Multiple-Item Risk Measures

Lukas Menkhoff and Sahra Sakha

Abstract

We compare seven established risk elicitation methods and investigate how they explain an extensive set of risky behavior with 800 respondents. The seven risk measures are positively correlated to each other but which one robustly explains behavior? Measures perform heterogeneously; their level of performance seems limited, and difficult to assess ex ante. Thus, we use an average of the seven risk elicitation methods which yields much more predictive power. Other reduced sets of multiple-item risk measures also perform clearly better than any single-item measure. Hence, multiple-item risk measures offer a more robust way explaining risk-related behavior.

JEL-Classification: D81 (decision making under risk and uncertainty); C93 (field experiments); O12 (financial markets)

Keywords: Risk attitude; lab-in-the-field experiments; household survey; economic development

February 13, 2015

We would like to thank participants at several conferences and seminars for valuable comments and suggestions, in particular Veronika Bertram-Hümmer, Elisa Cavatorta, Antonia Grohmann, Glenn Harrison, Stephan Klasen, Ulrich Schmidt, Ferdinand Vieider and Juliane Zenker. Financial support by the German Research Foundation (DFG) is gratefully acknowledged.

Lukas Menkhoff, Kiel Institute for the World Economy, 24100 Kiel, Germany, University of Kiel, and Leibniz Universität Hannover; e-mail: lukas.menkhoff@ifw-kiel.de.

Sahra Sakha, Department of Economics, Leibniz Universität Hannover, Königsworther Platz 1, 30167 Hannover, Germany, and Kiel Institute for the World Economy; e-mail: sakha@glad.uni-hannover.de.

Multiple-Item Risk Measures

1 Introduction

Economic decision-making and interactions involve risk. Thus, a substantial body of research tries to understand how decision makers incorporate risk into their choices. These analyses require a reliable measure of individual risk attitude. So far, most studies choose one of the existing methods in eliciting individual risk attitude and take the response to this specific item as “the” individual risk attitude. However, a troubling result from the experimental literature is that the degree of risk aversion varies for the same person across elicitation techniques (e.g., Isaac and James, 2000; Berg et al., 2005; Anderson and Mellor, 2009; Loomes and Pogrebna, 2014). Thus, the choice of risk measure can make a difference. If it makes a difference, it is imperative to know whether one risk measure is possibly superior in revealing risk attitude compared to others. This question is not only of academic interest but also highly relevant for various kinds of applications such as advice in financial or insurance affairs.

We address this largely unanswered question in our research. As a yardstick for identifying a good measure of risk attitude, we suggest its power in explaining risky behavior. So far, the literature uses one risk method and relates it with real world behavior, such as savings, lottery expenditure and occupational choice (e.g., Barsky et al., 2007; Bonin et al., 2010; Sutter et al., 2013; Vieider et al., 2013). Other studies show that some risk measures may work best in specific domains, for example, the attitude towards *financial* risk explains the choice for risky investments (Dohmen et al., 2011). We extend this literature in both directions: risk measures and risky behaviors. We examine in a within-subject design seven established but quite diverse measures of risk attitude and their ability to explain eleven kinds of risky behavior which are taken from an in-depth household survey.

We go beyond the literature by introducing multiple-item risk measures. They are created by combining the seven risk elicitation methods. In a similar study, Falk et al. (2014) investigate the predictability of various survey items on various economic preferences (i.e. risk taking, time discounting, and social preferences) and its predictive power in explaining behavior. Our study, however, differs insofar as we run several risk elicitation methods and use a combined measure thereof to measure its strength in explaining behavior. The motivation for our procedure is not to find an experimentally validated survey item on several preference parameters but rather the existence of within-subject heterogeneity of individual responses across elicitation techniques. This heterogeneity may partly reflect the specificity of each measure and partly reflect simple noise in responses. There is evidence showing that risk-taking behavior is domain specific (Weber et al., 2002; Dohmen et al., 2011). The consideration of noise in survey items or experimental measures has gained prominence, not only econometrically (Harless and Camerer, 1994; Loomes et al., 2002) but in particular for predicting economic outcomes (Beauchamp et al., 2012; Cutler and Glaeser, 2005). Beauchamp et al. (2012) find some stability in risk responses over time but also heterogeneity due to substantial measurement error. They examine predictors of the various risk measures and how the coefficient estimates change once they allow for measurement error. They document large differences in risk attitudes after measurement-error correction. Methodologically, they use approaches from psychometrics and adopt a general latent variable framework that accommodates measurement error across three measures of risk preferences and several behavioral outcomes. They infer that noise attenuates the relationship of risk attitude with other behavioral variables and failure to account for such errors can potentially lead to mistaken inferences.

This is an important issue that our paper attempts to address. We focus on the construction of a multiple-risk item that reduces noise and increase predictive power. A positive implication of our research is to rethink the experimental measurement of risk preferences because knowing ex ante which specific risk measure might be most appropriate, requires a general and more robust measure of risk attitude. To be precise, it requires a method that takes into account the existence of measurement-error and domain-specificity of individual preferences.

Our main finding is that averaging across single-item risk measures, i.e. creating a 'multiple-item risk measure', improves the predictive power in explaining behavior considerably. While all single-item risk measures have some power in explaining risky behavior, taking the average of various subsets of risk measures is superior.

We conduct seven established risk elicitation methods with more than 700 individuals in rural Thailand. We are able to link experimental and survey measures with risky behavior as part of a large household panel survey containing wider socio-economic information. We build on recent literature by eliciting risk preferences using incentivized risk tasks; the certainty equivalent task (CEquiv), two Eckel-Grossmann choice tasks (EG), one with loss treatment and one without (Eckel and Grossman, 2002, 2008), and an investment choice task similar to Gneezy and Potters (1997). In addition to these four experiment-based risk measures, we employ three non-incentivized survey-based measures on risk attitude from Dohmen et al. (2011), i.e. a general willingness to take risk (WTR Gen), the willingness to take risk in financial affairs (WTR Fin) and a hypothetical investment question (HInvQ). Detailed information about the experiments can be found in Appendix A, but key features will be described in the relevant sections below.

In the first step, we investigate the correlation between experiments and interpret conventional results as indicator for their quality: Measures of risk attitude are positively correlated to each other but most of them to a low degree, indicating large differences between measures (see, e.g., Crosetto and Filippin, 2013). As a result, relating risk measures to risky behavior leads to differences in their explanatory power which are related to domain specificity. The HInvQ, for instance, significantly explains investment expenditures or borrowing decisions.

In the second step, we go beyond existing literature and find that averaging across risk measures considerably increases power in explaining risky behavior. (1) We find, in particular, that a simple average across our seven measures has the highest predictive power in our sample; it significantly explains 9 out of 11 kinds of risky behavior, whereas the single-item measures explain between 1 and 5 kinds of behavior. (2) In order to reduce the necessary input and thus to come towards a more practical approach, we find that three factors extract most of the information from the seven single-item risk measures. Each of the three factors is dominated by one risk item. We find that the reduced set of risk items – the three-item measure – is still superior in explaining behavior to any single-item measure. (3) This result is also robust even if we restrict the average to the two most relevant items.

We are aware that our results are specific, i.e. the preference for specific multiple-item risk measures, may be the consequence of our selection of risk measures, risk behaviors, and the sample population. Thus, we do not recommend the inclusion of any specific risk items. However, one practical conclusion from our result is that researchers who try to reveal risk attitudes should consider using several, at least two or three, different measures to reduce noise, thereby enhancing external validity.

Our research is related to four strands of literature: (1) the wealth of studies examining measures of risk attitude (e.g., Dave et al., 2010; Reynaud and Couture, 2012; Deck et al., 2013), and in particular those studies which either (2) assess their consistency by comparing them to each other (e.g., Crosetto and Filippin, 2013; Loomes and Pogrebna, 2014) (3) assess their validity by testing the predictive content of risk measures (Dohmen et al., 2011; Sutter et al., 2013) (4) taken into account noise (Andersen et al, 2008; Kimball et al., 2008).

Our paper is organized in ten sections: Section 2 presents the survey data and collection process. Section 3 presents descriptive statistics of our sample and experiments. Section 4 demonstrates the relations between risk measures and thus our first minor finding. Section 5 presents results on predictive ability of risk measures. Section 6 outlines the performance of the simple averaging measure. Section 7 presents results from the factor analysis. Section 8 shows results from the reduced multiple-item measures, while we perform a sensitivity analysis in Section 9. Section 10 concludes.

2 Descriptions of the Survey and Risk Elicitation Tasks

2.1 Implementation

In August 2013 we conducted a risk survey in rural Thailand including experiments with households that also participated a few months earlier in the 5th wave of a larger household panel survey. In total, 830 households participated from 98 villages. We visited two villages per day, one in the morning and one in the afternoon. We cannot fully eliminate the possibility that information had spread between villages; yet this is rather unlikely because most of the villages are far away from each other (18km on average).

The study was carried out by local enumerators with one of the research fellows being present at all times to ensure compliance. Some enumerators were different from those conducting the household survey but had extensive interviewer skills acquired in other surveys. We do not find any systematic interviewer fixed effects. The survey was translated from English into Thai and vice versa and was cross-checked by a Thai economics professor to avoid semantic difficulties. The interviewer training lasted for a total of five days. During these five days, a pilot study was conducted in three villages.

In general, enumerators were instructed to select the household member (usually the household head) who was previously interviewed in the household survey to participate in the experimental study. In case that person was not available, enumerators selected the closest family member present. In 44 cases we interviewed households which had not participated at the household survey, so we miss baseline information about these households (and its members) and drop them from our current analysis. Further, we restrict our sample to respondents aged between 17 and 79 years. It is assumed that respondents with age above 80 or below 17 may have more difficulties in understanding the experiments. Hence, we drop another 26 observations. Ultimately, we work with 760 observations.

The experimental sessions were conducted in the village town hall. To avoid observation, we made sure that respondents were separated across the town hall. Furthermore, decision spillovers are unlikely because individuals responded at different pace levels. Of course, we cannot exclude the possibility of observation altogether.

Upon arrival, the experimenter reminded participants of the confidentiality of the data. In order to ensure incentive compatibility, subjects are informed that after the experiment a random device will determine which experiment will be paid out depending on their decision. The maximum number of participants in any session was 10. Care was taken to ensure that subjects understood the decisions they were to make.

Once all seven choices were made, one decision was randomly chosen from the incentivized part for payment. The respondents had to pick a number from a non-transparent bag to determine which experiment is played out and a coin was used to determine the outcome of the risk game. Average earnings were 150 Thai Baht (THB), i.e. approximately 4 € slightly less than a one-day salary of an unskilled worker. The show-up fee was 50 THB (approx. 1 €). The EG (Loss) included a negative outcome (-30 THB). We, however, avoided negative payoff by providing an initial fee of 30 THB equal to the maximum loss that could be incurred due to ethical reasons (in a manner similar to the Hey and Orme (1994) replication exercise done in Harrison and Rutström (2008), p.164). This is not given in the no loss experiment. It should be noted that this has the potential drawback that loss aversion might be underestimated. However, there is little evidence that the house money effect is likely to change the result when we compare the baseline study of Eckel and Grossman (2008) and our results. Each session included exactly the same set of instructions and was implemented in the same order. While the risk experiments took half an hour, the entire risk survey from the beginning to the final payoff took approximately two hours to complete.

2.2 Household Survey and Sampling Procedure

Our risk survey is administered as part of a larger household survey which collects data from approximately 2,200 households in three provinces in Thailand. The household selection process follows a three-stage stratified sampling procedure where provinces constitute strata and the primary sampling units are sub-districts. Within each province, we exclude the urban area around the provincial capital city and confine the sample to the remaining rural areas. Within each sub-district, two villages are chosen at random. In the third stage, a systematic random sample of ten households was drawn from household lists of the rural census ordered by household size. Overall, the sampled households are representative for the rural areas in the considered provinces. Compared to the household survey which ran in three provinces, our risk survey was conducted in the province of Ubon Ratchathani only, the largest of the three provinces in Northeastern Thailand.

Given the sampling procedure, we control for within-cluster error correlation. Instead of randomly drawing individuals from the entire population, costs are reduced by sampling only a randomly-selected subset of primary sampling units (sub-districts), followed by a stratified selection of people within the chosen sampling units (village level). Hence, we cannot assume that observations within villages have uncorrelated errors. Households of the same village might be more similar on a wide variety of measures than are households that are not part of the village. We, therefore, cluster the standard errors at the village level (Cameron and Miller, 2013).

2.3 Risk Elicitation Tasks

We began our risk survey with three non-incentivized hypothetical questions concerning risk attitude which have been used by Dohmen et al. (2011) (Details are shown in Appendix A). The first item is the general risk question from the German socio-economic panel study (SOEP) and asks "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?" Responses are given on an 11-point Likert scale where the value 0 means "not at all willing to take risks" and the value 10 means "very willing to take risks". The second question is domain-specific and refers to the financial affairs of the household. The third non-incentivized risk measure is the hypothetical investment question. Variations of these questions appear in several large panel surveys of U.S. households: the Health and Retirement Study (HRS), the Panel Study of Income Dynamics (PSID), and the National Longitudinal Survey of Youth 1979 (NLSY79).

Afterwards, we conducted four incentivized experiments. The first is a certainty equivalent task and has been implemented by Abdellaoui et al. (2011), Bruhin et al. (2010), Dohmen et al. (2011), Sutter et al. (2013), or Vieider et al. (2014). Appendix A illustrates the basic payoff matrix presented to subjects. The first row shows that the lottery offers a 50-50% chance of receiving either 0 THB or 300 THB and alternatively a safe payoff of 0 THB. The expected value of this lottery is 150 THB. Therefore, it is rational to choose the lottery over the safe payoff. The second row, however, already offers 10 THB as safe payoff. This provides the opportunity for risk-averse individuals to opt for the safe payoff over the lottery. The value of the safe payoff is increased in each row by 10 THB. The switching row from the lottery to the safe payoff designates individuals' risk attitude. We did not allow switching back and forth.

The second and third experiment is an adaptation of the Eckel and Grossman (2002, 2008) task. Subjects must play one out of five possible gambles. We employ two versions of the task with and without loss treatment. All the gambles involve a 50/50 chance of a low or high payoff. The range of gambles includes a safe alternative involving a sure payoff of 50 THB with zero variance in the loss treatment and 80 THB in the no-loss treatment. From here, the gambles increase in both expected return and risk (standard deviation) moving from Gamble 1 to 5. Losses are possible up to 30 THB. In the no loss framing, all payoffs are shifted up so that the minimum payoff is zero. Risk-averse subjects would choose lower-risk, lower-return gambles; while risk-neutral subjects are expected to choose Gamble 5 which has the highest expected rate of return.

The last experiment is similar to the one introduced by Gneezy and Potters (GP) (1997). Given its framing, it can be regarded as an incentivized version of the hypothetical investment question. Instead of choosing lotteries, subjects have to decide how to allocate a given endowment of 100 THB. They can choose to invest a fraction of their endowment in a risky lottery. The risky lottery means that with a 50:50 chance, they can either lose or win three times their money invested. In all cases the expected value of investing is higher than the expected value of not investing; thus, a risk-neutral (or risk-seeking) person should invest 100 THB, while a risk-averse person may invest less.

2.4 Risk Measures and Risk Preferences

The seven above introduced risk elicitation tasks all aim to reveal risk preferences but the methods are quite different. As we will sketch shortly, these measures are not fully comparable to each other in a strict sense. However, all of them are widely used as risk measures and from this applied perspective we are interested in their relative performance.

Among the four incentivized experimental elicitation methods the certainty equivalent task is our most precise measure of risk attitude. It is based on 20 choices between a risky lottery which offers either 300 Thai Baht or zero with equal probabilities and varying safe amounts s_j, j = 1, …, 20 ranging from zero to 190. For the sake of simplicity, we could assume for all four incentivized methods that risk preferences are represented by a Constant Relative Risk Aversion (CRRA) utility function defined as U(y) = (y1- *r*)/(1- *r*), where y is the lottery price and $r \neq 1$ is the CRRA coefficient to be estimated. For r =1, assume U(y) =ln(y) if needed. Thus, r is the coefficient of CRRA: r = 0 corresponds to risk neutrality, r<0 to risk loving, and r>0 to risk aversion. Thus, for the certainty equivalent task, for instance, we can calculate the range of the CRRA; that is when subjects choose to switch from the lottery to the safe payoff. For example, a subject that made 5 lottery choices and then switched to the safe payoff alternatives would have revealed a CRRA interval between 0.569 and 0.613.

However, our certainty equivalent task is the only measure showing a fairly complete range of preferences. The other three tasks, the GP and both EG tasks can only estimate r ≥0. In other words, they cannot distinguish risk neutrality from risk seeking. Charness and Gneezy (2012) claim that this is a minor problem because risk seeking preferences are seldom observed, although given our certainty equivalent task 21% of the subject pool is characterized by r >=1. Hence, we have a limitation using the CRRA because it restricts the analysis to a utility function that characterizes risk attitudes using only one parameter. Moreover, since the different tasks are also characterized by different ways of eliciting risk aversion parameters, the shape of the function linking choices to *r* can greatly differ across tasks (Harrison and Rutström, 2008). The case is even more problematic regarding the three survey items because they cannot be usefully transformed to a risk aversion parameter at all.

It is for these reasons that our analysis does not apply any specific form of utility function. So instead, we focus to investigate the external validity of our risk elicitation methods in relation to real-life choices.

3 Descriptive Statistics

3.1 Individual Characteristics

Table 1 presents individual characteristics of our sample in three panels. Panel A describes seven standard socio-demographic characteristics which we will regularly use as control variables in our regressions. A large proportion of our sample are woman (58%), on average 54 years old and 1,58 cm tall. 98% have attended school at some point with 5.7 years of school education on average. Given the average age of our respondents, 81% of our sample are married and live in households with approximately four other household members. The log per capita consumption of 7.6 reflects an annual total household consumption level of 6,073 $ PPP.

Panel B summarizes answers on various behavioral items and further sample characteristics. After the risk experiments have been completed, we asked the respondents six mathematical questions, including addition, multiplication, and percentage calculation (Details can be found in Appendix B). Our respondents have moderate algebra skills (3.63 out of six exercised were solved correctly on average). Further, 60% of the respondents are describing their own agricultural business as their main activity while only 14% report that they are self-employed. About 31 % of our sample did engage in lottery activities at least once over the past 12 months, devoting an average share of about 6% of their annual expenditures to legal and illegal lottery participation. 70% of our respondents hold insurances (1.95 on average). Although the majority of health care services in Thailand are delivered by the public sector, still six percent chose an additional health insurance package. Additionally, eight percent chose an accident insurance. Our sample made on average 4954$ investments in agricultural and non-agricultural sector in the last two years which is around half of the total income. It must be noted, however, that there is a large share of people who did not make any investments. Furthermore, it can be said that 70% of the respondents borrowed money in the last two years. When asked for its purpose, around 70 subjects report to have borrowed for business purposes. Moreover, at least 49% of our sample took any precautionary measures against future shocks and risks. The number thereof ranges from one to even eight risk-mitigating activities. The majority of our respondents have a BMI in the normal range.

3.2 Experimental Results

Table 2 shows the summary statistics of all seven risk elicitation methods in the order of the survey. It can be inferred that the WTR (Gen) has an average value of 6.9 for our sample. Our average value is higher than in the study of Dohmen et al. (2011) for Germany whose mean value in the experimental sample is 4.76, and also higher than responses of similar households in the same province of Thailand in 2008 (Hardeweg et al., 2013). What drives the result is that a large share of respondents also chose the highest risk seeking category of 10. This is also the case for financial matters albeit less than in the general question which corresponds to the study of Dohmen et al. (2011) where respondents are more risk-averse in the financial part than in the general question. Our results are also similar to Charness and Viceisza (2011) who conducted the same question in rural Senegal. In the robustness section (Section 9), we will show that our main results are not distorted due to unusually risk-seeking answers.

Turning to the next risk item, the average amount of investment is 50.88 THB. 60% of respondents choose the median amount of 50 THB. However, looking at the distribution, we find that the respondents tend slightly towards investing more than 50%. This also indicates some risk-seeking behavior. This result is similar to Hardeweg et al. (2013).

The average switching row in the CEquiv task is 7.93. This means that on average people choose lower switching rows and are, therefore, more risk-averse. To be precise, 76% of the respondents are risk averse, that is to say, they choose to switch before row 16, 3% are risk-neutral and 21% are risk seeking. Similar results are found by Hardeweg et al. (2013) whose mean switching row was 6.80 and where the majority of respondents prefer switching rows below row 16. Dohmen et al. (2011) found that the average German was risk averse with respect to their choices while Harrison et al. (2007) found similar results for the Danish population.

For both EG tasks, we find the median lottery choice to be 3 confirming risk averse behavior measured by the CEquiv task. We used both treatments in order to analyze the effect of loss-aversion. Given that loss coefficients smaller than 1, we can infer that that our respondents are overall gain-seeking, a common finding in the literature (Wakker, 2010).

Concerning the last incentivized task, the GP experiment, one can infer than people invest less in the risky option than in the hypothetical investment question. Only 7% chose to invest all their endowment in the risky option while nearly 30% chose to invest nothing, indicating strong risk-averse behavior. Compared to the distribution from Charness and Villeval (2009) for employees of two French firms where 19% of the sample invested all their money in the risky option, Thai households seem to be the relatively risk averse with respect to the GP task.

There seems to be a difference in risk attitude for the non-incentivized and incentivized version of essentially the same measure. Behavioral differences between the evaluation of hypothetical and real payoffs can be attributed to this incentive effect. Slovic (1969) discussed differential effects in real and hypothetical payoffs while Holt and Laury (2002) found that risk attitudes become more risk averse for high-stakes lotteries.

Overall, there seems to be evidence of heterogeneity of responses across our seven elicitation methods. On the one hand, we have the survey questions indicating risk-seeking behavior. On the other hand, the GP and the CEquiv task, for instance, exhibited risk-aversion. Non-conforming results are also to be found in the study by Vieider et al. (2013) who find low risk aversion amongst poor Vietnamese farmers and Charness and Viceisza (2011) for the Senegalese population. With regard to the results above, it seems that there are systematic differences in risk attitudes between developing and developed country and one should be careful in implementing the same procedures because other background factors, such as culture, belief in luck, etc. may play a role.

4 Relations of Risk Measures

In this section we document relations of risk measures, first with socio-economic variables (Section 4.1) and, second, with the other risk measures (Section 4.2). Despite the fact that we find high degree of heterogeneity across risk measures, statistically significant results are as expected.

4.1 Risk Measures and Socio-Economic Correlates

Table 3 explores the relationship between various risk elicitation methods and socio-economic correlates. In explaining the individual risk attitude, we rely on a set of seven standard variables which are potential determinants of risk attitudes (Dohmen et al., 2011). Noticeable is the reduction of the sample size from 760 to 715 which is due to missing observations in terms of schooling and consumption. We shortly comment on significant coefficients only.

We find that women tend to make more risk-averse choices, although this turns significant in two out of seven measures only. This finding is consistent with an emerging literature documenting differences in the risk preferences of men and women using various risk elicitation tasks (Croson and Gneezy, 2009). Age has an ambiguous relationship with risk attitude. It seems that younger people are more risk seeking in the WTR (Fin) as well as the HInvQ. This is in line with the results found in Dohmen et al. (2011). This result is different in both EG tasks where older people make more risk-seeking choices. The relationship with height is hardly significant and coefficients seem to be inconsistent. For marital status we find in three cases statistically significant evidence that married people make more risky choices. With regard to remaining variables, more education and higher consumption tend to go along with more risk tolerance. We do not find any significant relationship between risk attitude and household size. Overall, significant relations have the expected signs; only the relation to age is ambiguous.

4.2 Correlations between Risk Measures

Table 4 depicts the Spearman rank correlations between the various elicitation methods. Overall, we observe mostly positive correlations. 11 of the 21 coefficients are statistically significant and all of these significant coefficients are positive. Some coefficients have higher correlations, such as the two risk survey questions (0.36) and both EG tasks (0.43). Other coefficients are rather moderate, for instance between the HInvQ and the GP task (0.20). Moreover, within elicitation methods with similar framings, the degree of correlation is higher than across elicitation method.

Low correlation between tasks is a recurrent finding in the literature. Crosetto and Filippin (2013), for instance, perform a comparative analysis of five-incentivized tasks and also found low correlations. Their explanation is that when facing multiple decisions under uncertainty, subjects could maximize their utility in every period, thereby making the best choice every time. For example, subjects could make in the first two choices risk-averse decisions and risk-loving ones in the second two. If this is the case, the low correlation across tasks would be an artifact of the multiple decision framework rather than reflecting idiosyncratic features of different tasks. However, such effects should be marginal in our setting as participants did not know about the number and kind of tasks to be played at the beginning.

Vieider et al. (2014) found that correlation coefficients for gains tasks between countries vary, from about zero and even slightly negative to about 0.40. Another study that compared risk elicitation tasks is Deck et al. (2013). They compare four elicitation methods: Holt and Laury (HL), EG, the Balloon, and a version of 'Deal or Not Deal' TV show. They find a significant, though weak, correlation between the EG and HL and between the two visual tasks (The Ballon and Deal or Not Deal). Hey et al. (2009) compare willingness-to-pay, willingness-to accept, BDM measures and choices over pairwise lotteries. They found inconsistencies and in some cases even negative correlations between results of the different methods within individuals. Anderson and Mellor (2008) compare results of the method developed by Holt and Laury (2002) and survey results on gambles, finding that except for a small fraction of 'consistently consistent' decision makers, the methods did not provide consistent within-individual estimates of risk attitudes.

Overall, it can be said that given the varying degree of complexity and differences in methods, we find significant but low correlation across tasks indicating high noise levels across tasks. Further, we hypothesize that the degree of correlation is highest when two measures have similar frames (i.e. survey vs experiment) or by 'field' (i.e. here investment / financial issues).

5 Risk and Risky Behavior

In this section, we relate all the seven measures of risk attitude to eleven behaviors that according to theory should be greatly affected by risk attitude. We review theoretical arguments for the effects of risk attitude on individuals' or households' behavior and then test whether our measure of risk attitude has predictive power. We find unequivocal evidence that the direction of prediction is always correct, but that the degree of predictions is somewhat low. Section 5.1 discusses the results by the kind of risky behavior and Section 5.2 shortly reviews the same results from the perspective of the risk measures.

5.1 Areas of Risky Behavior

In this study we cover five domains of risky behavior which we capture by two or three concrete risky behaviors. These five diverse domains are: gambling (playing lottery), risky employment, financial behavior (investment, borrowing), risk avoidance (insurance), and behavior towards health.

Gambling (playing lottery). Expenditures for lottery and potentially other forms of gambling seem to be an important part of many poor household's budgets. Poor households do not spend all of their money on food and non-food items but instead entertainment related activities, i.e., alcohol, tobacco, festivals and also playing lotteries account for an important share of many poor household's budgets (Banerjee and Duflo, 2007).

The relationship between gambling and risk attitude is close because participation in a lottery is a risky decision. Hence the purchase of lottery tickets is a good indicator of risk-seeking behavior. The relationship is studied in numerous works (Clotfelter and Cook, 1990). Our risk survey measures the purchase of lottery tickets for the total household in the last 12 months. Thus, the link between respondent and the purchase of ticket is not perfect as other members of the household may be responsible for this expenditure. Nevertheless, most respondents are also the household head, who is defined as being responsible for the household expenditures. 56% of our respondents are the household head, 32% are the spouse of the household head, while the rest of the respondents are other members of the family. However, when the household head is not playing him/herself, he/she will typically agree that part of the household income is spent on buying lottery tickets so that we expect a relation between respondents' characteristics and lottery ticket purchase. Nevertheless, in the robustness section, we perform the same analysis using only household heads. Complementing the backward looking question on past lottery expenditure we also asked the respondent how much, he/she is willing to spend in the next lottery drawing.

We estimate an OLS regression of the effect of risk attitude on lottery expenditure as a share of total household expenditure. All statistically significant coefficients are presented in columns (1) and (2) in Table 5.

Risk attitude is significantly correlated to past lottery ticket purchase for the WTR (Gen) and the EG (Loss) employing a set of control variables. Both risk measures exhibit the expected signs indicating that risk-tolerance is associated with higher lottery expenditure. The EG (Loss) framing may be more crucial in explaining lottery expenditure since lottery playing itself can lead to gains or losses. Details of the full regression procedure are available on request; they show that being female and having higher consumption level are the most important variables in explaining a lower expenditure quota of lottery tickets.

With regard to the *future* lottery spending, we find that increased future spending on lottery ticket is positively correlated with increased risk-seeking behavior in the EG (Loss) task at the 5% significance level. This overlaps with the finding for past lottery expenditure. However, in addition to that and possibly due to the future outlook of the question, we find that the GP task also significantly reveals the relationship between future lottery spending and risk aversion. Moreover, while the WTR (Gen) lost its explanatory power for future spending, we find that the EG (No Loss) is now significant. These results seem more difficult to explain and indicate some heterogeneity in results.

Risky Employment. Entrepreneurship is another prominent example of risk behavior. Knight (1921) considered the factors which influence entry into *self-employment* and stressed the special role of the entrepreneur as operating under uncertainty and bearing risk of business failure. Since running a business is equivalent to the choice of a risky prospect, the less risk-averse will become entrepreneurs while the relatively risk-averse will prefer to be employees and work for a fixed wage.

In line with this theoretical prediction, the body of empirical evidence on risk, uncertainty and entrepreneurship shows risk tolerance of entrepreneurs. For example, risk tolerance explains undiversified portfolio holdings (Moskowitz and Vissing-Jorgensen, 2002). However, in a recent study, Holm et al. (2013) find that entrepreneurs do not generally differ from other people when it comes to behavior under uncertainty.

Eliciting risk attitudes on a sample of *farmers* is worth being undertaken for several reasons. First, farmers are used in their professional life to take decisions under uncertainty (they face production, market, and environmental risks). Second, being a farmer in a poorer rural area is often the last resort of those who are not entrepreneurial or mobile. Third, there is currently no consensus in the agricultural economics literature on the level of farmer's risk aversion (Reynaud and Couture, 2012). Hence, we do not expect ex ante a specific sign on the risk variables. We are aware that the decision for being self-employed (farmer) and lower (higher) risk aversion suffers from reverse causality. Since we cannot clearly identify causality we interpret the results as correlates.

We implement a Probit model to estimate the correlation between risk attitude and the probability of being self-employed. Column (3) in Table 5 displays the marginal effects at the mean observation. Risk attitudes are significantly related to self-employment which is revealed by the CEquiv and the EG (No Loss) task. Thus, our results are in line with the findings of Moskowitz and Vissing-Jorgensen (2002).

In column (4), we find that the CEquiv and the EG (No Loss) experiments significantly explain risk aversion of farmers at the 1% and 10%, respectively. This is in line with the finding of Reynaud and Couture (2012). Their study also shows that farmers appear to be more risk-averse using the HL and EG experiments. They also found inconsistent risk preferences of farmers which seem to be context-dependent. Our study, however, shows that apparently the EG (No Loss) and the CEquiv task best explain risky employment.

Financial Behavior. First, standard portfolio theory predicts that the share of wealth an individual is willing to *invest* in risky assets depends on his/her degree of risk aversion. Even though exact conditions are hardly met in reality, in particular as poorer farmers do not and cannot hold a market portfolio, the more risk-averse should hold safer portfolios and make less risky investments.

Second, to *plan an investment* in the future is embedded in uncertainty about the conditions under which the planned investment may take place. We hypothesize that risk-tolerant rather than risk-averse individuals should be more prone in planning to conduct considerable investments.

Third, *borrowing* can be generally seen as a decision which entails risk because the borrower has agreed to future repayment without knowing his future economic situation. Thus, the less risk-averse individuals should be more likely to borrow more for investment purposes.

As a regression model for explaining respondents' investment decision, i.e. the share of the income they invest as part of households income, we use least squares with clustered standard errors. We find in column (5) that the risk items which are closely correlated to investment, namely the HInvQ and the GP experiment, are able to explain significantly whether respondents invest a higher share of their income.

Using a probit model to estimate the correlation between risk attitude and planned investment with clustered standard errors, we find in column (6) that the CEquiv task is able to explain planned investment and is statistically significant at the 1% level. It is interesting to note, that the CEquiv task seems to capture forward looking risk attitude. It is successful in explaining future gambling behavior as well as now future investment decision.

We employ a probit model for borrowing and find in column (7) that the probability of borrowing is significantly explained by the WTR (Fin). Furthermore, since borrowing incorporates potential future investment, this may explain why the HInvQ is statistically significant at the 10% level in predicting the probability of borrowing.

Risk avoidance. Income risk is a central feature of rural areas in developing countries. A major concern is how well households are able to mitigate adverse effects of income risk on their welfare (Alderman and Paxson, 1992). In the absence of formal insurance markets, household undertake actions to reduce the variability of income. Risk-averse individuals may choose to implement or undertake more *risk-coping mechanisms* (i.e. substitute crops, diversify agricultural portfolio etc.) than a risk-seeking individual.

The classical model of the demand for casualty insurance elaborated by Mossin (1968) implies that risk-averse individuals should fully insure if *insurance* is offered at fair terms. If insurance is unfair, the amount purchased will depend on one's degree of risk aversion: the more risk-averse will demand more insurance coverage. Nevertheless, even some risk averse may choose not to insure if departure from fairness is significant. Thus, differences in risk aversion should predict not only the amount of insurance demand among insurance holders but also the decision to buy an insurance policy among risk-averse consumers.

We find a statistically significant relationship between risk attitude and the implementation of any precautionary measures against shocks and risks (see column 8): The more you are willing to invest in the HInvQ, the less likely are you to adopt risk-mitigating measures. The result is also robust in the EG (No Loss) experiment. The results are in line with findings in the literature. Risks cause farmers to be less willing to undertake activities and investments that have higher expected outcomes, but carry with them risks of failure (Yesuf and Bluffstone, 2007; Dercon and Christiaensen, 2011). In other words, households are reluctant to adopt new agricultural technologies when risk is involved.

Next, we examine the *number* of insurance contracts a household holds. Using a probit regression as shown by column (9), we find that more risk-seeking consumers are less likely to hold private insurances. This holds only for the EG (No Loss) risk item.

Behavior towards health. Regarding health issues we consider the case where next to the free health insurance from the state, respondents also chose to have an additional health insurance with better coverage. The expectation is about the same as for the number of insurance contracts analyzed before.

In the field of health economics, attitudes toward risk are also likely to affect the propensity to engage in behaviors that either increase or decrease mortality risk, such as cigarette smoking or seat belt use. Viscusi and Hersch (2001) and Anderson and Mellor (2008), for example, used smoking status to control for risk preference in terms of employment-related risk-taking and seat belt use. We compute the BMI of our respondents and use this measure to relate risk attitude with health decisions. The measure of BMI is also used in the study of Sutter et al. (2013) who found that the BMI of students is strongly associated with risk aversion. In the robustness section, we only consider overweight respondents.

For health insurance, we find that the WTR (Fin) and the HInvQ is able to predict risky behavior (see column 10). In the last column of Table 5, investigating the relationship between BMI and risk attitude, we find that higher risk-seeking behavior is correlated to higher BMI which is statistically significant in the HInvQ. These findings show (again) the relationship between risk attitude and risky health behaviors.

5.2 Predictive Ability of Single-item Risk Measures

While Section 5.1 focuses on the risky behaviors, Section 5.2 will investigate the outcomes per risk item more carefully. Considering the 11 x 7 matrix in Table 5, it becomes obvious that all items have some predictive ability - each of them has at least one significant coefficient. There are, however, larger differences. Some risk items have more strength and others more weaknesses in explaining risky behavior. The WTR (Gen), for instance, is only able to predict behavior in one out of our eleven cases, while the EG (No Loss) task is able to explain behavior in five cases. The two measures with more general ability are the HInvQ and the EG

(No Loss) item. Overall, it can be said that the predictive ability of the single risk items is disappointing in our sample. In only 20 out of 77 efforts of predicting behavior, we are successful. The good news is, however, that despite limited predictive ability there is never a wrong prediction since all significant coefficients in Table 5 have the expected sign.

Of course the specific numbers in this exercise should not be over-interpreted because other kinds of risk behavior or another sample population may deliver different results (see also our robustness section). Despite these unavoidable limitations, however, there seem to be four plausible and potentially robust lessons emerging: (1) It makes a difference which measure one takes (regarding explanatory power) due to heterogeneity across risk measures. (2) Our table indicates – in line with earlier findings – that there is an element of domain specificity in risk measurement. The WTR (Fin) best explains "borrowing" or HInvQ and GP best explain investment behavior. However, domain specificity is not the only part of the overall structure we find because beyond these close relations, some risk measures are able to explain various kinds of risky behavior whereas other measures cannot. (3) An interesting side-aspect here is that the more "precise" experimental measures do not show better predictive ability than the simple survey items (like the HInvQ) on average and in our setting. (4) Finally, and the most interesting result for our purpose, we find noise as a plausible reason of low explanatory power. In the robustness part, we will show that our results are not driven by domain specificity or a lack of understanding (because better educated or more intelligent participants do not provide much more consistent answers). Given these results, it seems well possible that participants are influenced by idiosyncratic factors, such as mood or subjective connotations of items etc. This motivates us to rely on several risk items in order to reduce noise in single-item responses.

6 Averaging of Risk Measures

In order to get more robust information about risk attitude, we take an average across responses and test whether our multiple-item risk measure performs better than any single-item risk measure validating the same risky behavior as before. We first describe methodology and then results.

6.1 Creating a Multiple-Item Risk Measure

We average the risk measures in our analysis so that the measures have a mean of zero and a standard deviation of one. Averaging facilitates interpretation of results because it makes sure all variables contribute evenly to a scale when items are added together. Therefore, coefficients can be interpreted directly showing the change in lottery expenditure. Our analysis uses a single combined measure of risk attitude which is constructed by averaging the seven standardized measures of risk attitude and then standardizing the resulting average. First, the mean is subtracted from the value of each item, resulting in a mean of zero. Then the difference between the individual's item and mean is divided by the standard deviation, which results in a standard deviation of one. This way of combining the measures has the practicality as it helps reducing measurement error and achieves a more reliable measure of risk attitude.

6.2 Multiple-Item Risk Measure and Risky Behavior

In this section, we perform the same analysis as in Section 5, however, this time using the average of the seven measures to explain behavior. We find that the resulting multiple risk item improves notably predictive power in explaining behavior. We show this with regard to the eleven kinds of risky behavior (Table 5, bottom). We only report core results while full tables are given in Appendix C. We find that this 'average measure' explains more risky behaviors than any single-item measure. While the best item in Table 5 – the HInvQ or the EG (No Loss) task – is only able to explain risky behavior in five cases, our multiple-item risk measure is able to explain them in nine cases.

Thus the average measure appears more robust. However, for some specific forms of risky behavior our single-item measure predicts better behavior. We assess the predictive ability by the level of significance reached. By this criterion, the average measure is best in predicting lottery expenditure as it reaches the 1%-significance level which is better than the 5%-levels reached by WTR (Gen) and EG (Loss) (see Table 5, column 1). We can say here that a one-standard deviation increase in risk-tolerance (of the average measure) increases the share of lottery expenditure by approximately 4%. Regarding future lottery expenditure, the average measure is as good as EG (No Loss) because both risk measures realize coefficients which at significant at the 1%-level. Regarding all other nine kinds of risky behavior, however, the average measure is never best, although it is significant in seven of the remaining nine cases. This indicates – from another perspective – that there seems to be a trade-off between robustness and precision in specific cases.

For practicality reasons, it would be interesting to see whether we can reduce the number of items considered and still keep the power in explaining behavior. For this, we employ a factor analysis below.

7 Factor Analysis

In this section we perform a standard procedure to reveal a reduced set of factors from the seven risk measures (Section 7.1). We use these factors to predict risky behavior and learn about the explanatory power of these factors (Section 7.2) and what might be substitutes for the factors.

7.1 Identifying the Factors

From the correlation matrix we saw varying degrees of correlation across risk elicitation methods. Hence, the question now is whether and to which degree we can reduce the information contained in the seven risk measures.

In order to reduce the number of variables and to detect structure in the relationships between risk items, we employ a standard factor analysis. The Kaiser-Meyer-Olkin (KMO) measure verifies the sampling adequacy for the analysis. All KMO values for individual items are above 0.5, supporting retention for the analysis. Factor analysis yields three factors with an eigenvalue of 1.16, 0.87 and 0.70. The first factor accounts for 43% of the variance and the loading are dominated by the HInvQ. The second factor explains 43% of all variance and is dominated by the two EG items. We can see that 74% of the common variance shared by the seven variables can be accounted by the first two factors. The third factor is dominated by the WTR (Gen) and to some extent by WTR (Fin) and has the lowest explained variance.

After careful examinations of eigenvalues, proportion of variance explained and Scree plot criterion, three factors are identified for further use. After rotation, we find a clearer picture of the relevance of each variable in the factor. We drop those variables with a loading smaller than 0.30 (see Table 6). Based on the a priori classifications, a clear and interpretable underlying structure is identified. We are able to confirm the result described above, in that factor 1 is mostly defined by the HInvQ, factor 2 is defined by the two EG experiments, while factor 3 is defined by the two WTR items.

7.2 Risk Factors and Risky Behavior

Next, we consider each factor and its power in explaining the same behavioral items as above (see Table 7). We only show statistically significant coefficients, employ the same control variables and report clustered standard-errors. We find that factor 1 has – as to be expected – the best explanatory power among the three factors as it explains risky behavior in 6 out of 11 cases. It is, for instance, able to explain investment and borrowing behavior at the 10% level, i.e. two behaviors from the financial domain. We also find the expected signs for the domains of risk avoidance and behavior towards risk. Thus, we find slight domain-specificity.

Factor 2, which captures the two EG items, is able to explain risky behavior also in the domain of risk avoidance but also in other areas other than factor 1. We can see that it explains future gambling behavior well (at the 5% significance level) but also occupational choices such as self-employment (at 10% significance level). Factor 3, relying on WTR, is only able to explain gambling behavior in the lottery expenditure at a 5% level.

Using factor analysis, we find that we can reduce our seven risk items to three factors. Each of the three factors captures the items which are closely related to each other (i.e. WTR-survey items or the two EG items). Moreover, running a regression with each factor as an explanatory variable with risky behavior, we find that the three factors are capturing different dimensions of risky behavior. However, it seems difficult – or at least highly speculative – to relate the factors to intuitive dimensions of risk attitude.

8 Averaging with Reduced Set of Items and Risky Behavior

We saw in the previous section that the factor analysis yields three factors which load on a very limited set of risk attitude items. Now we examine whether taking a reduced set of risk measure items directly, thus circumventing the reliance on the seven risk measure underlying the factor analysis, will be able to explain behavior well. Building on the factor analysis, we rely on either three (Section 8.1) or two risk items (Section 8.2).

8.1 Reduced Multiple-Item Risk Measure (3 Item) and Risky Behavior

As a first analysis in this direction, we extract one item each from the three factors, i.e. the WTR (Gen), the HInvQ, and the EG (No Loss) task. Then we take the average from these three standardized items. We follow the same methodological procedure as in Section 6.

Applying this reduced multiple-item risk measure on the seven areas of risky behavior we find that this measure is less robust in explaining behavior compared to the average of all seven items which is reasonable since it contains less variance and information on risk attitudes compared to the seven measures (Table 7, bottom). Yet it is still able to predict six risky behaviors which is still more than using the best of the single item risk measure – the HInvQ and the EG (No Loss). In other words, despite lacking the same strength as the average of seven items, using an average of three items has still more predictive ability than using any single measure alone in order to reveal risky behavior. Since significance for most of the single-items seems a bit erratic and arbitrary, we can carefully say that averaging still may provide more robust results when explaining risky behavior than using a single-item given the minimization of noise in the data.

8.2 Reduced Multiple-Item Risk Measure (2 Item) and Risky Behavior

Since even sometimes three items can in infeasible in the field, we reduce our single-item measure even further including only two risk items; the HInvQ and the EG (No Loss) item. We drop the WTR (Gen) because it was only able to explain past gambling behavior (see Section 7.2).

Table 7, bottom shows the predictive power of our reduced multiple-risk item measure with two items and risky behavior. We find that the multiple-item risk measure is not only better able to explain risky behavior than any single item, but it is also better than the three item multiple measures from above. We are able to explain seven risky behavioral items out of eleven and these seven behaviors cover all the five domains of risky behavior we had envisioned at the beginning. However, this measure is still less strong than the average of all seven risk items.

All in all, it can be said that our reduced multiple-risk item with either two or three risk items are still more fitting in revealing risky behavior than any single items.

9 Robustness

Robustness examinations cover four issues: We reexamine the correlations across risk measures for groups with potentially better understanding of these measures, such as having above average cognitive ability (Section 9.1). We analyze the WTR (Gen) item in more detail in order to see whether the highly risk-tolerant responses found above may distort later regressions (Section 9.2). We also analyze whether household heads make less heterogeneous decisions than the entire sample (Section 9.3) and we use further extensions of the behavioral items, including variations of consumption and income definitions (Section 9.4).

9.1 Correlations for Subgroups

In this section, we examine whether correlation among risk measures is higher for those individuals in our sample with longer education and higher cognitive abilities. Dohmen et al. (2010) measure risk (and time) preferences using a representative sample of 1,000 German adults. They find that people with low cognitive ability are more risk averse. Similar findings are found by Burks et al. (2009) using a sample of subjects in a trucking firm and Benjamin et al. (2012) in a sample of Chilean high school graduates.

These results, however, do not take into account the relationship between risk aversion, cognitive ability, and noise. Andersson et al. (2013) use a representative sample of the Danish population and two standard risk-elicitation tasks - one producing a positive and the other a negative correlation between risk aversion and cognitive ability. They found no significant relation between risk aversion and cognitive ability. Instead, cognitive ability is negatively correlated to the amount of noise. They conclude that errors can cause bias in the estimation of risk aversion from observed choices and that the direction of the bias depends on the specifics of the risk-elicitation task.

Further support that noise is heterogeneous and linked to cognitive ability is provided by Dave et al. (2010). They find that higher math scores are related to less noisy behavior in the multiple-price list task but are unrelated to risk taking. We test the assumption that cognitive ability leads to less noise and therefore improved correlation across elicitation methods. We hypothesize that highly skilled individuals should be making fewer errors and thus produce more consistent results across tasks.

After conducting the risk survey, we asked the respondents six mathematical questions, including addition, multiplication, and percentage calculation (Details can be found in Appendix B). In addition to that, we also tested for word fluency by asking them to verbally list as many animals as they could in 60 seconds. The correlation between the two cognitive ability measures is 0.355 (Spearman; $p<0.001$). Thus, the two tests capture a similar underlying trait but also distinct aspects of cognitive ability. We follow the same procedure as Dohmen et al. (2010) and use a single combined measure of cognitive ability using a principal component analysis.

Table 8 shows that better education and higher cognitive ability improve the correlation coefficients slightly but not dramatically compared to the coefficients for the full sample in Table 4. We find increased correlation between the survey items and between the GP and HInvQ. The largest difference can be seen in the EG experiments, where correlations are overall improved with the other non-incentivized survey items. Essentially, we can infer from the results above that education slightly improves correlation between the experimental measures where probabilities are part of the task. Hence, understanding seems to play some role, yet it is not the decisive factor explaining low correlations. These results partly confirm findings of Andersson et al. (2013) because they also found that noise is task-specific. Therefore, we cannot infer an overall positive direction between cognitive ability and the reduction in noise since we have many different risk elicitation tasks. Thus, we can work with the full sample and do not need to work with a subgroup (i.e. those with higher education or higher average IQ).

9.2 Further Analysis of WTR (Gen)

The responses of our sample population to the WTR (Gen) item indicate an unusually high degree of risk-taking willingness, compared to most other surveys using the same item. Thus we check whether this outcome may distort our findings.

As a first step we replace the WTR item from the risk survey by the same item from the household panel survey which was conducted only few months earlier (April 2013). It must be noted, however, that we lose observations because we did not always get the same subjects in August. Ultimately, we have information concerning the WTR (Gen) for 512 observations that could be matched. The average response in the household panel survey is 4.51 which – compared to the average response in our risk survey of 6.86 – comes closer to the findings of Dohmen et al. (2011) and Hardeweg et al. (2013).

Using the WTR item from the spring 2013, we find that it is able to explain households' past expenditure on lottery at the 10% significance level but it is unable to explain further risky behavioral variables (see Table 9); a result also found using the WTR item from August. This result also holds for other analyses, such as using the average of all seven risk items with the WTR item from the household survey; it is still significant in explaining 8 out of 11 items, compared to 9 items before (see Table 9, bottom). We conclude that the high level of risk tolerance in our risk survey does not reduce explanatory power of this item.

In the next step, we compile an average of the WTR item from spring and summer 2013 to see whether results hold in Table 5. Table 10 reports results. We find that the average of both WTR items from the household panel survey and risk survey does not change results. The average is able to explain the share of lottery expenditure at the 5% level but no other item which is similar to Table 11 and Table 5.

9.3 Restricting the Sample to Household Heads

Table 11 replicates the results of Table 5; however, using this time only the household heads as respondents. We find significant changes in results. Bacon et al. (2011) using the SOEP risk item found that there is a significant difference in risk attitude between family members. Household heads seem to be less risk tolerant compared to the spouse who often is a woman. The difference is risk attitude, therefore, goes back to the long-standing debate about gender differences in preferences (Croson and Gneezy, 2009). According to them, one major reason for gender differences in risk-taking is that women differ in their emotional reaction to uncertain situations and this differential emotional reaction results in differences in risk taking. Using household heads reduces the observation to around 400 subjects. Out of these 400 subjects, 303 are male respondents. Moreover, they also are slightly older than the average (59 years old).

Overall, our single-risk items are now able to explain 21 out of 77 risky behavioral items. We do, however, find significant heterogeneity in terms of the strength of various risk items. While the EG (No Loss) and HInvQ was able to explain five behavioral items in Table 5, most of our single-item risk measure like the WTR (Fin), HInvQ, EG (Loss), and EG (No Loss) are only able to explain three items. So it is more equally balanced. Except with the WTR (Gen) in column (7), all significant results have the expected signs. Moreover, it must be noted that the risk-mitigating measure is now explained by four instead of two items. In addition to the HInvQ and the EG (No Loss), we find now that WTR (Fin) and GP are able to explain risk averse behavior in terms of implementing risk-mitigating strategies at the 5% significance level. The same can be observed with health insurance. The EG (No Loss) complements the previous two risk items, the WTR (Fin) and HInvQ, in explaining the probability in choosing an additional health insurance at the 1% significance level. For most items, we have an increase in significance. Yet, as a downside, we find that some items are unable to be explained by any single-risk item such as the BMI.

Since we hypothesize that the difference in significant results may be due to gender difference, we run the same regression using men only (Results are available upon requests). We find similar results when using male respondents only comparable to Table 11.

Given the heterogeneity in results, it is important to investigate whether our results still hold using the average of all seven items given the subsample of household heads. We find that our multiple-item risk measure is still superior in explaining behavior than any of the single-risk item (see Table 11, bottom). It is able to explain six out of eleven items using the household heads only, while the best single item could only explain three items. The average of three risk items is able to predict five behavioral items out of eleven (Results are available upon request). In summary, given the change in subsample, i.e. household heads and reduction in observations, we still find is that our multiple-risk item measure has still greater external validity and predictive power than using each individual risk item alone.

9.4 Extensions of Risky Behaviors

As any set of risky behaviors is arbitrary we also document here either slight variations of already used measures or alternatives which are available from the questionnaire (Details on the dependent variable can be found in Appendix C). Overall, we present results for another eight risky behaviors.

(1) We use the share of past lottery expenditure as part of income instead of consumption. (2) We use the log of investment in our robustness section (instead of investment quota). This seems reasonable because we have a large share of respondents who made large amount of investments while others made none. Hence, in order to reduce the variation caused by extreme values, we take the log of investment and test whether the results are robust. It must be noted, however, that we will lose some observations, as those who made no investments will drop out. In previous tables we used the dependent variable the share of household investment as part of their income. In Column (3) we use the total amount of investment while in column (4) we use the share of household investment as part of their consumption. We use variations of the investment variable to show that the relation between risk and investment is not random. (5) In addition to borrowing, we use borrowing for business. The household survey not only asks whether they borrowed any loans in the last two years but also for which purpose, whether it was to repay back existing loans, to pay for medical bills, school fees, but also for business purposes among other things. (6) The number of risk-mitigating measures instead of the indicator variable. (7) We also consider accident insurance (as opposed to health insurance). (8) As another proxy for BMI, we will only consider those who are above average BMI.

Table 12 shows results which reproduce the former Table 5 with the exception that we take the alternative variables. At first glance, we see that in 17 out of 42 cases a single risk item is able to explain behavior. Hence, the main picture drawn from Table 5 is not changed. However, looking more carefully, we see that there are slight changes in significant results.

Taking the share of past lottery expenditure as part of income yields more predictive power because in addition to the WTR (Gen) and the EG (No Loss) the GP task seems to be significant now. Further, taking the log of investment we find improvement in coefficients and its power. Taking the total amount of investment, we find comparable results to Table 5. We find that the HInvQ and the GP task to be significant. This also holds when we take the share of investment made by the household as part of total consumption. The GP task is statistically significant at the 1% level for most of the investment variables while the HInvQ is mostly significant at the 10% level with the exception of the log investment. Hence, variations of the investment variable shows that the significant risk items remain constant.

For the indicator variable of borrowing in general, we found that the WTR (Fin) and the HInvQ was successful in revealing borrowing behavior. This time, however, instead of the WTR (Fin), we find significant relationship with the GP task at the 1% level but also the EG (Loss). In other words, borrowing for business also captures an investment feature which is why both investment questions seem to be significant. Moreover, we find even stronger domain-specific behavior for the number of risk-mitigating activities. The more risk-mitigating activities one decides to implement, the more risk-averse he/she is which are reported by the two investment-related risk item. To conclude with, we can say that despite new variables or an alternative structure thereof, using single-item measure is still unreliable as we succeed in only 17 out of 42 cases.

In the next step we test whether the average of seven is still significantly superior to the single item measure. In six out of eight cases, our multiple-risk item measure is successful (Table 12, bottom). Further, for four out of sex behavioral items, our multiple-risk measure is significant at the 1% significance level, indicating its robustness. Regarding factor analysis, again factor 1 is most relevant, then factor 2 and finally factor 3 (Table 13). The multiple-item risk measure with average of three and two risk items can explain six behaviors (Table 13, bottom).

Hence we conclude that our main findings – in particular the superiority of the explanatory power of various multiple-item risk measures over single-item risk measures – also hold for another eight risky behaviors.

10 Conclusion

Our research has an applied motivation because knowing a reliable and simple method to elicit risk attitude is of utmost importance for many applications. This is particularly crucial since empirical evidence has shown that there is considerable within heterogeneity in choices given various measures of risk preferences. Accordingly, to explain behavior, contributions in the literature rely on notions of stochastic elements in individual choices (e.g. Loomes and Sugden, 1998; Loomes et al., 2002). In other words, it has been found that heterogeneity is the result of measurement error and noise. Given that noise and error are inherent in any risk measure; the question that is pressing for application purposes is what kind of risk measure to use and implement in the field with high external validity. In contrast to the fundamental importance of a reliable knowledge about individual risk attitude stands the lack of reliability of the risk measures applied. Unfortunately, it is not known whether such single-item measures are reliable; it is simply assumed that they were. Hence, there is the problem of knowing ex-ante which measure is better to reveal behavior ex-post. In fact, the few available studies converge into the insight that each risk elicitation method captures something different. They may be related to each other, however, to such a limited degree that the choice of any measure can lead to divergent conclusions. Our paper attempts to address this issue.

This is the first study in which a comprehensive external validation of various risk elicitation methods has been conducted. Since researchers do not know which measure is ex-ante the best choice to predict behavior, this study offers meaningful insight. We show in our study that risk measures are not only different but that they also differ in their explanatory power. They have specific ability in explaining particular forms of risky behavior. Some measures seem to perform generally better than others, at least with respect to our sample population and overall design. We find that a large part of observed heterogeneity comes from noise in measurement and one way to reduce this noise is by taking the average across all seven risk elicitation methods.

Our resulting multiple-item risk measures offer a behaviorally meaningful alternative in revealing preferences in a reliable way. Our finding shows that such multiple-item risk measures perform better than any single-item measure. In many detailed analyses we support this finding and show that it is robust to several concerns. Therefore, our study not only informs us about the behavioral validity of each item but also offers an alternative for a reliable and behaviorally valid risk measure.

Nevertheless, this is just a single study and it would be interesting to learn from more research whether this main finding largely holds and in which ways it could be improved. What still needs to find out is whether there is indeed one risk measure that not only captures measurement error and noise but is also externally valid capturing domain-specificity. From a puristic economic viewpoint this direction of research may be questionable but for all kinds of practical applications the improvement on simple and at the same time reliable measures of risk attitude is urgent.

References

Abdellaoui, Mohammed, Aurelien Baillon, Laetitia Placido, and Peter P. Wakker (2011), The Rich Domain of Uncertainty: Source Functions and Their Experimental Implementation, *American Economic Review*, 101, 695–723.

Andersen, Steffen, Glenn W. Harrison, Morten I. Lau and E. Elisabet Rutström (2008), Lost in State Space: Are Preferences Stable? *International Economic Review*, 49, 1091-1112.

Andersen, Steffen, Glenn W. Harrison, Morten I. Lau and E. Elisabet Rutström (2006), Elicitation Using multiple price list formats, *Experimental Economics*, 9, 383–405.

Anderson, Lisa R. and Jennifer Mellor (2008), Predicting Health Behaviors with an Experimental Measure of Risk Preference, *Journal of Health Economics*, 27, 1260-1274.

Andersson, Ola, Jean-Robert Tyran, Erik Wengström, and Håkan J. Holm (2013), Risk Aversion Relates to Cognitive Ability: Fact or Fiction? *IFN Working Paper, No. 964.*

Bacon, Philomena M., Anne Conte, and Peter G. Moffat (2011), The Analysis of Risk Attitude Among Family Members, *Jena Economic Research Papers, 069.*

Banerjee, Abhijit. V. and Ester Duflo (2007), The Economic Lives of the Poor, *Journal of Economic Perspectives*, 21, 141-167.

Barsky, Robert B., F. Thomas Juster, Miles S. Kimball and Matthew D. Shapiro (1997), Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study, *Quarterly Journal of Economics*, 112, 537-579.

Beauchamp, Jonathan, David Cesarini, and Magnus Johannesson (2012), The Psychometric Properties of Measures of Economic Risk Preferences, Harvard University Working Paper.

Benjamin, Daniel J., Sebastian A. Brown, and Jesse M. Shapiro (2013), Who is 'Behavioral'? Cognitive Ability and Anomalous Preferences, *Journal of the European Economic Association*, 11, 1231-1255.

Berg, Joyce, John Dickhaut, Kevin McCabe and Vernon Smith (2005), Risk Preference Instability across Institutions: A Dilemma, *Proceedings of the National Academy of Sciences*, 201, 4209-4214.

Bruhin, Adrian, Helga Fehr-Duda, and Thomas Epper (2010), Risk and Rationality: Uncovering Heterogeneity in Probability Distortion, *Econometrica*, 78, 1375-1412.

Burks, Stephen V., Jeffrey P. Carpenter, Lorenz Götte and Aldo Rustichini (2009), Cognitive Skills Explain Economic Preferences. Strategic Behavior, and Job Attachment, *Proceedings of the National Academy of Sciences*, 106, 7745-7750.

Cameron, Colin and Douglas Miller (2013), A Practitioner's Guide to Cluster-Robust Inference, *Journal of Human Resources*, forthcoming.

Charness, Gary and Uri Gneezy (2012), Strong Evidence for Gender Differences in Risk Taking, *Journal of Economic Behavior and Organization*, 83, 50-58.

Charness, Gary and Angelino Viceisza (2011), Comprehension and Risk Elicitation in the Field: Evidence from Rural Senegal, IFPRI Discussion Paper 01135.

Charness, Gary and Marie-Claire Villeval (2009), Cooperation and Competition in Intergenerational Experiments in the Field and the Laboratory, *American Economic Review*, 3, 956-978.

Choi, Syngjoo, Raymond Fisman, Douglas Gale and Shachar Kariv (2007), Consistency and Heterogeneity of Individual Behavior under Uncertainty, *American Economic Review*, 97, 1921-1938.

Clotfelter, Charles T. and Philip J. Cook (1990), On the Economics of State Lotteries, *Journal of Economic Perspectives*, 4, 105-119.

Crosetto, Paolo and Antonio Filippin (2013), A Theoretical and Experimental Appraisal of Five Elicitation Methods, *SOEP Working Paper*, 574.

Croson, Rachel and Uri Gneezy (2009), Gender Differences in Preferences, *Journal of Economic Literature*, 47, 448-474.

Cutler, David and Edward Glaeser (2005), What Explains Differences in Smoking, Drinking, and Other Health Related Behaviors, American Economic Review, 95, 238-242.

Dave, Chetan, Catherine C. Eckel, Cathleen .C. Johnson and Christian Rojas (2010), Eliciting Risk Preferences: When is Simple Better? *Journal of Risk and Uncertainty*, 41, 219-243.

Deck, Cary, Jungmin Lee, Javier A. Reyes and Christopher C. Rosen (2013), A Failed Attempt to Explain within Subject Variation in Risk Taking Behavior Using Domain Specific Risk Attitudes, *Journal of Economic Behavior and Organization*, 87, 1-24.

Dercon, Stefan and Luc Christiaensen (2011), Consumption Risk, Technology Adoption and Poverty Traps: Evidence from Ethiopia, *Journal of Development Economics*, 96, 159-73.

Dohmen, Thomas, Armin Falk, David Huffman and Uwe Sunde (2010), Are Risk Aversion and Impatience Related to Cognitive Ability? *American Economic Review*, 100, 1238-1260.

Dohmen, Thomas, Armin Falk, David Huffmann, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner (2011), Individual Risk Attitudes: Measurement, Determinants and Behavioral Consequences, *Journal of the European Economic Association*, 9, 522-550.

Dohmen, Thomas, Armin Falk, David Huffman, Anke Becker and Uwe Sunde (2014), An Experimentally Validated Preference Survey Module, mimeo.

Eckel, Catherine C. and Philip J. Grossman (2002), Sex Differences and Statistical Stereotyping in Attitudes toward Financial Risk, *Evolution and Human Behavior*, 23, 281-295.

Eckel, Catherine C. and Philip J. Grossman (2008), Forecasting Risk Attitudes: An Experimental Study Using Actual and Forecast Gamble Choices, *Journal of Economic Behavior and Organization*, 68, 1-17.

Falk, Armin, Anke Becker, Thomas Dohmen, David Huffman, and Uwe Sunde (2014), An Experimentally Validated Preference Survey Module, Working Paper.

Gneezy, Uri and Jan Potters (1997), An Experiment on Risk Taking and Evaluation Periods, *Quarterly Journal of Economics*, 112, 631-645.

Gheyssens, Jonathan and Isabel Günther (2012), Risk Experiments in Gains and Losses: A Case Study for Benin, *UNU-WIDER Working Paper No. 38*.

Hardeweg, Bernd, Lukas Menkhoff, and Hermann Waibel (2013), Experimentally Validated Survey Evidence on Individual Risk Attitudes in Rural Thailand, *Economic Development and Cultural Change*, 61, 859-888.

Harless, David.W. and Colin F. Camerer (1994), The Predictive Power of Generalized Expected Utility Theories, *Econometrica*, 62, 1251-1289.

Harrison, Glenn W., Morten I. Lau and Elisabet E. Rutström (2007), Estimating Risk Attitudes in Denmark: A Field Experiment, *Scandinavian Journal of Economics*, 109, 341-368.

Harrison, Glenn W. and Elisabet Rutström (2008), Risk Aversion in the Laboratory. In: J.C. Cox and Glenn W. Harrison (Eds), *Risk Aversion in Experiments*, Research in Experimental Economics, vol. 12. Greenwich, CT: JAI Press.

Hersch, Joni and Kip W. Viscusi (1990), Cigarette Smoking, Seatbelt Use, and Differences in Wage-Risk Tradeoffs, *Journal of Human Resources*, 25, 202-227.

Hersch, Joni and Kip W. Viscusi (2001), Cigarette Smokers as Job Risk Takers, *Review of Economics and Statistics*, 83, 269-280.

Hey, John D. and Chris Orme (1994), Investigating Generalizations of Expected Utility Theory Using Experimental Data, *Econometrica*, 62, 1291-1326.

Hey, John D., Andrea Morone, and Ulrich Schmidt (2009), Noise and Bias in Eliciting Preferences, *Journal of Risk and Uncertainty*, 39, 213-235.

Holt, Charles A. and Susan K. Laury (2002), Risk Aversion and Incentive Effects, *American Economic Review*, 92, 1644-1655.

Holm, Hakan J., Sonja Opper and Victor Nee (2013), Entrepreneurs under Uncertainty: An Economic Experiment in China, *Management Science*, 7, 1671-1687.

Isaac, Mark J. and Duncan James (2000), Just Who Are You Calling Risk Averse? *Journal of Risk and Uncertainty*, 20, 177-187.

Jaeger, David A., Holger Bonin, Thomas Dohmen, Armin Falk, David Huffman and Uwe Sunde (2007), Direct Evidence on Risk Attitudes and Migration, *Review of Economics and Statistics*, 3, 684-689.

Kimball, Miles S., Claudia R. Sahm, and Matthew D. Shapiro (2008), Imputing Risk Tolerance from Survey Responses, *Journal of the American Statistical Association*, 103, 1028-1038.

Knight, Frank (1921), *Risk, Uncertainty, and Profit*, Hart, Schaffner and Marx; Boston: Houghton Mifflin Company, The Riverside Press, Cambridge.

Loomes, Graham and Robert Sugden (1998), Testing Different Specifications of Risky Choice, *Economica*, 61, 581-598.

Loomes, Graham, Peter G. Moffatt, and Robert Sugden (2002), A Microeconometric Test of Alternative Stochastic Theories of Risky Choice, *Journal of Risk and Uncertainty*, 24, 103-130.

Loomes, Graham and Ganna Pogrebna (2014), Measuring Individual Risk Attitudes when Preferences are Imprecise, *Economic Journal*, 124, 569-593.

Meier, Stephan and Charles Sprenger (2010), Present-Biased Preferences and Credit Card Borrowing, *American Economic Journal: Applied Economics*, 2, 193-210.

Moskowitz, Tobias and Annette Vissing-Jorgensen (2002), The Returns to Entrepreneurial Investment: A Private Equity Premium Puzzle? *American Economic Review*, 4, 745-778.

Mossin, Jan (1968), Aspects of Rational Insurance Purchases, *Journal of Political Economy*, 91, 304-311.

Reynaud, Arnaud and Stephan Couture (2012), Stability of Risk Preference Measures: Results from a Field Experiment on French Farmers, *Theory and Decision*, 73, 203-221.

Sahm, Claudia R (2007), How Much Does Risk Tolerance Change? Board of Governors of the Federal System Finance and Economics Discussion Series 1007-66.

Schoemaker, Paul. J. H. (1990), Are Risk Preferences Related across Payoff Domains and Response Modes? *Management Science*, 36, 1451-1463.

Slovic, Paul (1969), Differential Effects on Real Versus Hypothetical Payoff on Choices Among Gambles, *Journal of Experimental Psychology*, 80, 434-437.

Sutter, Matthias, Martin G. Kocher, Daniela Glätzle-Rüetzler and Stefan T. Trautmann (2013), Impatience and Uncertainty: Experimental Decisions Predict Adolescents' Field Behavior, *American Economic Review*, 103, 510-531.

Tanaka, Tomomi, Colin Camerer and Quang Nguyen (2010), Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam, *American Economic Review*, 100, 557-571.

Vieider, Ferdinand M., Mathieu Lefebvre, Ranoua Bouchouicha, Thorsten Chamura, Rustamdjan Hakimov, Michal Krawczyk, and Peter Martinsson (2014), Common Components of Risk and Uncertainty Attitudes across Contexts and Domains, *Journal of the European Economic Association*, forthcoming.

Vieider, Ferdinand M., Nghi Throng, Peter Martinsson and Pham K. Nam (2013), Risk Preferences and Development Revisited: A Field Experiment in Vietnam, *WZB Discussion Paper*, 401.

Von Gaudecker, Hans-Martin, Arthur van Soest and Erik Wengstrom (2011), Heterogeneity in Risky Choice Behavior in a Broad Population, *American Economic Review*, 101, 664-694.

Wakker, Peter P. (2010), Prospect Theory: For Risk and Ambiguity, Cambridge University Press, Cambridge, UK

Weber, Elke U., Ann-Renée Blais and Nancy E. Betz (2002), A Domain-Specific Risk-Attitude Scale: Measuring Risk Perceptions and Risk Behaviors, *Journal of Behavioral Decision Making*, 15, 263-290.

Yesuf, Mahmud and Randal Bluffstone (2009), Risk Aversion in Low Income Countries – Experimental Evidence from Ethiopia, *American Journal of Agricultural Economics*, 91, 1022-1037.

Table 1: Summary Statistics of Individual Characteristics

	Mean	Std.Dev.	Min	Max	Median
	(1)	(2)	(3)	(4)	(5)
	Panel A				
Female	0.58	0.49	0	1	1
Age	54.47	12.49	17	79	55
Height	158.15	7.66	140	185	158
Years of Education	5.68	3.12	1	17	4
Marital Status	0.83	0.37	0	1	1
Household Size	4.09	1.71	1	12	4
Log per capita consumption	7.57	0.60	6	10	8
	Panel B				
Basic Algebra	3.63	1.31	0	6	4
Farmer	0.65	0.48	0	1	1
Self-Employed	0.14	0.34	0	1	0
Lottery Expenditure	632.79	2413.39	0	36000	0
Future Lottery Expenditure	28.60	172.73	0	2934	0
Investment	4953.92	12051.28	0	124496	298
Planned Investment	0.47	0.50	0	1	0
Borrowing	0.71	0.45	0	1	1
Borrowing for Business	0.08	0.28	0	1	0
Risk-Mitigating Measures	0.49	0.50	0	1	0
Number of Risk Measures	0.91	1.20	0	8	0
Number of Insurances	1.95	1.75	0	10	2
Health Insurance	0.06	0.23	0	1	0
Accident Insurance	0.08	0.27	0	1	0
Body Mass Index	23.06	3.74	13	39	23
Overweight	0.44	0.49	0	1	0
Observations	760				

Notes:
Height is in cm. Household size is the headcount of persons living in the household for at least 180 days. Log consumption refers to the natural logarithm of consumption divided by OECD adult equivalents AE (AE = 1+0.7*(adults-1) + 0.5*children). Overconfidence is the difference between believed and actual algebra skills. Basic algebra consists of six numerical questions. Lottery expenditure is the total annual lottery expenditure in the last 12 months. Future Lottery expenditure is the expected lottery expenditure in the next drawing. Investment is amount of investment reported by the household. Planned Investment is if the household plans any investment in the next five years. Risk-mitigating measures indicate whether respondents took up any measures in order to prevent any future shocks/risks. Health and accident insurances are the voluntary health/accident insurance take-up. BMI is computed weight/height^2. Overweight are those above average BMI. We employ the subsample between 17-79 years old.

Table 2: Summary Statistics of Risk Measurements

	Mean	Std. Dev	Min	Max	Median
	(1)	(2)	(3)	(4)	(5)
Willingness to take risk (General) (WTR Gen)	6.86	3.02	0	10	7
Willingness to take risk (Finance) (WTR Fin)	6.48	3.28	0	10	7
Hypothetical Investment Question (HInvQ)	50.88	21.38	0	100	50
Certainty equivalent (CEquiv)	7.96	7.14	1	20	4
Eckel-Grossman Loss (EG Loss)	3.18	1.56	1	5	3
Eckel-Grossman No Loss (EG No Loss)	3.02	1.49	1	5	3
Gneezy-Potters (GP)	36.37	30.60	0	100	50
Observations	760				

Notes:
This table shows the estimates of all risk elicitation methods. The general willingness to take risk item question, an 11-point Likert scale, asks "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?" The financial willingness to take risk asks, also an 11-point Likert scale, asks "When thinking about investing and borrowing are you a person who is fully prepared to take risk or do you try and avoid taking risk?" The hypothetical question asks "Imagine you just won 100 000 Baht in a lottery and you can invest this money in a business. There is a 50 % chance that the business is successful. If the business is successful you double the amount invested after one year. If it is not successful you will lose half the amount you invested. What fraction of the 100 000 Baht would you invest in the business?" We report results that are divided by 100. The certainty equivalent task is an experiment with a lottery that offers a 50-50% chance of receiving either 0 THB or 300 THB and alternatively a safe payoff of 0 THB. Each row, the value of the safe payoff is increased by 10 THB. In the Eckel-Grossman experiment subjects must play one out of five possible gambles. All the gambles involve a 50/50 chance. With loss treatment involved a negative payoff of -30 THB. The Gneezy-Potters experiment subjects have to decide to allocate a fraction of 100 THB in a risky business or saving it.

Table 3: Determinants of Risk Measures

	WTR (Gen)	WTR (Fin)	HInvQ	CEquiv	EG (Loss)	EG (No Loss)	GP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.358	-0.033	-4227.939**	-1.317**	-0.052	0.023	-4.589
	[0.284]	[0.284]	[1995.637]	[0.660]	[0.167]	[0.153]	[2.809]
Age	0.011	-0.024**	-343.722***	-0.014	0.013**	0.017***	-0.199
	[0.010]	[0.011]	[72.896]	[0.024]	[0.006]	[0.005]	[0.123]
Height	0.008	-0.006	165.905	-0.064	-0.002	0.007	-0.299*
	[0.019]	[0.019]	[117.287]	[0.044]	[0.012]	[0.009]	[0.167]
Years of Education	0.055	0.001	65.223	0.104	0.033*	-0.023	0.422
	[0.034]	[0.046]	[276.693]	[0.111]	[0.020]	[0.019]	[0.401]
Marital Status	0.754**	0.800**	6954.973***	0.644	0.077	-0.006	3.906
	[0.348]	[0.363]	[2289.043]	[0.759]	[0.152]	[0.136]	[3.321]
Household size	0.013	0.121	361.617	0.188	-0.049	-0.015	0.525
	[0.084]	[0.074]	[444.766]	[0.180]	[0.036]	[0.036]	[0.745]
LPCC	0.035	0.198	2804.049**	0.429	-0.113	-0.085	3.101
	[0.252]	[0.198]	[1366.472]	[0.450]	[0.100]	[0.101]	[1.960]
Constant	3.502	6.152*	17.177.055	14.546*	3.714*	1.759	66.093**
	[3.666]	[3.703]	[21630.560]	[7.841]	[2.063]	[1.618]	[31.631]
R^2	0.01	0.02	0.09	0.01	0.01	0.03	0.02
Observations	715	715	715	714	714	715	715
Estimator	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Notes:
The dependent variable are risk elicitation methods. Columns 1-7 report estimates of a least square estimation. Female is a dummy (1=yes, 0=no). Age is age of respondents in years. Height is in cm reported by the respondent. Marital Status is a dummy (1=yes, 0=no). Log consumption refers to the natural logarithm of household consumption per day divided by OECD adult equivalents AE (AE = 1+0.7*(adults-1) + 0.5*children). We employ the subsample of 17-79. Clustered errors on the village level are in brackets. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4: Spearman's rank correlations across elicitation methods

	WTR (Gen)	WTR (Fin)	HInvQ	CEquiv	EG (Loss)	EG (No Loss)	GP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WTR (Gen)	1.00						
WTR (Fin)	0.36***	1.00					
HInvQ	0.08**	0.12***	1.00				
CEquiv	0.03	0.00	0.08**	1.00			
EG (Loss)	0.09**	0.03	0.07*	0.10***	1.00		
EG (No Loss)	0.03	-0.01	0.01	0.07**	0.43***	1.00	
GP	0.03	0.04	0.20***	0.03	0.08**	0.10***	1.00
Observation	760						

Notes:
The table reports pairwise Spearman rank correlation coefficients for the subsample with age of 17-79.
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively
.

Table 5: Single and Multiple–Item Risk Measures

	Lottery Expend/Cons	Future Lott Expenditure	Self-Employment	Farmer	Investment Expend/Income	Plan to Invest	Borrowing	Risk-Mitigating	Number of Insurances	Health Insurance	BMI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
WTR (Gen)	0.011**										
	[0.005]										
WTR (Fin)							0.021***			-0.005**	
							[0.010]			[0.000]	
HInvQ					0.008*		0.002*	-0.002***		-0.001***	0.014**
					[0.004]		[0.000]	[0.000]		[0.000]	[0.006]
CEquiv			0.004**	-0.009***		0.008***					
			[0.000]	[0.000]		[0.000]					
EG (Loss)	0.027**	10.570**									
	[0.011]	[4.468]									
EG (No Loss)		16.073***	0.024**	-0.023*				-0.027*	-0.103**		
		[5.733]	[0.010]	[0.010]				[0.010]	[0.044]		
GP		0.519**			0.007***						
		[0.212]			[0.002]						
Observations	711	710	715	710	715	715	708	715	715	715	710
Average of 7 Items	0.042***	12.893***	0.025*	-0.035*	0.120*	0.046**	0.040**	-0.053**		-0.019**	
	[0.015]	[4.531]	[0.010]	[0.020]	[0.065]	[0.02]	[0.02]	[0.02]		[0.01]	
Observations	709	709	713	709	713	713	713	713		713	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	Probit	Probit	OLS	Probit	Probit	Probit	OLS	Probit	OLS

Notes:
The dependent variables are the behavioral variables from the household survey. See Appendix B for details. Controls include Female, Age, Height, Marital Status, Household Size, Education and log per capita consumption. We employ the subsample of 17-79. Clustered errors on the village level are in brackets.
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 6: Rotated Factors

Variables	Factor 1	Factor 2	Factor 3
WTR (Gen)			0.7548
WTR (Fin)			0.4852
HInvQ	0.9591		
CEquiv			
EG (Loss)		0.6216	
EG (No Loss)		0.7085	
GP			

Notes:
Factor analysis pattern matrix. Rotation method is promax with Kaiser normalization. Table shows for each risk elicitation method the factor loadings that are greater than 0.3.

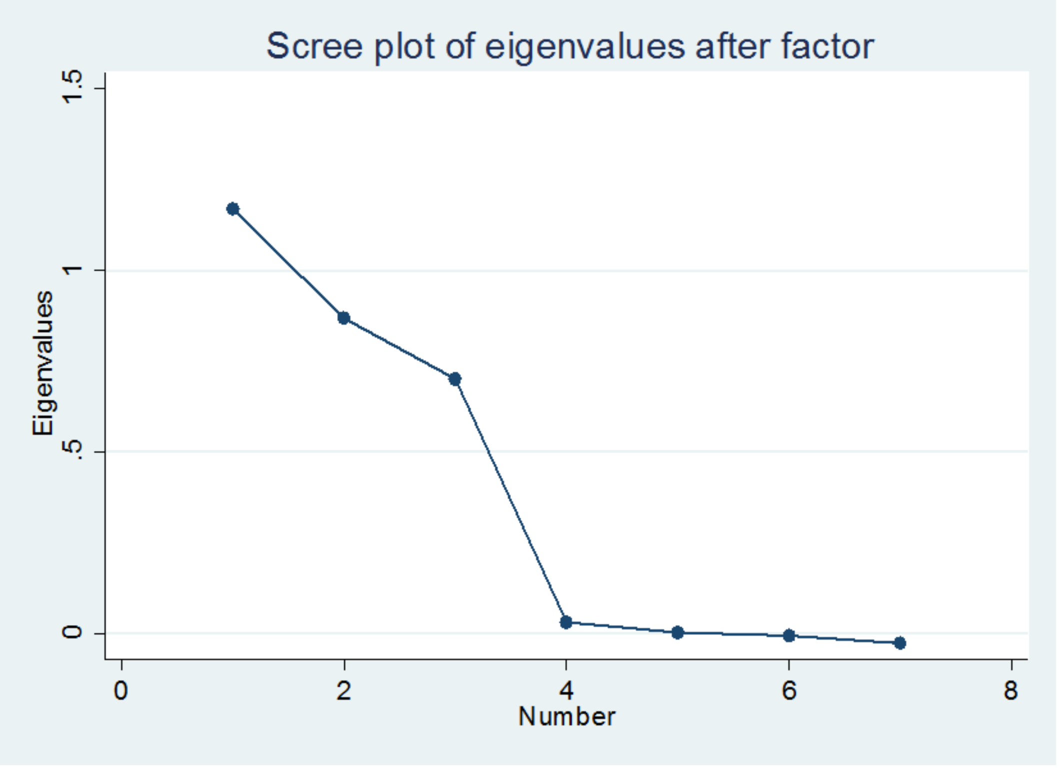

Table 7: Factor Analysis and Multiple–Risk Items

	Lottery Expend/Cons	Future Lott Expenditure	Self-Employment	Farmer	Investment Expend/Income	Plan to Invest	Borrowing	Risk-Mitigating	Number of Insurances	Health Insurance	BMI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Factor 1					0.176*		0.041*	-0.056***	-0.110*	-0.030***	0.308**
					[0.093]		[0.02]	[0.02]	[0.065]	[0.01]	[0.143]
Factor 2		28.750**	0.031*					-0.047*	-0.169*		
		[10.991]	[0.02]					[0.03]	[0.086]		
Factor 3	0.033**										
	[0.016]										
Observations	709	709	713		713		713	713	713	713	709
Average of 3 Items	0.046**	17.074***			0.120*			-0.167***		-0.144*	0.318**
	[0.021]	[5.486]			[0.068]			[0.055]		[0.082]	[0.135]
Average of 2 Items		27.326**	0.127**		0.153*			-0.161***	-0.108**	-0.161**	0.285**
		[11.341]	[0.059]		[0.080]			[0.050]	[0.054]	[0.081]	[0.128]
Observations	711	711	715		715			715	715	715	710
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	Probit	Probit	OLS	Probit	Probit	Probit	OLS	Probit	OLS

Notes:
The dependent variables are the behavioral variables from the household survey. See Appendix B for details. Controls include Female, Age, Height, Marital Status, Household Size, Education and log per capita consumption. We employ the subsample of 17-79. Clustered errors on the village level are in brackets.
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 8: Spearman's rank correlations across elicitation methods for subsamples

	WTR (Gen)	WTR (Fin)	HInvQ	CEquiv	EG (Loss)	EG (No Loss)	GP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WTR (Gen)	1.00						
WTR (Fin)	a) 0.38*** b) 0.40***	1.00					
HInvQ	a) 0.13** b) 0.03	a) 0.04 b) 0.09*	1.00				
CEquiv	a) -0.00 b) 0.11**	a) 0.07 b) 0.01	a) 0.03 b) 0.05	1.00			
EG (Loss)	a) 0.13** b) 0.15***	a) 0.01 b) 0.04	a) 0.03 b) -0.03	a) 0.15** b) 0.16***	1.00		
EG (No Loss)	a) 0.07 b) 0.07	a) 0.02 b) 0.01	a) -0.04 b) -0.05	a) 0.10 b) 0.11*	a) 0.36*** b) 0.41***	1.00	
GP	a) 0.07 b) 0.06	a) 0.04 b) 0.02	a) 0.25*** b) 0.26***	a) 0.01 b) -0.01	a) 0.10* b) 0.13**	a) 0.17*** b) 0.10**	1.00

Notes:
The table reports pairwise Spearman rank correlation coefficients for a subsample of 17-79 and

a) Having high education (more than 5 years), (N=288)
b) Having above average IQ, (N=367)

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 9: HH WTR and Risky Behavior

	Lottery Expend/Cons	Future Lott Expenditure	Self-Employment	Farmer	Investment Expend/Income	Plan to Invest	Borrowing	Risk-Mitigating	Number of Insurances	Health Insurance	BMI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
HH WTR (Gen)	0.016*										
	[0.009]										
WTR (Fin)							0.021***			-0.005**	
							(0.01)			(0.00)	
HInvQ					0.008*		0.002*	-0.002***		-0.001***	0.014**
					[0.004]		(0.00)	(0.00)		(0.00)	[0.006]
Cequiv			0.004**	-0.009***		0.008***					
			[0.000]	[0.000]		[0.000]					
EG (Loss)	0.027**	10.570**									
	[0.011]	[4.468]									
EG (No Loss)		16.073***	0.024**	-0.023*				-0.027*	-0.103**		
		[5.733]	[0.010]	[0.010]				(0.01)	[0.044]		
GP		0.519**			0.007***						
		[0.212]			[0.002]						
Observations	477	710	715	710	715	715	708	715	715	715	710
Average of 7 Items	0.050**	10.446**	0.043**		0.189**	0.064**	0.064**	-0.045*		-0.021*	
	[0.022]	[4.850]	(0.02)		[0.073]	(0.03)	(0.03)	(0.02)		(0.01)	
Observations	709	709	713		713	713	713	713		713	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	Probit	Probit	OLS	Probit	Probit	Probit	OLS	Probit	OLS

Notes:
The dependent variables are the behavioral variables from the household survey. See Appendix B for details. Controls include Female, Age, Height, Marital Status, Household Size, Education and log per capita consumption. We employ the subsample of 17-79. Clustered errors on the village level are in brackets.
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 10: Single-Item Risk Measures and Risky Behavior (WTR Over Time)

	Lottery Expend/Cons	Future Lott Expenditure	Self-Employment	Farmer	Investment Expend/Income	Plan to Invest	Borrowing	Risk-Mitigating	Number of Insurances	Health Insurance	BMI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
WTR Over Time (Gen)	0.061**										
	[0.026]										
WTR (Fin)							0.021***			-0.005**	
							[0.010]			[0.000]	
HInvQ					0.008*		0.002*	-0.002***		-0.001***	0.014**
					[0.004]		[0.000]	[0.000]		[0.000]	[0.006]
CEquiv			0.004**	-0.009***		0.008***					
			[0.000]	[0.000]		[0.000]					
EG (Loss)	0.027**	10.570**									
	[0.011]	[4.468]									
EG (No Loss)		16.073***	0.024**	-0.023*				-0.027*	-0.103**		
		[5.733]	[0.010]	[0.010]				[0.010]	[0.044]		
GP		0.519**			0.007***						
		[0.212]			[0.002]						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	477	710	715	710	715	715	708	715	715	715	710
Estimator	OLS	OLS	Probit	Probit	OLS	Probit	Probit	Probit	OLS	Probit	OLS

Notes:
The dependent variables are the behavioral variables from the household survey. See Appendix B for details. Controls include Female, Age, Height, Marital Status, Household Size, Education and log per capita consumption. We employ the subsample of 17-79. Clustered errors on the village level are in brackets.
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 11: Single and Multiple–Item Risk Measure (Only HH)

	Lottery Expend/Cons	Future Lott Expenditure	Self-Employment	Farmer	Investment Expend/Income	Plan to Invest	Borrowing	Risk-Mitigating	Number of Insurances	Health Insurance	BMI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
WTR (Gen)	0.016**						-0.014**				
	[0.007]						(0.01)				
WTR (Fin)							0.019**	-0.017**		-0.006**	
							(0.01)	(0.01)		(0.00)	
HInvQ							0.000*	-0.000*		-0.000**	
							(0.00)	(0.00)		(0.00)	
CEquiv			0.007**	-0.010***		0.009**					
			(0.00)	(0.00)		(0.00)					
EG (Loss)	0.036**								-0.115**	-0.017***	
	[0.016]								[0.051]	(0.01)	
EG (No Loss)		13.944**	0.030**					-0.039**			
		[5.665]	(0.01)					(0.02)			
GP					0.010***			-0.002**			
					[0.003]			(0.00)			
Observations	392	392	396	394	396	396	396	396	396	396	
Average of 7 Items	0.049*	10.191*	0.034*		0.188**			-0.079***		-0.032**	
	[0.026]	[5.260]	(0.02)		[0.092]			(0.03)		(0.01)	
Observations	391	391	395		395			395		395	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	Probit	Probit	OLS	Probit	Probit	Probit	OLS	Probit	OLS

Notes:
The dependent variables are the behavioral variables from the household survey. See Appendix B for details. Controls include Female, Age, Height, Marital Status, Household Size, Education and log per capita consumption. We employ the subsample of 17-79. Clustered errors on the village level are in brackets.
***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 12: Single and Multiple–Item Risk Measure (Robustness)

	Lottery Expend/Income	Log Investment	Total Investment	Investment Expend/Cons	Borrowing Business	No. of Risk-Mitigating	Accident Insurance	Overweight
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WTR (Gen)	0.007**							
	[0.003]							
WTR (Fin)								
HInvQ		0.009***	41.230*	0.016*	0.001***	-0.004*		0.002**
		[0.003]	[23.236]	[0.010]	(0.00)	[0.002]		(0.00)
Cequiv								
EG (Loss)					0.012**		-0.013**	
					(0.01)		(0.01)	
EG (No Loss)	0.016**						-0.016***	
	[0.006]						(0.01)	
GP	0.001*	0.010***	31.929**	0.014***	0.001***	-0.003**		
	[0.000]	[0.002]	[15.676]	[0.005]	(0.00)	[0.001]		
Observations	711	390	715	715	715	715	715	715
Average of 7 Items	0.026***	0.195***		0.244*	0.314***	-0.122***	-0.152*	
	[0.009]	[0.063]		[0.129]	[0.072]	[0.043]	[0.079]	
	709	389		713	713	713	713	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS	Probit	OLS	Probit	Probit

Notes:
The dependent variables are the behavioral variables from the household survey. See Appendix B and D for details. Controls include Female, Age, Height, Marital Status, Household Size, Education and log per capita consumption. We employ the subsample 17-79. Clustered errors on the village level are in brackets. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 13: Factor Analysis and Multiple-Risk Items (Robustness)

	Lottery Expend/Income	Log Investment	Total Investment	Investment Expend/Cons	Borrowing Business	Number of Risk-Mitigating	Accident Insurance	Overweight
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Factor 1		0.219***	954.31*	0.378*	0.028***	-0.087*		0.048**
		[0.070]	[528.502]	[0.226]	(0.01)	[0.046]		(0.02)
Factor 2	0.022*				0.022*		-0.034***	
	[0.013]				(0.01)		(0.01)	
Factor 3	0.020*							
	[0.011]							
Observations	709	389	713	713	713	713	713	713
Average of 3 Items	0.029**	0.180***			0.243***	-0.100**	-0.126*	0.083*
	[0.013]	[0.067]			[0.072]	[0.042]	[0.072]	[0.047]
Average of 2 Items		0.191***		0.308*	0.213***	-0.082*	0.223***	0.090**
		[0.070]		[0.185]	[0.075]	[0.044]	[0.079]	[0.045]
Observations	711	390		713	715	715	715	715
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS	Probit	OLS	Probit	Probit

Notes:
The dependent variables are the behavioral variables from the household survey. See Appendix B and D for details. Controls include Female, Age, Height, Marital Status, Household Size, Education and log per capita consumption. We employ the subsample of 17-79. Clustered errors on the village level are in brackets. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Appendix A: Risk Elicitation Methods

In our data collection process for the experiment, we tried to keep the enumerator instructions as short and simple as possible in order to facilitate the understanding.

1. Self-reported risk attitude: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk? (Please choose a number on a scale from 0 to 10)

2. Attitudes towards risk change in different situations. When thinking about investing and borrowing are you a person who is fully prepared to take risk or do you try and avoid taking risk? (Please choose a number on a scale from 0 to 10)

3. Imagine you just won 100 000 Baht in a lottery and you can invest this money in a business. There is a 50 % chance that the business is successful. If the business is successful you double the amount invested after one year. If it is not successful you will lose half the amount you invested. What fraction of the 100 000 Baht would you invest in the business? _______________ (THB)

4. Holt and Laury Experiment: This is game 1. It has 20 rows. In each row a decision has to be made. In each row we would like you to choose option A or option B. Option A is a certain amount of THB. It starts with 0 and goes up by 10 THB in every row. Option B is a lottery where a coin is thrown. If "King" falls you win 300 Baht. If "Palace" falls you get nothing. *(Enumerator shows the coin).* Please make your choice of Option A or B for each row. If this game is selected to be played with real money, you will be asked to draw a number from a bag. The bag contains the numbers 1 to 20 for the 20 rows. We will play with real money according to your choice. **For example:** If you draw the number X (Enumerator ID) from the bag, we play the game at this row for money. That means: If you chose option A you will receive ___ . If you chose option B we will toss a coin. If "King" you win 300 Baht. If "Palace" you win nothing.

Row	Option A	Tick Box		Tick Box	Option B
	Certain Amount				King : Palace
1	0				300 THB : 0 THB
2	10				300 THB : 0 THB
3	20				300 THB : 0 THB
4	30				300 THB : 0 THB
5	40				300 THB : 0 THB
6	50				300 THB : 0 THB
7	60				300 THB : 0 THB
8	70				300 THB : 0 THB
9	80				300 THB : 0 THB
10	90				300 THB : 0 THB
11	100				300 THB : 0 THB
12	110				300 THB : 0 THB
13	120				300 THB : 0 THB
14	130				300 THB : 0 THB
15	140				300 THB : 0 THB
16	150				300 THB : 0 THB
17	160				300 THB : 0 THB
18	170				300 THB : 0 THB
19	180				300 THB : 0 THB
20	190				300 THB : 0 THB

5. This is game 3. There are 5 options. Please choose the one option that you would like to **play the most**. In each of the five options we flip a coin to determine the real money payoff. *(Enumerator shows coin)*. Please see the table on the showcard:
   In option 1 you win 80 Baht if King falls and 80 Baht if Palace.
   In option 2 you win 120 Baht if King falls and 60 Baht if Palace.
   In option 3 you win 160 Baht if King falls and 40 Baht if Palace.
   In option 4 you win 200 Baht if King falls and 20 Baht if Palace.
   In option 5 you win 240 Baht if King falls and get nothing if Palace. Now we ask you to make your decision *(Enumerator: Please tick box!)*
   Which of these 5 options do you prefer?

Option	1	King	50	
		Palace	50	
	2	King	90	
		Palace	30	
	3	King	130	
		Palace	10	
	4	King	170	
		Palace	-10	
	5	King	210	
		Palace	-30	

6. This is game 3. There are 5 options. Please choose the one option that you would like to **play the most**. In each of the five options we flip a coin to determine the real money payoff. *(Enumerator shows coin)*. Please see the table on the showcard:
   In option 1 you win 80 Baht if King falls and 80 Baht if Palace.
   In option 2 you win 120 Baht if King falls and 60 Baht if Palace.
   In option 3 you win 160 Baht if King falls and 40 Baht if Palace.
   In option 4 you win 200 Baht if King falls and 20 Baht if Palace.
   In option 5 you win 240 Baht if King falls and get nothing if Palace.
   Now we ask you to make your decision *(Enumerator: Please tick box!)*
   Which of these 5 options do you prefer?

Option	1	King	80	
		Palace	80	
	2	King	120	
		Palace	60	
	3	King	160	
		Palace	40	
	4	King	200	
		Palace	20	
	5	King	240	
		Palace	0	

7. This is the last game. We offer you 100 Baht. There are two options for this money: you can keep money for certain and you can use money to play a game. We ask you to decide, how much of the 100 Baht you want to use for these two options each. You can split the money in any way between these two options.

Proportion of 100 Baht for these two options:

Keep money to save
___________THB

________________THB

King

Palace

Get 3 times money

Lose money

Appendix B: Variable Description

Variable	Description
Female	Dummy Variable. Takes the value 1 for female and 0 for male
Age	Age in years
Height	Height in meters
Years of Education	Education in years
Marital Status	Dummy Variable. Takes the value 1 if married and 0 otherwise
Household Size	Household size is the headcount of persons living in the household for at least half 180 days in the household.
LPCC	Log consumption refers to the natural logarithm of household consumption per day divided by OECD adult equivalents AE (AE = 1+0.7*(adults-1) + 0.5*children).
Farmer	Dummy variable. Takes the value 1 for being a farmer and 0 otherwise.
Self-employed	Dummy variable. Takes the value 1 for being self-employed and 0 otherwise.
Lottery Expenditure	Total amount of household expenses for lotteries in in the last 12 months
Future Lottery Expenditure	How much money will you spend for the next drawing of the state lottery?
Investment	Total amount of household purchases above 5000 THB and used for longer than a year since 2011
Planned Investment	Do you plan to invest in the next five years in the agri/non-agricultural business?
Borrowing	Dummy variable. Takes the value of 1 if the household borrowed since 2011
Borrowing for Business	Why did you apply for credit? Dummy 1 for those who answered business investment, 0 otherwise
Risk-Mitigating measures	Dummy variable. Takes the value of 1 if the household implemented risk measures since 2011
Number of Risk Measures	Number of actual implemented risk-mitigating measures since 2011
Number of Insurances	Total sum of voluntary insurances of the household
Health Insurance	Dummy variable. Takes the value of 1 if the household took up additional health insurance next to the public one, 0 otherwise
Accident Insurance	Dummy variable.Takes the value of 1 if the household took up additional accident insurance 0 otherwise
Body Mass Index	Is computed weight/height^2
Overweight	Dummy variable. Takes the value of 1 if the person is above average BMI.
Numeracy Question 1	What is 45 + 72?
Numeracy Question 2	You have 4 friends and you want to give each friend 4 sweets. How many sweets do you need?
Numeracy Question 3	What is 5% of 200?
Numeracy Question 4	You want to buy a bag of rice that costs 270 Baht, You only have one 1000 Baht note How much change will you get?
Numeracy Question 5	In a sale, a shop is selling all items at half price. Before the sale a mattress costs 3000 Baht. How much will the mattress cost in the sale?
Numeracy Question 6	A second-hand motorbike dealer is selling a motorbike for 12000 Baht. His is two thirds of what it costs new. How much did the motorbike cost new?
Word fluency	I would like you to name as many different animals as you can in 60 seconds.

Appendix C: Detailed Description of Key Explanatory Variables

Lottery Expend/Cons	Total amount of household expenses for lotteries in in the last 12 months as a share of total consumption
Lottery Expend/Income	Total amount of household expenses for lotteries in the last 12 months as as a share of total income
Future Lott Expenditure	Total amount of household expenses for the next drawing
Investment Expend/Income	Total amount of household investment in the last two years as a share of total income
Log Investment	Log investment of household
Investment Expend/Cons	Total amount of household investment in the last two years as a share of total consumption
Total Investment	Total amount of household investment in the last two years