Chapter 1

Behavioral Economics and Climate Change Adaptation: insights from experimental economics on the role of risk and time preferences

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Climate change adaptation is fundamentally a decision to incur certain costs now in return for uncertain benefits and costs sometime in the future. Thus humans' time and risk preferences will shape how individuals and groups adapt on their own and in response to public policies and programs. Experimental behavioral scientists are doing important research to elucidate these preferences. We summarize the relevance of this research for the design of adaptation policies and programs. Recent research suggests a great deal of heterogeneity in risk and time preferences among individuals, which has implications for designing risk communication strategies and adaptation program incentives. It also highlights that more effort to reduce the perceived uncertainty about the efficacy of available adaptation options may be more fruitful than current efforts to increase the perceived certainty about the damages from climate change. Moreover, experimental estimates of individual discount rates are sufficiently high to make adaptation for climate events twenty or more years in the future unprofitable for most individuals (time inconsistent preferences in some people only reduces the perceived returns further). We outline a research agenda that can shed more light on aspects of time and risk preferences that are relevant for climate change adaptation.

1. Introduction

The global climate is changing and will continue to change in the future [IPCC, 2012]. Although scientists do not yet know with great certainty the full extent of these changes, they expect that weather variability and the probability of extreme climate events will increase. The damages from these changes will vary across regions and population. In particular, low-latitude countries are predicted to incur more than three-fourths of global climate damages [IPCC, 2012].

Mendelsohn [2012] argues that, regardless of the success of current mitigation actions, every society will have to adapt to climate change in some way or another. According to the IPCC [2012], “adaptation is the process of adjustment to actual or expected climate and its effects, in order to either lessen or avoid harm or exploit beneficial opportunities.” These adjustments can take many forms. For example, individuals can acquire insurance, they can save money for the future, or they can invest in technologies (water storage, floating houses, water-conserving technologies, efficient irrigations systems, change in crops, etc.). Communities or governments can invest in collective infrastructure (e.g., sea walls) that can also help people adapt to climate change. These groups can also develop policies and programs that augment adaptation capacity and encourage adaptation actions. To develop these policies and programs, we must understand the factors that shape individual and collective adaptation decisions.

This chapter focuses on two of these factors: risk and time preferences, in both individual and group decisions. Investment in adaptation to future shocks is fundamentally an inter-temporal decision under risk in which we would expect individuals’ discount rates, degree of present-bias, degree of risk aversion, and degree of probability weighting to be important moderating factors. To understand these factors, we draw on modern behavioral theories and emphasize the experimental evidence that is relevant for adaptation decisions.

With a better understanding of human risk and time preferences, adaptation proponents will have a greater chance of developing policies and programs that achieve adaptation goals. In the next section, we describe the theoretical literature on risk preferences and the experimental evidence on the relationship between risk preferences and adaptation to climate change, focusing on decisions related to insurance, savings, and adoption of new technologies. In section 3, we follow the same structure for time preferences. In section 4, we summarize the key conclusions and highlight future research areas

2. Risk and Adaptation to Climate Change

Risk preferences are the focus of an extensive theoretical literature, which we cannot fully cover. In the next subsection, we summarize the relevant ideas from this literature and examine them from the perspective of adaptation to climate change. Then, in the second subsection, we look at the relevant experimental evidence.

2.1. *Theories of Risk Preferences and Implications for Climate Change Adaptation*

2.1.1. *Expected Utility Theory (EUT)*

The most common theoretical framework to model decisions under risk is the expected utility theory (EUT) from Neumann and Morgenstern [1947]. In this framework, the expected utility of any risky choice is the sum of the utility of the possible outcomes, weighted by the known probabilities of each outcome. In the EUT framework, risk aversion is formally characterized as individuals' aversion to variability of final outcomes and is characterized by the concavity of the utility function. As is standard in the risk literature, when we refer to risk aversion, we use the Arrow-Pratt measures: (a) relative risk aversion and (b) absolute risk aversion.

The EUT framework has been applied to explain choices that are relevant to climate change adaptation: technology adoption, insurance purchases, and savings decisions. In the context of technology adoption, individuals decide whether or not to adopt a technology, taking into account two sources of risk: risk related to the effectiveness of the technology (e.g., yield, resources saved) and risk related to future climate change (often called "production risk"). With risk related to the effectiveness of the technology, more risk-averse individuals are less likely to adopt the technology. This risk declines with more information, and thus the probability of adoption increases when information about the new technology increases [Feder et al., 1985; Besley and Case, 1993]. With risk related to climate change, such as weather variability or changes in prices, more risk-averse individuals are more likely to adopt technologies that reduce the exposure to climate change risk. Thus, when both sources of risk are present, the effect of risk aversion on technology adoption is ambiguous.

For example, Koundouri et al. [2006] develop a theoretical framework in which they introduce output risk and incomplete information about the technology. In their case, the technology is for irrigation and climate is the main source of production risk. The new technology increases water-use efficiency and thus reduces production risk during years of water shortage. Risk-averse farmers have a higher probability of adopting the technology because they want to hedge against climate change risk. But there is also risk related to future profit flows because of uncertainty about the performance of the new technology. In their model, when farmers are certain about the performance of the new technology, farmers adopt the technology if the expected gains from adopting and reducing the production risk are higher than the expected gains from not adopting. With uncertainty about the technology performance, farmers may delay adoption to obtain more information. Thus, adoption occurs only when the expected gains are higher than the expected value of the new information.

In the context of purchasing insurance, more risk-averse individuals in the EUT framework always demand more insurance. But if people are unclear about the efficacy of the insurance product to protect them in the case of unexpected weather changes, risk aversion can have an ambiguous impact on insurance take up, as in the case of technology adoption. For example, weather index insurance leaves some part of farmers' risk uncovered (called the "basis risk"), thus discouraging weather index insurance adoption.

In the context of savings, a well-developed theoretical literature highlights that people save not only to smooth consumption over time, but also to buffer against shocks. This insurance component of savings is called precautionary savings. According to Kimball [1990], more prudent individuals (measured as a function of the third derivative of the utility function) will have more precautionary savings. In comparison to risk neutral individuals, risk-averse individuals are typically more prudent and thus are predicted to save more to buffer against shocks.

2.1.2. *Rank Dependent Utility Theory (RDU) and Cumulative Prospect Theory (CPT)*

The EUT framework has been criticized because it does not explain some commonly observed behaviors: people have a preference for gambling and people do not take insurance against natural disasters, even though they represent large losses [Richter el al., 2014; Kunreuther and Pauly, 2004;

Gardenton et al., 2000]. These inconsistencies in the EUT model have inspired the development of modifications to explain decisions under risk [Richter el al., 2014; Cox and Sadiraj, 2008; Harrison and Rutstrom, 2008].

Two popular non-EUT frameworks are Rank Dependent Utility Theory (RDU) [Quiggin, 1982) and Cumulative Prospect Theory (CPT) [Tversky and Kahneman, 1992][a]. Under EUT, risk aversion is formally characterized as aversion to variability of final outcomes and is captured by the curvature of the utility function. In contrast, under RDU, risk aversion is formally characterized as aversion to variability of final outcomes, as well as "pessimism" or "optimism" over probabilities, which is captured through a probability weighting function (pwf) [Quiggin, 1982]. The pwf transforms the cumulative distribution of the objective probabilities so that outcomes are weighted differently than they are under EUT. RDU assumes that peoples' decisions are affected not simply by the objective probabilities of an event, but rather by peoples' attitudes towards those probabilities. Thus under RDU, risk aversion is explained by the properties of both the utility function and the pwf [Harrison and Rutstrom, 2008].

If, for example, individuals follow RDU and their behavior is consistent with a concave utility function and a convex pwf, the individuals are averse towards variability of outcomes, overweight bad outcomes and underweight good outcomes (they are often termed "pessimistic probability weighters"). When these individuals consider the decision to adapt to climate change by investing in a new technology or taking insurance, their overweighting of the worst scenarios increases the likelihood of them adapting, as long as there is no uncertainty about the efficacy of the technology or insurance. If, however, individuals are uncertain about efficacy, they also overweight the worst scenario, in which the technology does not work as expected. Thus in adaptation decisions by pessimistic probability weighters, uncertainty about product performance can be a countervailing force to the uncertainty about climate change. Policymakers interested in promoting more adaptation investment among such individuals should consider mitigating subjective beliefs about the potential worst-case outcome when products are ineffective (i.e., damages are lower than previously believed) and enhancing beliefs about the

[a] For the interested reader, we recommend Cox and Harrison (2008).

potential damages of the worst-case scenario caused by climate change (i.e., damages are higher than previously believed).

In contrast, if people's behavior is consistent with a concave pwf, they will underweight the worst outcome and overweight the best outcome. When there is no uncertainty about the efficacy of the technology or insurance, their "optimistic" behavior towards probabilities makes them underestimate the potential damages of climate change and invest less in adaptation. If such risk preferences are widespread, policy makers would want to emphasize the large potential damages from climate change damages in order to offset the probability weighting effect.

Some scholars have proposed an S-shaped or inverted S-shaped pwf instead of a strictly concave or convex pwf. When individuals consider only two possible scenarios – climate change or no climate change – in their decisions to adapt, an inverted S-shaped pwf implies that individuals overweight the small probabilities and underweight the high probabilities and an S-shaped implies the opposite. When individuals consider more than two scenarios – no climate change, medium climate change and high climate change - an inverted S-shaped pwf implies they overweight the best and worst outcomes and an S-shaped pwf implies they underweight the best and worst outcomes. Under such pwfs, the implications for climate change adaptation are unclear.

In contrast to RDU theory, CPT extends the concept of risk aversion by allowing preferences to depend on the sign of the outcomes: gains or losses. Under CPT, an individual reference point m (not necessarily m=0) defines gains as values greater than m and losses as values lower than m. The utility functions and probability weighting functions can vary depending on whether the outcome is a gain or a loss. Individuals are loss-averse when the disutility of losses is greater than the utility of gains of the same size. If individuals are loss-averse, then policy makers' messages should emphasize the losses related to climate change in order to motivate loss-averse individuals to invest in adaptation technology. If climate change risk is fundamentally about losses and individuals are loss-averse, adaptation decisions will depend on the shape of the pwf for losses (see above discussion related to RDU and pwf). However, the concavity of the pwf for losses does not affect probabilities in the same way as in the case of gains. If, for example, the pwf is concave and the efficacy of adaptation decision is certain, individuals overweight, instead of underweight, the worst outcomes and underweight the best outcomes. They will thus be more likely to invest in adaptation. If the pwf is convex, individuals underweight the worst outcomes and overweight the best outcomes. They will thus be less likely to invest in adaptation.

2.1.3. *Rich vs Poor*

Individual measures of risk aversion are local, but risk aversion can change when wealth changes. An individual shows constant (CRRA), decreasing (DRRA) or increasing (IRRA) relative risk aversion if risk aversion remains constant, decreases or increases with a percentage change in individual's wealth. Which of the three versions most accurately captures human preferences is an empirical question.

Empirical evidence on relative risk aversion is important because risk preferences and wealth levels may interact in ways that aggravate the effects of climate change. Poor people are more vulnerable to weather shocks than rich people, but with DRRA and uncertainty over the efficacy of adaptation technologies or insurance products, poor people may be the least likely group to invest in these technologies or products. Furthermore, when a climate shock arrives, a larger percentage of their wealth will drop, which could lead to a poverty trap where poor individuals become even less willing to invest (or save).

2.1.4. *Group vs Individual*

Until now we have assumed that the decision to adapt is taken by the individual and thus we have focused on individual risk preferences. But what happens if the necessary adaptation actions require a household decision, or the group decision of a committee or a village? Can we assume that the preferences of a group are the simple average of the preferences of the individuals that comprise the group? Or might the preferences of one person in the group (e.g., head of household) be more influential than the other members?

An extensive theoretical literature on group and household decision theory exists in which the collective decision is modeled as a function of the individual preferences [e.g., Manser and Brown, 1980; Chiappori, 1988; Browning and Chiappori, 1998; Mazzocco, 2004 and 2007]. In the case of the household, for example, economists typically apply bargaining models where the household preferences are represented as the weighted sum of the spouses' preferences and the weights stand for the decision powers inside the household. The same collective model has been extended to several individuals [Chiappori, 2006].

Theory is ambiguous on the best way to model group preferences. Mazzocco (2004) provides non-experimental evidence that household savings decisions depend on both spouses' preferences. Using data from the Health and Retirement survey, he finds that the relationship between the average saving of the couple and the husband's risk aversion and prudence is u-shaped, not positive as we would expect if we assume that household decision are uniquely determined by the preferences of the husband. There are no empirical studies that show the relationship between individual and household risk preferences and other risky decisions like investment decisions to adapt to climate change, nor any empirical studies of larger groups. We would expect such evidence to point in a similar direction to the results of Mazzocco: a weighted mix of group member preferences will explain decisions better than the preferences on an individual in the group.

Other theoretical studies argue that individuals with RDU preferences will experience a group shift; i.e. in groups, they will show more or less risk aversion than if the decision was taken by the individual alone [Eliaz, 2006]. The shift in the individual decision is influenced by the social norm or what is considered the will of the majority. Once again, the individual preferences will not be informative of the group preferences without an understanding of how individual preferences are transformed in group decision-making contexts.

2.2. *Experimental Evidence Supporting the Theories*

2.2.1. *EUT vs RDU vs CPT*

Experimental studies have compared the EUT, RDU and CPT frameworks and much of the evidence favors the non-EUT frameworks [e.g., Wu and Gonzales, 1996; Starmer, 2000; Harrison and Rutstrom, 2009; Harrison et al., 2010, Tanaka et al., 2010, Barseghyan et al., 2013]. The shape of the probability weighting function is still inconclusive, but in most studies it follows an inverted-S.

Despite the evidence for the non-EUT frameworks when studying the average behavior, researchers have pointed out that not all individuals necessarily follow the same framework. New evidence that allows for heterogeneous preferences is consistent with some individuals' preferences matching a EUT framework and others matching a non-EUT framework. To explore such heterogeneity, researchers have applied mixture models which assume that the sample's preferences are better fitted by at least two frameworks. Harrison and Rutstrom [2009] and Harrison et al. [2010] show that mixture models of EUT and CPT better fit behavioral patterns in two samples, one from Denmark and the other from Ethiopia, India and Uganda, than single behavioral type models.

2.2.2. *Low income vs High Income within Nations*

We first consider the experimental evidence about risk preferences among rich and poor individuals in the same nation. In experiments that examine relative risk aversion, the constructs of CRRA, DRRA and IRRA refer to how relative risk aversion varies when the experimental stakes (payoffs) vary rather than the wealth or income of the decision-makers. Nevertheless, when individuals make risky decisions, they may take into account not only the stakes but also their outside-the-lab wealth (in other words, they may not asset integrate). Thus, many studies also include an analysis of preferences conditional on income, in which researchers estimate how relative risk aversion changes when income varies. In this section, we will consider both types of heterogeneity – by stakes and by subject income – because both variables shed light on how income/wealth impacts individual decisions related to adaptation.

Most experimental studies use university students as subjects, which often yields little variation in individual characteristics compared to variation in the overall human population. Using a sample of US students, Holt and Laury [2002] find that the risk aversion measure increases with the stakes, while being weakly negatively correlated with income.

Artefactual field experiments, which use lab experiment designs with non-student subject pools [Harrison and List, 2004], provide more representative samples, but they are rarely nationally representative. One exception is Harrison et al. [2007], which uses a representative sample of the Danish population. The authors find that the estimated relative risk aversion coefficient did not vary with the lottery stakes or income. They thus conclude that the CRRA utility specification is a good representation for the Danish population. Other studies do not have a nationally representative sample. Binswanger [1980] uses a sample of 240 Indian farming households and concludes that the risk aversion coefficient increases with the stakes, but the relationship between risk aversion and wealth is imprecisely estimated. Engle-Warnick et al. [2007] uses a sample of 160 farmers in rural Peru and finds that their risk aversion estimate decreases with wealth. Tanaka et al. [2010] uses a sample of 180 individuals of nine Vietnamese villages and, assuming preferences are best characterized by CPT, conclude that neither the curvature of the utility function or the loss aversion parameter varies with household income but that individuals living in wealthier villages are less risk averse and less loss averse. Tanaka et al. assume participants use a power utility function where the relative risk aversion is constant and thus cannot test how risk aversion varies with stakes. Using a sample of 262 Ethiopian farmers, Yesuf and Bluffstone [2009] find that the risk aversion coefficient increases with higher stakes and wealthier Ethiopian farmers show lower risk aversion. In sum, the studies provide support for both CRRA and IRRA in stakes, and they have either uncovered no effect or a negative effect of income on risk aversion.

Whether the patterns observed in these studies differ because of differences in samples, differences in risk elicitation procedures, or differences in econometric methods is difficult to determine. More research will be required to disentangle competing explanations for the inconclusive results. But understanding how risk preferences vary with the stakes, income or wealth is important for climate change. If people become more risk-averse when the stakes are higher this discourages relatively big investments. Furthermore, if high levels of risk aversion are related to low levels of income or wealth, and there is uncertainty among the poor about the efficacy of adaptation actions, the most vulnerable population to the effects of climate change will be the least likely to adapt.

2.2.3. *Low income vs High Income across Nations*

As with the studies of risk preferences across populations within country, comparing risk aversion across countries that vary in income can be difficult when the elicitation procedures and econometric methods differ. To increase the comparability across populations, we select studies that use similar experimental designs and methods and estimate CRRA coefficients.

Three studies examine risk preferences among U.S. students. Using data from Hey and Orme [1994], Harrison and Rutstrom [2008] estimate CRRA levels between 0.66 and 0.8. Holt and Laury [2002] estimate that the majority of their sample have CRRA values between 0.3 and 0.5. Harrison and Rutstrom [2009] estimate a mixture model of EUT and CPT in which about half of the sample fits an EUT model with CRRA=0.846

(about half overweights small probabilities with inverse-S probability weighting). Applying only the EUT framework, the authors find similar CRRA levels (0.867).

For developing countries, one of the most well-cited studies is Binswanger [1980] who uses a sample from Indian farming households and estimates CRRA coefficients between 0.32 and 1.7. For poor people in India, Ethiopia and Uganda, Harrison et al. (2010) estimates a CRRA coefficient of 0.536[b]. For a sample of Vietnamese villagers, Tanaka et al. [2010] estimate CRRA coefficients between 0.37 and 0.41.

Thus, the literature has not demonstrated any clear differences in risk aversion levels across low and high-income nations. In another review of the literature, Cardenas and Carpenter [2008] draw a similar conclusion.

2.2.4. *Group vs Individual*

Four of the most cited studies that experimentally elicit group risk preferences provide conflicting results. Baker et al. [2007] and Shupp and Williams [2008] conclude that groups are more risk averse than individuals, but Rockenbach et al. [2007] and Zhang and Cassari [2012] draw the opposite conclusion. All four studies used subjects from high-income countries.

A few studies examine the risk preferences of married couples (household risk preferences). Bateman and Munro [2005] and Abdellaoui et al. [2013a] use subjects from high-income countries, while Carlsson et al. [2013] elicit risk preferences for households in rural China. Bateman and Munro [2005] find that that couples show more risk aversion when making choices jointly rather than individually. Abdellaoui et al. [2013a] find that women show more risk aversion than couples and men. They also find that spouses have equal weight in the household decision. The authors also test for joint and individual differences using the RDU framework and find little differences: both individuals and couples overweight small probabilities and underweight high probabilities (although men seem to overweight small probabilities more and underweight high probabilities less than women and couples). Carlsson et al. [2013] conclude that the individual and joint decisions are not statistically different from each

[b] Their preferred specification is a mixture model where half of the individuals fit an EUT model with a CRRA estimate of 0.796 and the other half fit a CPT model with a convex utility function and a probability weighting function that underweight probabilities.

other, but that the joint decisions are typically closer to the husbands' decisions.

As with the evidence about relative risk aversion, the evidence about risk preferences and group decision-making is inconclusive. Some studies have found no differences between group and individual decision-making, and the studies that have found differences do not agree on the direction of those differences.

2.3. *Evidence for Investments in New Technologies*

Although studies that seek to clarify the factors that determine technology adoption have a long history, few empirical studies assess the role of risk aversion. Some studies elicit risk aversion from survey data and correlate these measures with technology adoptions [e.g., Koundouri et al., 2006; Bozzola, 2014], but experimental measures of risk aversion using salient incentives are scarce. Liu [2013] studies the case of Chinese cotton farmers who were offered the option to adopt genetically modified cotton to deal with bollworms, the primary cotton pest. The author uses survey questions and experiments to elicit risk preferences, and the econometric methodology of Tanaka et al. [2010] to estimate aversion to variability in gains and losses and probability attitudes (assumes that individuals' utility function is a power function and that individuals weigh probabilities according to Prelec [1998], who allows for inverted S-shape or S-shape functions). Liu finds that more risk-averse farmers and more loss-averse farmers adopt the new cotton variety later, and that farmers with an inverted S shape pwf adopt the new cotton variety earlier. Liu argues that farmers with an inverted S shape pwf overweight the small probability of severe bollworm infestation and thus adopt the technology earlier than other farmers.

Lui's evidence supports theoretical predictions that risk-averse individuals postpone technology adoption and provides the first exploration of the effect of attitudes towards probabilities. More research is needed in order to assess whether these results can be generalized to other populations.

2.4. *Evidence for Investments in Insurance Products*

Insurance against natural disasters is considered a tool for adaptation to climate change [Bouwer and Vellinga, 2005]. The literature on insurance highlights a stylized fact across both developed and developing countries: take-up of insurance against natural disasters and weather insurance is low. In the case of developing countries, the literature shows a very low take-up of weather derivatives, commonly known as weather index insurance, in the countries where it has been offered [Cole et al., 2012].

In developed countries, the most commonly studied weather or disaster-related context is flooding. Even though flood insurance premiums are often subsidized, take-up is very low among residential and commercial property owners. In the U.S., for example, flood insurance is mandatory by law for what is termed a Special Flood Hazard Area (SFHA) and the insurance is subsidized by the government-funded National Flood Insurance Program (NFIP). Despite the mandate and the subsidies, only 49% of residential properties in the SFHA held NFIP insurance [Petrolia et al., 2013]. In Germany, market penetration for supplemental flooding coverage is around 10% for household contents and 4% for residential buildings [Thieken et al., 2006].

The basic theoretical model of insurance shows that there is a positive relationship between risk aversion and insurance take up. But in the context of natural disaster insurance, there is little empirical evidence for this positive relationship. We know of only a single study. Petrolia et al. [2013] studied NFIP insurance demand and consider risk preferences, risk perception, charity hazard and insurer credibility as potential determinants. They elicited risk aversion in the gain and loss domain using a multiple price list design, following Holt and Laury [2002]. They find that risk aversion in the loss domain was positively correlated with the take-up of insurance, as predicted by theory, but risk aversion in the gains domain exhibited no correlation. Proxies for risk perception, hazard aid and insurer credibility were also found to explain take-up.

If individuals exhibit CPT preferences and underweight low probability events, like natural disasters, they will likely underinsure against these events. In laboratory experiments, two studies examined the relationship between insurance take-up and the probabilities of loss when losses are large but realized with low probabilities. Laury et al. [2009] find no evidence of underinsurance when an event has a very low probability. In contrast, Barseghyan et al. [2013] find that probability distortions affect household's deductible choices in ways that can lead to underinsurance of low probability events.

In the developing country context, several studies examine the determinants of the take-up of index insurance. Index insurance is a derivative that pays insured individuals based on the realization of publicly verifiable index, such as a rainfall level or a crop yield. This kind of insurance is designed to be inexpensive to administer because payouts are determined by observable factors unrelated to the individual decisions but correlated with losses, thus mitigating adverse selection or moral hazard issues. Nevertheless, the product’s efficacy may be uncertain to potential buyers because the index may not capture crop outcomes in all areas and thus individuals may not be reimbursed when a loss occurs.

In contrast to theoretical models that predict a positive relationship between risk aversion and insurance take-up, studies have found a negative relationship between risk aversion and the take-up of index insurance [Cole et al., 2013; Gine et al., 2008; Hill et al. 20013a, 2013b; Clarke and Katani, 2011]. To explain these results, Clarke [2011] presents a new model for weather derivatives in which he takes into account the joint probability structure of the index insurance and the individual’s loss. In the model, an individual may incur a loss without receiving a payment and the vice-versa. The model shows that infinitively risk-averse individuals do not demand index insurance. Demand for actuarially unfair index insurance is hump-shaped in risk aversion (increasing and decreasing) while demand for actuarially favorable index insurance is either decreasing or decreasing-increasing-decreasing in risk aversion. Cole et al. [2013] and Gine et al. [2008] explain their estimated negative relationships differently. They argue that people are unfamiliar with the product. To analyze this possible reason, Gine et al. [2008] use interaction variables between risk aversion and measures of households’ familiarity with the insurance company and insurance in general. They find some evidence that risk aversion leads to low take-up when people are not familiar with the product.

In the spirit of Clarke [2011], Vargas Hill et al. [2013a, 2013b] seek to estimate a hump-shaped relationship between risk aversion and the take-up of index insurance, but they cannot detect such a shape in their data. In Vargas Hill et al [2013a], the authors detect no significant effect of different degrees of risk aversion on insurance take-up. In Vargas Hill et al. [2013b], the authors detect only a negative, monotonic relationship between their measure of risk aversion and the willingness to pay for index insurance.

In all of the cited studies about index insurance, risk aversion is measured using the lottery questions from Binswanger [1980] and real or hypothetical payments. The simplicity of the Binswanger design has made it very popular in developing countries contexts where researchers use pictures and oral explanations to make risky choices understandable. Nevertheless, this design only allows one to estimate risk preferences within simple frameworks like EUT; it is not possible to test non-EUT models like RDU with this design [Harrison and Rutstrom, 2008)]. There are many other designs [Harrison and Rutstrom, 2008] that are suitable to capture non-EUT models, and more effort needs to be made in order to apply these designs to illiterate populations.

Thus, although we observe a low take-up of natural disaster and weather index insurance throughout the world, the empirical evidence on the role of risk preferences is weak. In the case of the natural disaster insurance, there are few studies to guide us. In the case of the weather index insurance, a set of studies have concluded that, in contrast to simple theories of insurance demand, more risk averse individuals buy less insurance. One possible explanation for this result is uncertainty over the efficacy of the insurance product. For all contexts, there are no studies exploring the relationship between risk aversion and insurance in a non-EUT framework, even though there is evidence consistent with people exhibiting different attitudes towards probabilities and losses [Harrison et al., 2009; Barseghyan et al., 2013].

2.5. *Evidence for Investments in Savings*

People who do not have access to insurance could use savings as a means to insure against future shocks from climate change. The available empirical evidence shows a positive relationship between measures of prudence and savings (Carroll and Sandwick, 1997) in the developed world. In developing countries, there is little evidence and what evidence exists does not find statistically significant effects of risk preferences on savings [Bauer et al., 2012].

3. Time preferences and Adaptation to Climate Change

Adaptation to climate change is an intertemporal decision. Individuals need to invest today in order to be protected in the future against changes in the weather. In this section, we focus on the relationship between individual time preferences and adaptation decisions. Our discussion refers to individual discount rates, the rate at which individuals trade current consumption for future consumption [Coller and Williams, 1999], not to the discount rate of the social planner that has been the central topic in the literature about climate change mitigation. First, we briefly describe discounting models and their relationship with climate change. Then we show the empirical evidence for those theories. Finally, we point to the literature that has studied the connection between individual time preferences and adaptation decisions.

3.1. *Theories of Time Preferences and Implications for Climate Change and Adaptation*

3.1.1. *Constant Discount Rate*

The discounting utility (DU) model of Samuelson is the traditional framework applied by economists to explain intertemporal decisions and is represented by the exponential discounting function. One of the key features of the DU model is a constant discount rate for different time horizons. A constant discount rate means that if, in period t, a person prefers ten dollars in future time t_1 to eleven dollars in time t_{1+X} then in period t the person must prefer ten dollars in future time t_2 to eleven dollars in t_{2+X}. A constant discount rate also implies that intertemporal preferences are time-consistent, which means that decisions made today are confirmed in the future [Frederick et al., 2002]. For example, I have time-consistent preferences if I choose today to invest next season in a new fertilizer and, when the season arrives and nothing about my original calculations of costs and benefits have changed, I invest. People show time-inconsistent preferences when they do not do what they planned, despite no change in conditions.

3.1.2. *Hyperbolic Discounting*

In contrast to the constant discounting assumption of the DU model, some empirical evidence suggests that discount rates are not constant over time. People instead apply discount rates that decline over time "as the discounted event is moved further away in time" [Laibson, 1997]. This form of discounting is known in the literature as hyperbolic discounting. A variety of models have been proposed to capture declining discount rates: e.g., the quasi-hyperbolic model of Phelps and Pollak [1968]; the fixed cost model of Benhabib et al. [2010]; the general hyperbolic discounting function of Mazur [1984].

People are said to exhibit hyperbolic discounting when, for example, the average annual discount rate over one year is much smaller than the average annual discount rate over a week from today. A declining discount rate also implies that intertemporal preferences are time-inconsistent and people exhibit preference reversals. People who discount hyperbolically do not fulfill the plans they make today because when the time to commit arrives present consumption seems more valuable than the future profits of the new endeavor. Such time inconsistency has clear implications for adaptation to climate change: individuals will delay investing in adaptation. In the presence of time inconsistency, adaptation policies and programs must carefully consider the timing of assistance and consider the role of commitment devices that bind people to the future plan they make today.

3.1.3. *Rich vs Poor*

Discount rates can be heterogeneous across individuals and depend on observable characteristics like wealth, culture, education. Becker and Mulligan [1997] posit a model where impatience is a weakness that needs to be overcome by investing in future-oriented capital that increases the appreciation of future pleasures like a college degree, pension, savings, etc. In this model, the discount rate is a negative function of the resources invested. Moreover, rich people have the largest incentive to invest in future-oriented capital because they have high future utilities and low costs of investing. As the future-oriented capital increases, discount rates decline, which implies that rich people are predicted to have lower discount rates than poor people. Similar predictions come from other models that relate discount rates to constraints in credit markets [Holden et al., 1998]. Compared to poor individuals, rich people have better access to credit markets and face lower interest rates. Therefore, poor people are predicted to have higher discount rates than rich people. With higher discount rates, poor people are more focused on present consumption and less likely to invest in adaptation to protect them against future climate change events.

3.1.4. *Group vs Individual*

As noted in the section on risk preferences, some important adaptation actions require a household decision, or the group decision of a committee or a village. As in the case of risk preferences, understanding how group time preferences differ from individual time preferences may be important for designing climate change adaptation policies and programs.

The theoretical literature in this area is still inchoate. In the context of households, Mazzocco (2007) creates a theoretical model that considers both spouses' utilities and discount rates and the weights that each spouse has in the decision. Moreover, the household discounting function is affected by the magnitude of the differences in the spouses' preferences. Although this model does not shed light on time-consistency, household time preferences are likely to be the result of a bargaining process within the household. It is plausible that renegotiation processes within the household could lead to time-inconsistency.

In the context of groups, Adams et al.'s [2014] model implies that time inconsistency in a group decision process could come from individuals' time inconsistency. Jackson and Yariv's [2014] theory predicts more broadly that group preferences are always time-inconsistent, even if the individual preferences are time-consistent. Were this theory to be accurate, it would have important implications for adaptation policies and programs: in addition to the free-riding incentives and coordination costs that are inherent in group adaptation investments and serve as obstacles to adaptation, time-inconsistency may further reduce the effectiveness of policies and programs aimed at encouraging group adaptation responses.

3.2. *Evidence Supporting the Theories*

3.2.1. *Constant Discounting vs. Hyperbolic Discounting*

In an intertemporal decision, individuals compare a utility level today versus a utility level in the future. Thus, a key feature of any good experimental design that seeks to elucidate discounting behavior is consideration of the curvature of the utility function. Many experimental studies that test for the presence of hyperbolic discounting, particularly earlier studies, fail to consider this curvature, which could bias their results.

Coller et al. [2012], Andersen et al. [2014] and Andreoni and Sprenger [2012] introduce the shape of the utility function in their estimation. In Coller et al. [2012], the authors estimate exponential and quasi-hyperbolic models as well as a mixture model of both discounting functions[c]. They find that the sample follows both discounting functions in similar proportions. In contrast, neither Andersen et al. [2014] nor Andreoni and Sprenger [2012] find hyperbolic discounting in their samples. Andersen et al. [2014] posit that one explanation for the difference between their results and Coller et al.'s results is that they use a sample of Danish individuals, whereas Coller et al. [2012] use students in the U.S. The authors suggest that more studies should be done with a variety of populations.

3.2.2. *Low income vs High Income within Nations*

There is little evidence about how discount rates vary with income within nations and the evidence that does exist is hard to compare because of differing samples and designs. Using a representative sample of the Danish population and a structural estimation procedure where the curvature of the utility function is included, Andersen et al. [2014] find no relationship between income and the discount rate from an exponential discounting model. Using a sample of U.S. students and interval regression, Coller et al. [1999] estimate a positive correlation between discount rates and income. Using an instrumental variable approach, Tanaka et al. (2010) finds that the long term discount rate and household income and village mean income correlate negatively. Using a small sample of villagers from India, Pender [1996] estimates that wealthier individuals have lower discount rates over payments in one of the two groups that participated. Kirby et al. [2002] estimate a negative relationship between discount rates and income but did not find significant results for the relationship between discount rates and wealth. With the exception of Andersen et al. [2008], none of the studies mentioned consider the shape of the utility function. Thus, the available evidence seems to weakly support a negative correlation between discount rates and income/wealth, but the evidence is far from conclusive.

With regard to time inconsistency, we know of only one study that examines its relationship with income or wealth (and it does not incorporate the curvature of the utility function in the analysis). Tanaka et

[c] Two well-cited studies that do not consider the shape of the utility function in their analysis find evidence of hyperbolic discounting (Benhabib et al. 2010; Tanaka et al., 2010).

al. [2010] do not find a statistically significant effect of income on present-bias coefficient in their model.

3.2.3. *Low income vs High Income across Nations*

There is some evidence of variability in the discount rates that researchers have found across rich and poor nations, but the literature is too small and the results too mixed to draw definitive conclusions. From low-income countries, Tanaka et al. [2010] find annual discount rates of around 3 million percent for a week horizon (i.e. a weekly discount rate of 22%). From high income nations, there are a few more studies that use experimental data. Using a representative sample of the Danish population and a structural estimation procedure where the curvature of the utility function is included, Andersen et al. [2014] estimate an annual discount rate of 9% in an exponential discounting model[d]. Most of the studies that estimate discount rates in high-income nations use samples of university students. Andreoni et al. [2012] estimate constant annual discount rates between 25% and 35%, depending on the estimation procedure. Coller et al. [2012] estimate a discount rate of 28% when using an exponential model. In their mixture model of exponential discounting and quasi-hyperbolic discounting, they estimate annual discount rates from 32% to over 1000% in the 60 days of analysis. For example, the estimated annual discount rate for a decision over a single week's time is 1069%[e]. Using a design that does not include the curvature of the utility function, Coller et al. [1999] estimate average annual discount rates between 15-17.5%.

Although the evidence about individual discount rates in high and low-income nations is scant, the ranges of the few studies that do exist suggest substantial discounting. Excluding the Danish study, all studies estimate annual discount rates over 15%, and very high discount rates (>30%) are common. Should such high discount rates be generalizable to human populations around the globe, they suggest adaptation policies and

[d] Assuming a linear utility function instead (i.e. ignoring the shape of the utility function) leads to a doubling of the estimated discount rate, which shows the importance of incorporating some structure on the curvature of the utility function.

[e] In a model that does not adjust the estimates for the curvature of the utility function, Benhabib et al (2010) estimates individual average annual discount rates in a fixed cost discounting function (hyperbolic discounting) of 475% (some individuals show annual discount rates of 18 000% in a week).

programs will find it difficult to induce people to act now for climate events that will take place tens of years from now.

3.2.4. *Group vs Individual*

We are aware of only three experimental studies that have elicited discount rates at the household level. Using a sample of 101 married couples in a rural area of China, Carlsson et al. [2012] find that none of the individual or joint decisions exhibit quasi-hyperbolic discounting, joint decisions are in between the individual choices, and husbands have a stronger influence on joint decisions than wives. Using a sample of French couples and longer time horizons than Carlsson et al. [2012)] (1 month up to 2 years, rather than 4 up to 8 days), Abdellaoui et al. [2013b] find that couples are more patient than individuals and that couples discount rates cannot be expressed as a convex combination of spouses' rates. The authors also find increasing and then decreasing annual discount rates over time for individual and joint decisions, contrary to hyperbolic behavior (and thus contrary to time inconsistency). Kono et al. [2012] use a sample of Vietnamese couples and find that individuals show more patience when they make the decision jointly. Only Abdellaoui et al. [2013b] takes into account the curvature of the utility function.

3.3. *Evidence for Investments in New Technologies*

We know of only one study that examines the relationship between time preferences and the adoption of technologies relevant for climate change adaptation. Duflo et al. [2011] develop a theoretical model that includes present-bias to predict fertilizer take-up by farmers in West Kenya. In the model, naïve hyperbolic farmers who plan to buy fertilizer in the future may procrastinate and end up not buying it. The model predicts that a small, time-limited discount on the cost of acquiring fertilizer (in the form of free delivery immediately after harvest rather than prior to planting) increases the quantity of fertilizer that farmers buy, which increases crop yields. In a randomized field experiment, this prediction is verified.

3.4. *Evidence for Investments in Insurance Products*

Although there is empirical evidence that present-bias preferences affect different types of financial behavior, like the choice of pensions, credit, savings and annuities in developed and developing countries [Choi et al., 2011; Brown and Previtero, 2014; Schreiber and Weber, 2014], there is little evidence about the effects of such preferences on insurance purchases. Moreover, although standard economic theory predicts that the willingness to pay for weather index insurance will decline with higher discount rates, Vargas Hill et al. [2013b] finds the opposite pattern.

3.5. *Evidence for Investments in Savings*

Present-biased preferences limit people's ability to save. People might plan to save, but when the time arrives to save, their desire to save is overpowered by their desire to consume. In the developed world, studies have shown that present-biased preferences are associated with people that contribute less to their pension plans and that are less likely to participate in voluntary savings plans [Choi et al., 2011; Brown and Previtero, 2014]. In the developing world, studies have shown that saving is difficult for poor people not because they are poor but because they have to overcome certain barriers, like present-biased preferences. Thus, present-biased individuals are more likely to choose commitment devices that help them to save consistently, even though they need to pay for them or the devices make savings illiquid: microcredit [Bauer et al., 2012], rotating savings and credit associations called ROSCAS [Gugerty, 2007; Dupas and Robinson, 2013], saving contracts [Ashraf et al., 2006], etc. If people are present-biased, commitment savings devices will help them save in the event of a shock and reduce individuals' vulnerability.

4. Conclusion

Theory and empirical evidence from experimental economics strongly suggest that risk and time preferences are important factors that affect human proclivity to adapt to climate change. However, the way in which they will influence adaptation investments is uncertain because the theory and empirical evidence are poorly developed and, sometimes, conflicting.

Nevertheless, a few conclusions can be drawn and priority areas for future research can be identified. First, with regard to conclusions, it is clear that risk aversion may reduce adaptation investments as long as people are uncertain about the efficacy of the available adaptation options. The more we can increase the certainty about their efficacy, the more likely that the typical risk aversion observed in human beings will be a factor that encourages adaptation investments rather than discourages it.

Second, the experimental estimates of individual discount rates are sufficiently high to make adaptation for climate events 20 or more years in the future unprofitable for most individuals. Excluding a study from Denmark, all studies estimate annual discount rates over 15%, with very high discount rates (>30%) common. Should such high discount rates be generalizable to human populations around the globe, they suggest adaptation policies and programs will find it difficult to induce people to act now for climate events that will take place tens of years from now. Time inconsistency, about which the empirical evidence is weakly supportive, only makes the situation more difficult. Thus policymakers must either emphasize short-term benefits from adaptation or subsidize adaptation under a public goods argument.

Third, recent research suggests a great deal of heterogeneity in risk and time preferences among individuals. Some individuals are time-consistent and others appear to be time-inconsistent. Some behave in accordance with expected utility theory, while others appear to weight objective probabilities in unusual ways. Such heterogeneity implies that one-size-fits-all policies and programs may fail to induce sufficient adaptation investment and instead policymakers and program designers may need to create a menu of options and target these options to the relevant groups that will most likely prefer them.

With regard to future research priorities, the extent and nature of probability weighting must be clarified in order that communication strategies for adaptation programs can be better designed. For example, if a large segment of a society can be characterized as “pessimistic probability weighters,” policymakers interested in promoting more adaptation investment would want to focus on changing subjective beliefs about the potential worst-case outcome when adaptation options are ineffective (i.e., convince people that damages are lower than they believed) and changing beliefs about the potential damages of the worst-case scenario caused by climate change (i.e., convince people that damages are higher than they believed). Whereas if individual risk preferences are best characterized by an S-shaped probability weighting function, effective adaptation communication will be difficult and entirely new strategies will need to be developed.

Second, given the high degree of vulnerability to climate change among the poorest segments of society, within and across countries, much stronger evidence on the relationship between risk preferences and income or wealth is needed. If high levels of risk aversion are related to low levels of income or wealth, as popular wisdom seems to imply, and there is uncertainty among the poor about the efficacy of adaptation actions, the most vulnerable population to the effects of climate change will be the least likely to adapt. That behavioral pattern would exacerbate poverty over time without countervailing collective action.

Third, stronger evidence about how risk and time preferences are affected when decisions are made at the household level or larger group levels is needed. Adaptation programs can encourage individual actions, household actions and collective actions. If, for example, groups of individuals making a decision together have lower discount rates (are more patient) than the individuals in the group (as some studies suggest), programs may wish to encourage collective actions, despite the incentives for free-riding and the additional transaction costs.

Fourth, stronger evidence on the prevalence of time inconsistency is needed. In the presence of time inconsistency, adaptation policies and programs must carefully consider the timing of assistance and consider the role of commitment devices that bind people to the future plan they make today. Such policies and programs will be far more complicated to design and more expensive to implement. We should not undertake such efforts until we have better evidence about the degree to which vulnerable populations are time-inconsistent.

Climate change adaptation is fundamentally a decision to incur certain costs now in return for uncertain benefits and costs sometime in the future. It should thus not be surprising that humans' time and risk preferences will shape how individuals adapt on their own and in response to public policies and programs. Experimental behavioral scientists can play an important role in elucidating these preferences and their implications for adaptation policy and program designs. But, in order to make more substantial contributions, we need more targeted experimental research that addresses the specific aspects of time and risk preferences that are relevant for climate change adaptation.

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