=R})|y_{i,k} = 0)$

Where y_i=1(0) denotes the choice of the *Risky* (*Safe*) option by participant *i* in task *k*.

5.1. *Structural Estimation Results*

Table 6 presents the results of the structural estimations. Models 1and 2 are the CRRA specifications and Models 3 and 4 are the CARA specifications, for comparison. The estimated models confirm what we could see in the descriptive statistics and simple regression analysis: risk aversion is increasing in *SoloLargeHH* and *SoloKidsPerRoom*, and decreasing in *SoloManyKids*, and *SoloPersonsPerRoom*. The coefficients are all significant at a level of 1% or higher. The constant term in the *r* equation is significantly different from risk neutrality in both the CRRA and the CARA specifications. The Fechner errors are around 0.15, implying that there is not much noise in the choices but they are fairly close to deterministic.[15]

Including the control variables in Model 1 makes the coefficient estimates of *SoloManyKids* and *SoloKidsPerRoom* more significant. In Model 3 they improve the significance level of *SoloPersonsPerRoom*. While in the logit models we found no other variables than household vulnerability that were significant, here we find significant effects on risk aversion from one financial variable: *WorkEarningsPerHour*. It is significant at a level of 1% or higher in Models 1, 3 and 4.

6. Conclusions

We present estimates that relate risk attitudes to several measures of vulnerability that are induced by poverty for the working poor in a rich country, the US. Our measures of vulnerability include both those related to finances, but also several vulnerability measures related to household composition that have been identified in the poverty literature. With the exception of hourly work earnings, we do not find significant effects from the financial variables. Neither unemployment nor the amount of underemployment are significant, and we also do not find education to have much impact. On the other hand, four of our household composition measures are strongly significant, all relating to solo household heads: the number of dependants, the number of dependant kids, and the crowdedness of the home as a function of the number of dependants, both adults and kids. Risk aversion is decreasing with the number of kids, as long as crowdedness is not more severe. However, risk aversion increases strongly with crowdedness as additional kids stretch housing resources, and the net effect is to increase risk aversion. On the other hand, when households have many dependant adults resulting in crowdedness, the net effect is a decrease in risk aversion. We speculate that this may be due to a selection effect where less risk averse heads of households surround themselves with friends and adult children who are unable to be financially independent. Decreasing risk aversion due to increased vulnerability is consistent with observations made in the gambling literature that poverty tends to increase interest in lottery purchases and gambling. Many of these lotteries in rich countries offer very large prizes, perhaps therefore seen as a chance to get a life altering income boost, opening up opportunities that would otherwise be unreachable. While our lottery prizes are much more modest, they still are 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 \$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%. This suggests that the higher lottery prizes may be viewed by some of the participants as providing them with an opportunity to get something valuable that otherwise would not be attainable.

This qualitative heterogeneity in risk attitudes has implications for public policy as well as for the design of insurance and credit instruments for this population. The individual's choice to either self-insure

[15] In Appendix B we also include models where we estimate μ as a function of vulnerability and control variables in the same way. We do this 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 $p<.01$ and we are therefore confident that our risk aversion effects are not confounded by decision errors. Appendix B is available as a CEAR working paper 2018-05 at https://cear.gsu.edu/category/working-papers/wp-2018/.

through savings, to rely on credit, to purchase formal insurance products, or to depend on publicly provided safety-nets will vary with what type of vulnerabilities that characterizes their household.

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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 Vulnerability Measures

	Description	Mean (stdev) Wave 1 and 2	Wave 3	Pooled	Test of diff. p-value
SoloResponsible	*Sole head of the HH*	40%	34%	38%	.61
SoloLargeHH	*Interaction between SoloResponsible and HH size*	3.6 (2.1)	2.5 (1.9)	3.2 (2.1)	.12
SoloManyKids	*Interaction between SoloResponsbile and number of kids*	2.2 (2.0)	2.1 (2.1)	2.1 (2.0)	.85
SoloNoKids	*SoloResponsible with no kids in the HH*	30%	27%	29%	.18
SoloManyKids cond. on having kids	*Interaction between SoloResponsible and num. of kids when there is at least one kind in the HH*	3.1 (1.7)	2.9 (2.0)	3.0 (1.7)	.60
HHSIZE unconditional	*Household size (excluding the respondent)*	2.8 (2.3)	1.4 (1.6)	2.3 (2.2)	.004
Single Households	*Share of one person HH*	18%	34%	24%	.09
HHSIZE conditional on non-single household	*Size of HH excluding single HH*	3.4 (2.1)	2.1 (1.5)	3.0 (2.0)	.01
NKids unconditional	*Number of kids in the HH*	1.5 (1.9)	.9 (1.6)	1.3 (1.8)	.08
Proportion with no kids	*Share of HH without kids*	48%	66%	55%	.12
Nkids conditional on having kids	*Number of kids in the HH when excluded HH with no kids*	2.9 (1.6)	2.5 (1.8)	2.8 (1.7)	.36
SoloPersonsPerRoom	*Interaction between SoloResponsible and number of persons per bedroom (excluding the respondent)*	1.3 (0.8)	1.1 (.7)	1.2 (.8)	.46
SoloKidsPerRoom unconditional	*Interaction between SoloResponsible and number of kids per bedroom*	0.8 (0.9)	0.9 (.9)	0.8 (.9)	.90
SoloKidsPerRoom conditional on having kids	*Interaction between SoloResponsible and number of kids per bedroom when excluded HH with no kids*	1.1 (0.9)	1.2 (.8)	1.2 (.8)	1.00
BEDROOMS if SoloResponsible	*Number of bedrooms if SoloResponsible*	2.9 (0.9)	2.3 (1.1)	2.6 (1.0)	.14
BEDROOMS if not SoloResponsible	*Number of bedrooms if not SoloResponsible*	2.5 (1.1)	2.3 (1.1)	2.4 (1.1)	.74
Unemployed	*Unemployment rate*	44%	47%	45%	.80
HrsWorkTotalMonth unconditional	*Total amount of working hours per (last) month*	70.0 (66.3)	122 (128.2)	91.1 (98.9)	.14
Proportion zero hours	*Share of people with no hours work last month*	32%	41%	35%	.43
HrsWorkTotalMonth conditional on working	*Total hours for those with positive working hours (last) month*	106.2 (52.6)	205.5 (100.9)	143.9 (88.3)	<.001
WorkEarningsPerHour unconditional	*$ per hour*	7.2 (8.0)	10.8 (13.3)	8.6 (10.5)	.41
WorkEarningsPerHour proportion $0	*Share of 0$ per hour*	32%	44%	35%	.28
WorkEarningsPerHour conditional on positive	*$ per hour excluding the 0$ per hour*	10.9 (7.5)	19.2 (12.3)	13.9 (10.2)	.002
EducNHS	*Share of Not graduated from High School*	32%	22%	28%	.32

Notes: SoloResponsible does not include single households. HHSIZE does not include the respondent. Test of differences in proportions done with chi-square tests. Test of differences in continuous variables done using ranksum tests. 82 participants.

TABLE 3 Control Variables

	Description	Mean (stdev) Wave 1 and 2	Wave 3	Pooled	Test of difference p-value
DEMOGRAPHICS					
Male		50%	31%	43%	.09
Young (<36)		26%	25%	26%	.92
Mid (36 – 49)		20%	25%	22%	.60
Old (>49)		54%	50%	52%	.72
INCOME					
OtherMoneyTotalMonth unconditional	*Total ($) income by other sources than work per month*	390.5 (431.0)	1904.0 (2621.2)	1003.7 (1843.8)	<.001
Proportion with no other income	*Share of respondents with no other income*	23%	0%	14%	.003
OtherMoneyTotalMonth conditional on positive income	*Total ($) income for those with other sources than work*	509.9 (426.0)	1904.2 (2621.2)	1166.0 (1940.5)	<.001
WEALTH					
HomeLowEquity	*Paying rent or mortgage.*	80%	94%	85%	.086
PersonsPerRoom unconditional	*Number of persons per bedroom (excluding the respondent)*	1.0 (0.8)	0.6 (.7)	0.9 (.8)	.012
PersonsPerRoom conditional on non-zero	*Number of persons per bedroom (excluding the respondent) when more than one person in the HH*	1.3 (0.7)	.9 (.6)	1.2 (.7)	.041
KidsPerRoom unconditional	*Number of kids per bedroom*	0.6 (0.7)	0.4 (.7)	0.5 (.7)	.087
Proportion with zero kids	*Share of HH with no kids*	46%	66%	54%	.214
KidsPerRoom conditional on non-zero	*Number of kids per bedroom excluding HH with no kids*	1.0 (.7)	1.0 (.7)	1.0 (.7)	.788
EducMHS	*Share of those with education level beyond highschool*	34%	47%	39%	.244

Note: PersonsPerRoom does not include the respondent. Test of differences in proportions done with chi-square tests. Test of differences in continuous variables done using ranksum tests. 82 participants.

TABLE 4 Safe Choice Proportion by Treatment

	Wave 1 and 2	Wave 3	p-value of difference
Low Stakes	30%	20%	.02
High Stakes	48%	48%	.74
p-value of difference	<.001	<.001	

TABLE 5: Logit Regressions of Safe Choices in Lottery Tasks

	Model 1	Model 2	Model 3	Model 4	Model 5
SoloResponsible	-0.215***		-0.196**	-0.170**	-0.026
SoloLargeHH	0.220***		0.222**	0.241***	0.291***
SoloManyKids	-0.375****		-0.338***	-0.353***	-0.405****
SoloPersonsPerRoom	-0.313		-0.383*	-0.455**	-0.855***
SoloKidsPerRoom	0.781***		0.783***	0.832***	1.269****
EducNHS		-0.048	-0.031	-0.026	0.057
Unemployed		-0.015	0.001	-0.004	0.033
HrsWorkTotalMonth		-0.000	-0.000	0.000	0.000
WorkEarningsPerHour		-0.008**	-0.008**	-0.009**	-0.009**
ProbHigh	-1.658****	-1.604****	-1.680****	-1.685****	-1.717****
HighStake	0.205****	0.218****	0.212****	0.211****	0.202****
CumW	0.001	0.000	0.001	0.001	0.001
Male				-0.005	-0.015
Mid				-0.095*	-0.147**
OtherMoneyTotalMonth					0.002**
HomeLowEquity					0.109
PersonsPerRoom					0.212**
KidsPerRoom					-0.271*
EducMHS					0.075

Note: All coefficients are marginal effects on the probability of selecting the safe lottery evaluated at the means of the variables. * indicates pvalue<.1, ** pvalue<.05, *** pvalue<.01, **** pvalue<.001. N=770.

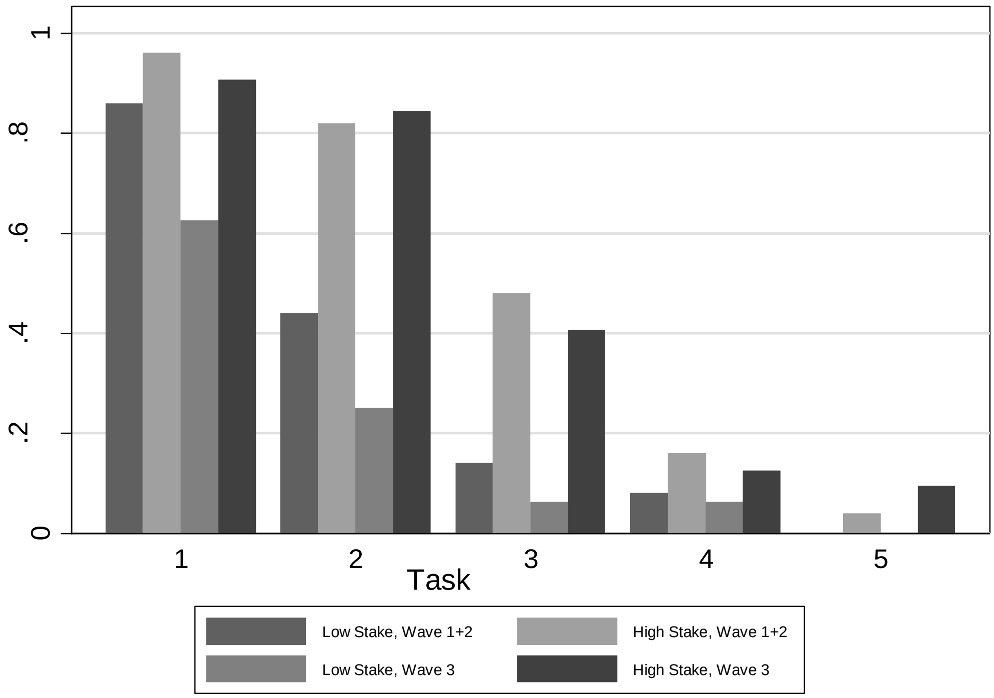
TABLE 6: Structural Estimations of EUT Models

	Model 1 CRRA	Model 2 CRRA	Model 3 CARA	Model 4 CARA
r equation				
Constant	0.407***	0.665****	0.136**	0.241****
SoloResponsible	-0.021	-0.195**	-0.001	-0.076
SoloLargeHH	0.321***	0.247***	0.137***	0.114***
SoloManyKids	-0.428****	-0.364***	-0.208***	-0.192***
SoloPersonsPerRoom	-0.959***	-0.450*	-0.406***	-0.203*
SoloKidsPerRoom	1.365****	0.840***	0.655***	0.453**
EducNHS	0.056	-0.048	0.009	-0.027
Unemployed	-0.027	-0.075	0.004	-0.015
HrsWorkTotalMonth	0.000	0.000	0.000	0.000
WorkEarningsPerHour	-0.012***	-0.011**	-0.005***	-0.005***
Male	0.009		0.012	
Mid	-0.180**		-0.069**	
OtherMoneyTotalMonth	0.001*		0.001	
HomeLowEquity	0.073		0.028	
PersonsPerRoom	0.241**		0.115**	
KidsPerRoom	-0.310*		-0.141*	
EducMHS	0.097		0.042	
CumW	-0.001	-0.001	-0.001	-0.001
μ equation				
Constant	0.138****	0.138****	0.157****	0.157****
LL	-271.82	-277.99	-286.23	-291.64

Notes: Model 1 estimates *r*, employing the CRRA utility specification, as a function of vulnerability and control variables. Model 2 estimates *r* by including vulnerability measures only. Model 3 and Model 4 employ the CARA utility specification and estimates *r* as a function of vulnerability and control variables. *=pvalue<.1 **=pvalue<.05 ***=pvalue<.01 ****=pvalue<.001 N=770

FIGURE 1 Sample Image Page for Binary Lottery Choice Task

FIGURE 2 Proportion of Safe Choices in Lottery, by Task Number



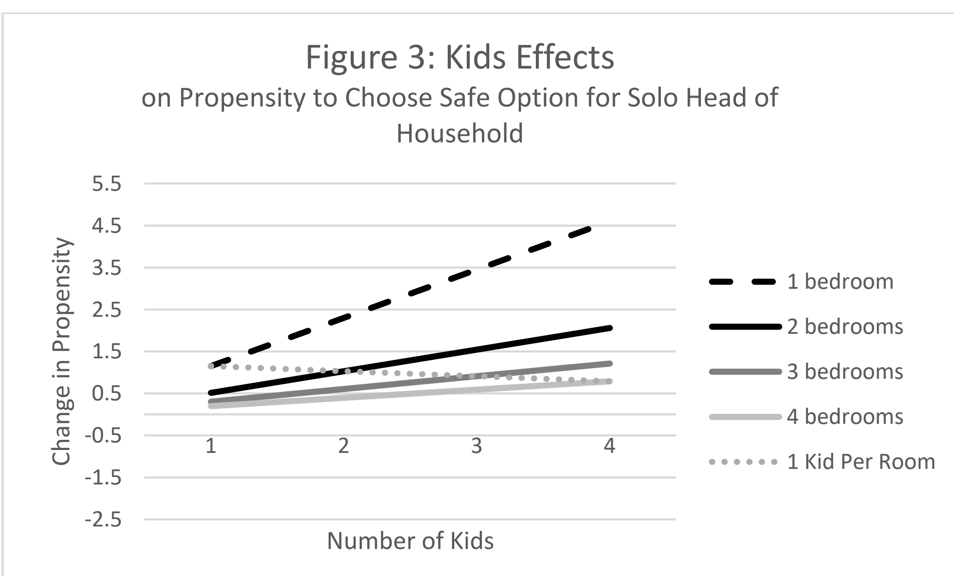


Figure 3: Kids Effects
on Propensity to Choose Safe Option for Solo Head of Household

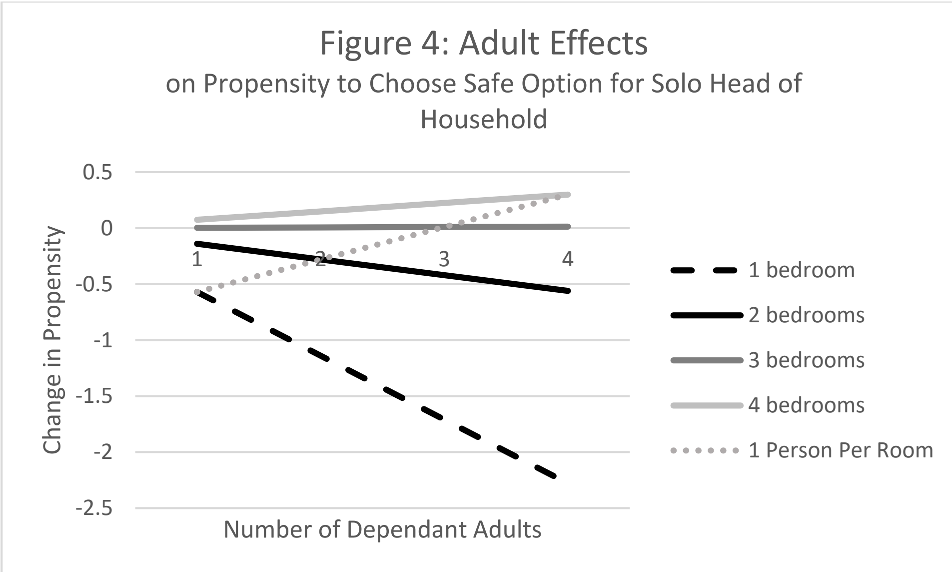


Figure 4: Adult Effects
on Propensity to Choose Safe Option for Solo Head of Household
0.5
0
-0.5
-1
-1.5
-2
-2.5
1
2
3
4
Change in Propensity
Number of Dependant Adults
1 bedroom
2 bedrooms
3 bedrooms
4 bedrooms
1 Person Per Room