An Overview of Risk Preferences in Developing Countries*

In preparation for the *Handbook of Experimental Development Economics*

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February 2023

1 Introduction

Risk preferences are an important factor in economic decisions made by individuals. Examples include choices about the optimal amount of savings, investments in agriculture, human capital and health, and entrepreneurship attitudes, among others. Risk preferences are particularly important in developing countries as the influence of risk on choices can have a large impact on welfare.

The research studying the influence of risk on behavior in developing countries has generated a large and growing body of evidence since (e.g., Binswanger (1980)). One common stream of literature argues that poor farmers are risk averse and use risk-averse income smoothing strategies (Rosenzweig and Binswanger, 1993; Haushofer and Fehr, 2014; Guiso and Paiella, 2008). This leads to the low rates of adoption of new agricultural technology (Munshi, 2004;

*We are grateful to Utteeyo Dasgupta and Pushkar Maitra for inviting us to contribute to this volumne, and to an anonymous reviewer for their comments.

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Giné and Yang, 2009), education and health services (Checchi et al., 2014; Eckel et al., 2007; Breen et al., 2014; Dohmen et al., 2017), and has also been found to be associated with lower rates of migration (Bryan et al., 2014). These behaviors make it difficult to escape poverty, potentially contributing to the perpetuation of poverty in this setting (Haushofer and Fehr, 2014; Liu, 2013; Liu and Huang, 2013).

A parallel set of work has also examined the role of shocks in shaping risk preferences, for instance, due to experiences of violence (Callen et al., 2014; Jakiela and Ozier, 2019; Brown et al., 2019) and natural disasters such as earthquakes and floods (Eckel et al., 2009; Said et al., 2015a; Cameron and Shah, 2015; Hanaoka et al., 2018; Brown et al., 2018; Beine et al., 2020). Individuals in developing countries are especially exposed to the vagaries of chance, since their largely agricultural income strongly depends on highly variable weather patterns and formal insurance against adverse events is rarely adopted. Additionally, informal insurance – an important risk-coping mechanism – often has the characteristic that risk sharing is incomplete in developing countries (Rosenzweig, 1988; Townsend, 1994; Kinnan, 2021).

A third set of literature focuses on the methods associated with measuring risk. A number of incentivized experimental methods have been developed such as the Holt and Laury (2002b) method which utilises choice over lotteries. There are also a large number of unincentivized survey methods which are often cheaper and simpler to implement (Dohmen et al., 2011a). While there are potential downsides to uncentivized survey measures, in some contexts they appear to produce similar findings to experiments. Moreover, there may be additional challenges in developing countries to measuring risk preferences due to a number of factors ranging from lower numeracy to a lack of trust by participants that the payoffs will be paid by the experimenter.

In this book chapter, we attempt to summarise the recent key research examining risk preferences in developing countries. In Section 2, we summarise common methods to measure

risk. We pay particular attention to the practical issues with measuring risk in developing countries. In Section 3, we focus on the research investigating the influence of risk in the domains of agriculture, health and education. These are three areas where risk has shown to be important in understanding decision making. We finish this section by discussing evidence on the stability of risk preferences as well as the factors that have been shown to change risk. Section 4 concludes the chapter and offers some suggestion on future research.

By collating the most recent literature studying this topic we hope to provide a useful guide for researchers and policy makers to ensure the influence of risk is adequately accounted for in research and program design.

2 Measurement of risk preferences

In economics and finance, risk preference commonly refers to the tendency to choose an action that involves higher variance in potential monetary outcomes, relative to another option with a lower variance of outcomes (with equal expected value). However, outside the context of a direct monetary payoff, risk preferences can describe the propensity for an individual to engage in behavior with the potential for loss or harm such as willingness to engage in behavior that has a higher potential for unhealthy outcomes.

In this chapter, we refer to any measure that elicits a willingness to take risk as a risk preference, in line with many previous studies (Falk et al., 2018; Hanaoka et al., 2018; Schildberg-Hörisch, 2018; Dohmen et al., 2017; Cheung, 2015; Chuang and Schechter, 2015; Becker et al., 2012; Einav et al., 2012; Frey et al., 2017). In general, models of risk preferences describe attitudes towards a portfolio of lottery choices. Different models describe how people evaluate lotteries, their subjective beliefs about the likelihood of different outcomes and, hence, their choices. We provide a non-exhaustive and a simplified overview of theoretical models that have been estimated using data from the field. It is useful to stress that the exact choice of the model should be informed by the research question and the characteristics of the

sample (Charness et al., 2013).[1] For interested readers, Appendix A contains a discussion of Expected Utility Theory, Rank Dependent Expected Utility, and Cumulative Prospect Theory.

Given the different theoretical frameworks and domains of risk, multiple methods have been used to measure risk preferences. They can be classified into two broad groups: (i) the first uses a survey to elicit self- reported risk preferences and (ii) the second uses some type of lottery task with real monetary consequences. We expand on both below.

2.1 Survey-based measures

The most common survey method of eliciting risk is to directly ask individuals to make a global assessment of their willingness to take risks: "Rate your willingness to take risk in general", with subjects choosing a number from 0 implying that they are completely unwilling to take risk, up to 10 implying they are completely willing to take risk. This is the question used in the German Socio-Economic Panel among others. There are also other variants such as asking (on the same $0-10$ scale): "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?". As discussed below, this measure has been validated using incentivized experiments by Becker et al. (2012); Dohmen et al. (2011a); Hardeweg et al. (2013), who show that the risk preference measure is strongly predictive of actual risky behavior.

A criticism of this survey method is that it is not domain specific. This could be important as some research suggests risk taking varies depending on the context of the decision. The DOSPERT scale was designed for this purpose (Weber et al., 2002). It measures risk in multiple domains - health and safety, financial, social, ethical and recreational. Respondents rate the likelihood that they would engage in risky activities in each domain. While more common in psychology, an alternative measure is the Zuckerman Sensation Seeking Scale

[1] O'Donoghue and Somerville (2018) and Barseghyan et al. (2018) provide excellent reviews of prominent models of risk preferences.

which is a 40-question survey instrument designed to assess individual differences in optimal levels of stimulation (Zuckerman, 1979). There are four 10-item factors: (1) Thrill and Adventure Seeking (e.g., parachute jumping), (2) Experience Seeking (e.g. exploring strange cities or towns alone), (3) Disinhibition (e.g., participating in drug use), and (4) Boredom Susceptibility (e.g., preference for unpredictable friends). A downside of these domain-specific measures is that they tend to be more lengthy, and many of the questions are tailored to a developed country population.

2.2 Incentivized measures

As economists have long noted, there are significant issues with survey measures of risk. Survey measures are not incentive compatible – there is no cost to misrepresenting one's true preferences in a survey – whereas incentivized elicitation methods are designed to have individuals truthfully reveal their risk tolerance. Providing a financial stake when making risky decisions can be a more powerful motivator than simply answering questions about hypothetical situations. This lack of financial incentive may be especially pertinent if elicitation is prone to social desirability bias.[2] Additionally, incentivized measures can provide an estimate of an individual's utility function. For these reasons, incentivized methods are viewed as the gold standard for eliciting preferences. We will first describe the various incentivized methods that have been developed and used and then discuss research that examines the extent to which survey measures are correlated with incentivized measures.

One of the earliest incentivized measures of risk preferences used a lottery approach with actual payoffs, and compared it to a non-incentivized interview where certainty equivalents are measured (Binswanger, 1980). In the lottery, subjects choose one of several 50%–50% gambles with varying loss and win payouts that spanned from a small guaranteed payout in the first option to progressively more extreme spreads. The subjects were unskilled laborers in rural India. Binswanger reports bias in the elicitation using CEs and also confirms that

[2]This may be a particularly true when eliciting risky behaviour in some domains such as health.

Table 1: Ten Decisions used in Low Payoff treatment by Holt and Laury (2002)

Option A	Option B
$\frac{1}{10}$ of \$2.00, $\frac{9}{10}$ of \$1.60	$\frac{1}{10}$ of \$3.85, $\frac{9}{10}$ of \$0.10
$\frac{2}{10}$ of \$2.00, $\frac{8}{10}$ of \$1.60	$\frac{2}{10}$ of \$3.85, $\frac{8}{10}$ of \$0.10
$\frac{3}{10}$ of \$2.00, $\frac{7}{10}$ of \$1.60	$\frac{3}{10}$ of \$3.85, $\frac{7}{10}$ of \$0.10
$\frac{4}{10}$ of \$2.00, $\frac{6}{10}$ of \$1.60	$\frac{4}{10}$ of \$3.85, $\frac{6}{10}$ of \$0.10
$\frac{5}{10}$ of \$2.00, $\frac{5}{10}$ of \$1.60	$\frac{5}{10}$ of \$3.85, $\frac{5}{10}$ of \$0.10
$\frac{6}{10}$ of \$2.00, $\frac{4}{10}$ of \$1.60	$\frac{6}{10}$ of \$3.85, $\frac{4}{10}$ of \$0.10
$\frac{7}{10}$ of \$2.00, $\frac{3}{10}$ of \$1.60	$\frac{7}{10}$ of \$3.85, $\frac{3}{10}$ of \$0.10
$\frac{8}{10}$ of \$2.00, $\frac{2}{10}$ of \$1.60	$\frac{8}{10}$ of \$3.85, $\frac{2}{10}$ of \$0.10
$\frac{9}{10}$ of \$2.00, $\frac{1}{10}$ of \$1.60	$\frac{9}{10}$ of \$3.85, $\frac{1}{10}$ of \$0.10
$\frac{10}{10}$ of \$2.00, $\frac{0}{10}$ of \$1.60	$\frac{10}{10}$ of \$3.85, $\frac{0}{10}$ of \$0.10

the experimental measure of risk aversion explains a portion of the observed variation among individual farmers' agricultural decisions, with the more risk averse choosing the more conservative option. Additional work along the same lines is reported in Binswanger (1981) where risk aversion is measured by the same lottery procedure.

Probably the most common measure of risk was developed by Holt and Laury (2002a), it is based on the multiple price list method.[3] An alternative to eliciting *certainty equivalent*, the objective is to find the *probability equivalent*, or the point at which the subject is indifferent between a safe gamble and a risky one. Subjects are asked to make ten decisions choosing between two lotteries in each case: Option A, a safe binary gamble, and Option B, a risky binary gamble with more variable outcomes. For each of the 10 choices the individual has to choose Option A or Option B. At some point, we expect subject's to switch from choosing Option A to choosing Option B. The point at which they switch can be used as a measure of risk aversion. Someone who switches early is risk loving while someone who switches later is risk averse. See Table 1 for the ten decisions used in their low payoff treatment.

[3]This is likely the most utilized method for measurement, judging from the nearly 7000 citations to the paper. For recent use in developing countries, see de Brauw and Eozenou (2014); Alpizar et al. (2011); Callen et al. (2012); Cassar et al. (2017); Cook et al. (2013); Nielsen et al. (2013).

An alternative is the Becker-DeGroot-Marschak (BDM) method, proposed by Becker et al. (1964). It is a theoretically elegant solution to get participants to reveal their CE as truthful reporting is a weakly dominant strategy. Participants are presented with a series of lotteries or *prospects* that they own and are asked for the minimum price they would be willing to sell it for.[4] However, this method is not as intuitively appealing as, say the HL, and participants can have difficulty understanding the logic (Zhou and Hey, 2018).[5]

Recent research suggests that the experimental measures discussed above are too complex for a developing country context, where education is low, increasing the proportion of subjects giving erroneous answers and ultimately leading to bias in the measurement of risk (Cook, 2015; Filiz et al., 2020; Crosetto and Filippin, 2016; Dave et al., 2010). Cook (2015) describes confusion with some of the methods described above, especially when used to measure risk preferences in less educated communities. The author "examines four recent studies in low-income countries and finds that the empirical distribution of risk aversion in one *American Economic Review* study is statistically indistinguishable from that of confused subjects making choices at random." Along similar lines, Branas-Garza et al. (2021) raise important concerns about incentivized measures, especially when used in the field with lower income subjects. Their concern is two-fold: that it might be unfair to subjects due to inequalities in earnings produced by the lottery and that it might be unsafe for researchers to hold and distribute large amounts of money, particularly in areas with high rates of poverty. In a pre-registered study with subjects in Honduras, Nigeria and Spain, they implement a short version of the Holt and Laury measure. They find that not paying at all or paying with and without probabilistic rules makes no difference to behavior. As a result, they argue that the hypothetical version "makes our measurement of risk cheaper, fairer and safer." Finally, there are concerns about the external validity of the measures with respect to their

[4] A version of this task provides participants the option to buy the lottery, and to provide the maximum price they would be willing to buy it.

[5] Burchardi et al. (2021) report conditions when the measure can be highly accurate, including elicitation with multiple price lists as in Andersen et al. (2006).

relationship with risk-taking in the field (Charness et al., 2020).

A simpler experimental method is the Eckel and Grossman (2008) (EG) design. Participants are presented with 6 gambles and asked to choose one to be played for payment. All of the gambles involve a $\frac{50}{50}$ chance of a low or high payoff. Gamble 1 is the safest option with a sure payoff of 14. For Gambles 2 to 5, the expected payoff increases linearly with the standard deviation. Gamble 6 involves only an increase in variance with the same expected payoff as Gamble 5. This format allows one to distinguish between types. More risk-averse subjects would choose lower-risk, lower-return gambles; risk-neutral subjects would choose Gamble 5 or 6, which have the highest rate of return; only risk-seeking subjects would choose Gamble 6. An individual's choice of a gamble, from Gamble 1 to Gamble 6 – where lower numbers indicate safer choices – is used to construct the variable, 'risk tolerance', in regressions.

A further simpler alternative is the Bomb Risk Elicitation Task (BRET), an intuitive procedure aimed at measuring attitudes towards risk (Crosetto and Filippin, 2013). In the static version, subjects have one decision to make: how many of a total of 100 boxes to collect. For each collected box, subjects receive a payment of €0.10. The catch: one of the boxes contains a 'bomb'. Whether or not the bomb explodes is determined as follows. A number between 1 and 100 is drawn from an urn. If the number drawn is $\leq$ the number of collected boxes the subject wanted to collect, then the 'bomb' has exploded and the result is that the payment is gone. If the number drawn is $>$ the number of collected boxes, the 'bomb' does not explode so the subject receives a payment for each of the collected boxes. The subjects thus have to weigh how much risk they are willing to tolerate relative to the likelihood of the bomb exploding and zero payment.

Filiz et al. (2020) propose another simple measure. Using two decks of cards, the first deck is a 'low-risk' deck and the second deck is a 'high-risk' deck. Both of the decks have the same expected value but Deck A has a lower standard deviation whereas Deck B has a higher standard deviation. Subjects are told about this fluctuation around the expected value. The

decision subjects make are from one of the following: (1) to choose a card from Deck A; (2) choose a card from Deck B; or (3) to be indifferent between Deck A and Deck B. This simple procedure clearly categorizes subjects into risk categories: If subjects choose the first deck, they are considered to be risk-averse; if they choose the second deck they are considered to be risk-seeking; if they are indifferent to which deck they choose, they are categorized as risk-neutral.

Some of these simpler versions have been tested in a developing country context to check for measurement error. Comparing across two easily comprehensible incentivized methods – a modified EG task and an investment game – in India, Dasgupta et al. (2019) find generally consistent measures from the two tasks.[6] The two tasks have a series of similarities in terms of complexity and design, e.g. both require only single decision from participants, with probability of outcomes held at 50 percent, and a safe option in the choice set, which may explain the generally consistent results.

With risk elicitation measures varying in levels of complexity, the choice of the exact measurement method will ultimately depend on the characteristics of the sample, the research question and the precision required in measurement. A poorly understood measure may induce noise, leading to biased estimations. It is also worth noting that, depending on the research question, seemingly inconsistent behavior using certain methods, such as expressions of indifference and 'multiple switches' under the HL method, may be a deliberate design choice, not an indication of poor participant understanding.

Relationship between survey measures and incentivized measures. While survey elicitation of risk preferences may have issues, they are relatively easy to understand and cheap to administer compared to incentivized measures. Research has investigated the extent to which the two ways of measuring risk are correlated. There is some evidence that

[6]The modified EG task more closely resembles that in Dave et al. (2010) with a choice between six gambles. The investment game has subjects divide an allocation between a safe and risky asset, which has a 50% chance of success earning three times the amount invested.

survey measures are correlated with incentivized measures, although the relationship is not necessarily strong and is dependent on which survey measure is being implemented. In a German, representative sample (using the German Socio-Economic Panel), Dohmen et al. (2011a) show that a survey question asking respondents how willing they are to take risks, *in general*, correlates well with measures obtained via incentivized lottery choices and also other measures such as the frequency one gambles. Similar results are found by Falk et al. (2016) using a sample of University of Bonn (Germany) undergraduates.

More recently, researchers have tested the validity of these survey measures in developing countries. Bauer et al. (2020) find a correlation between non incentivized measures of risk and an experimental measure using a sample of low-income individuals in Nairobi, Kenya. Hardeweg et al. (2013) compare the correlation between an incentivised lottery and the German Socio-Economic Panel survey question, using a representative sample in rural, Northern Thailand. They similarly, find a high correlation between the survey and the experimental measure. Vieider et al. (2015), using data from 30 countries, also conclude that survey instruments aimed at measuring risk attitudes correlate with decisions in which real money is at stake. Taken together, these findings provide evidence across a variety of samples that a simple self-assessment of risk attitude provides a useful "general" measure of risk preferences, potentially suggesting that future research can reliably rely on survey measures in cross country comparisons of general population samples.

3 Risk and decision-making

In the following subsection, we discuss the recent risk literature focusing on the themes of agriculture, education and health.

3.1 Agriculture

A large part of the literature investigating risk in developing countries focuses specifically on the context of agriculture and in particular, the influence of risk—both external shocks and individual risk preferences – on farmers' decision making. This research has implications for poverty, since a majority of the world's poor reside in rural areas and depend directly on agriculture (United Nations, 2022). These agricultural communities face constant and at times increasing levels of risk such as higher temperatures, reduced rainfall, prolonged droughts, floods, hailstorms, and pest outbreaks and a multitude of risks associated with agricultural prices variation and imperfect credit markets (Barnett and Mahul, 2007; Ward and Singh, 2014). This is compounded as farmers are often found to be risk averse suggesting both the setting and individual risk preferences can have important implications (e.g.,(Binswanger, 1981; Akay et al., 2012; Senapati, 2020).[7]

One common concern is that households knowing the potential for weather and other related shocks may decide to avoid investing in risky productive technologies. Instead, they adopt low-risk, low-return investment strategies that reduce their exposure to extreme weather events but also keep the household trapped in chronic poverty (Rosenzweig and Binswanger, 1993; Carter and Barrett, 2006; Christiaensen and Demery, 2007). This phenomena suggests the potential existence of a risk induced agricultural poverty trap (Sandmo, 1971; Eswaran and Kotwal, 1990). A number of researchers have attempted to study this possibility. There are generally two routes. The first is to study the correlation between negative shocks such as extreme weather on income or welfare (Vieider et al., 2019). A second possibility is to study the relationship between individual risk preferences or attitudes and farmer decision making. We discuss each in turn.

[7]Most studies measure risk aversion but ignore uncertainty. Exceptions include Engle-Warnick et al. (2009) and Akay et al. (2012). Akay et al. (2012) shows that most farmers are both risk averse and ambiguity averse while Engle-Warnick et al. (2009) conclude that farmers who are more ambiguity averse are less likely to diversify across different crops.

Taking the first route, Rosenzweig and Binswanger (1993) study the correlation between weather risk and income. They find that a one standard deviation decrease in weather risk increases average profits by up to 35% among the lowest wealth quintile in their sample of Indian farmers. Similarly, farmers in Tanzania, with a higher potential exposure to risk, were found to grow lower return, but safer crops foregoing up to 20% of their income (Dercon, 1996). While in Ethiopia, using panel data researchers have shown that when harvests fail due to a negative weather shock, those with lower consumption are 16% less likely to use a productivity enhancing input, such as fertiliser, reducing welfare (Dercon and Christiaensen, 2011). Mixing both the first and second route, Jayachandran (2006) studies the relationship between individual risk preferences and exposure to shocks. The author shows that the effects of negative shocks on welfare are particularly relevant for risk averse individuals. A risk-averse landowner is better off on net when good and bad profit swings are dampened.[8]

The second route, focusing on the implications of farmer risk preferences. A significant body of research in this field concentrates on the relationship between risk preferences and the demand for new agricultural technologies (Knight et al., 2003). Using a field experiment, Liu (2013) specifically measure individual risk attitudes and study the role of individual risk attitudes on the decision to adopt a new form of agricultural technology in China. The paper finds that farmers who are more risk averse or more loss averse are less likely to adopt new agricultural technology, the paper also shows that farmers who overweight small probabilities adopt the new technology earlier. Although they don't use an experiment, making causal claims difficult, Giné and Yang (2009) use a large scale survey from India and show that farmers that are risk averse are less likely to take up agricultural insurance, contradicting the standard neoclassical model. These findings suggest that risk may indeed induce the

[8]When studying risk, nearly all the existing literature focus on a single individual within the household, usually the male household head. However, households at times make decisions jointly. Magnan et al. (2020) study the influence of risk preferences of both the male and female household members. In particular, they focus on the relationship between risk preferences and agricultural technology adoption. The authors find that risk averse women are less likely to adopt new agricultural inputs, but there is no relationship for male household members.

persistence of poverty by trapping individuals in low return, low risk agriculture. There is also some research showing that risk aversion is correlated with environmental overuse. Brick et al. (2012) study the influence of risk attitudes on the overuse of a natural resource-fish- in South Africa. Their results show that the average participant is moderately risk averse, and that those individuals who are risk averse (especially females) were more likely to comply with fisheries regulation.

Despite these findings, it is not completely clear that risk aversion is always negatively correlated with the use of new agricultural inputs. A small number of studies contradict these findings. For example, in the context of Cambodia Shimamoto et al. (2017) examine the correlation between risk aversion and the adoption of post harvest practices–agricultural moisture meters. The authors show that risk averse farmers may be more worried about the risks of manually measuring seed moisture, making them more likely to adopt seed moisture measurement tools. Gong et al. (2016), also finds that risk averse Chinese farmers are more likely to use pesticides, this is especially true for subsistence farmers (who don't sell to the market) and for plots used by non subsistence farmers to sell to the market. Rather than simply measuring agricultural choice via a survey, Ward and Singh (2015), combine a risk measure and a discrete choice experiment between new and familiar rice seeds in India. The authors show that risk averse individuals are more likely to switch to the new seeds (Ward and Singh, 2015). Research by Mohan (2020) studies the influence of risk attitudes on the willingness to change agricultural methods and become certificated to an agricultural standard, such as fair trade or organic. The study shows that farmers who were classified as risk-averse in an experiment were significantly more likely to be certified organic. This positive relationship between certification and risk aversion suggests that while certification may be perceived as risky, it is part of a contract that provides access to risk protection such as support from the certification board and larger markets, which in turn reduces exposure to risk. The mixed findings on the relationship between risk and technology adoption suggests that further work is needed to understand this relationship, a meta analysis for instance may

help summarise existing research.

The potential importance of risk on agricultural decision making and welfare has pushed policy makers to develop and encourage the adoption of tools to reduce potential negative implications of risk. One potential solution to reduce the impact of negative shocks and mitigate potential risk is to register for agricultural insurance (see e.g.,Carter et al. (2016)). Agricultural insurance that pays out in times of weather shocks is expected to smooth income and reduce the impact of climate shocks. To understand the benefits of agricultural insurance particularly in relation to an income shock, Karlan et al. (2014) conduct a large scale experiment. The authors provide a randomized subset of farmers with cash grants or access to rainfall insurance or both. They find that farmers assigned to receive agricultural insurance significantly increase their agricultural investment, while the effects of cash grants are much smaller. This suggests that risk is a critical factor in agricultural investment. With insurance against weather-related risks, farmers are able to access resources to improve agricultural investment.. This result is consistent with Mobarak and Rosenzweig (2013) who randomly offers agricultural insurance and shows that those given insurance have higher yield and profit than the control group.

Although this suggests that insurance has potentially large benefits, a key issue is that the take up of insurance, and other risk mitigation strategies, are often low. For example, in India, despite having access to a heavily subsidized agricultural insurance scheme and the high probability of a weather related shock, take up is less than 10% in some states (Cecilia and Yashodha, 2022). To investigate this low take up, Cole et al. (2013) estimates the slope of the demand curve by randomly varying the price of agricultural insurance, and find that a 10% price decline leads to around a 12% increase in take-up. However, they also show that even under heavy discounts with prices far better than actuarally fair, less than half of households took up insurance. To study other explanations, the authors use experimental variation and show that trust in the insurance product produces higher rates

of take up.[9]

3.2 Education

Investment in education has received considerable attention in the literature on risk aversion. Like agricultural investments, educational investments can be risky — the returns, which are realized in the future, are unknown and uncertain, while much of the investment requires frequent lumpsum payments in the present. Parents have limited knowledge of the motivation and ability of their children when making decisions about investment in education. Education decisions often involve weighing substantial cost outlays against uncertain labor market conditions in the future. Faced with this uncertainty, risk averse and liquidity constrained parents may opt for low risk alternatives that provide immediate but low returns, such as farm labor.

A considerable literature explores the role of parental risk aversion in the schooling decisions for their children (Checchi et al., 2014; Eckel et al., 2007; Belzil and Leonardi, 2013), and the role of students' risk aversion on their academic performance (Breen et al., 2014; Hanushek et al., 2021). While evidence points towards a systematic correlation between risk aversion and educational choices[10], determining causality remains a methodological challenge (Dohmen et al., 2018). For instance, while risk aversion may determine the probability of investing in education; increasing levels of education can also affect individual preferences for taking risky decisions. Chew et al. (2016) use a sample of adult twins in China and exploit within-pair fixed effects to understand if education can impact risk preferences. They find

[9]See also non experimental evidence by Guiso and Paiella (2008) that liquidity constraints reduce demand. They find that providing cash for one insurance policy increases demand by 140%. Additional Casaburi and Willis (2018) study the take up of insurance for agricultural production. They show that when the time dimension (i.e., typically paying a premium in advance, whereas the potential payout is delivered with a delay) of a typical insurance contract is removed such that only the risk dimension remains, take-up increases dramatically to 72%, compared to 5% for the standard pay-up-front contract. Together, this suggests that although agricultural insurance is promising, further work is needed

[10]See, for instance, evidence from Denmark, Italy and Canada that associates increasing risk aversion with decreasing probability of investment in education Breen et al. (2014); Belzil and Leonardi (2013); Checchi et al. (2014); Eckel et al. (2007).

that college education reduces an adults' degree of risk aversion towards moderate gains and losses, validating concerns about reverse causality.

A body of literature examines the relationship between an individual's level of risk aversion and decisions they make about their own human capital, by exploring the relationship between parental risk aversion and enrollment decisions for their children, ruling out any possibility of reverse causality. For instance, parental risk aversion is negatively correlated with investments made for children in poor households in rural Uganda (Tabetando, 2019). However, this negative correlation is valid only for the sub-sample of credit constrained households, suggesting that the generally negative association between risk aversion and educational investment may be subject to considerable heterogeneity. Frempong and Stadelmann (2021) uses a quasi-experimental design and find that when the household head is risk-averse, children are more likely to be working and spend less time in school, resulting in lower overall household investment in education.

The importance of risk preferences on education may be especially large if preferences are transmitted across generations. To investigate the causal impact of intergenerational risk preferences on performance in school, Hanushek et al. (2021) combine two large data sets – the Global Preference Survey by Falk et al. (2018) that provides a validated, unincentized survey measure of risk aversion from 76 countries and the Programme for International Student Assessment (PISA) which measures test performance 15-year-old students in math, science and reading tests in 86 countries. To uncover a causal relationship, they restrict the analysis to a sub-sample of migrant students, assigning origin country risk preferences to students observed in the same residence country and controlling for residence country fixed effects. They find students with 1 standard deviation higher levels of risk taking in their origin countries perform 0.3 standard deviations worse on the PISA, implying that intergenerational risk preferences can affect academic performance of students.

3.3 Health

Risk preferences have been studied in the domain of health economics for the last few decades. Earlier evidence from developed contexts suggest that risk taking individuals are expected to be more tolerant of risky health behaviors, such as smoking, excessive drinking, obesity, and less likely to undertake preventative behaviors, such as exercise, testing or purchase health insurance (Barsky et al., 1997; Picone et al., 2004; Dohmen et al., 2011b). While theoretical models seem to validate this association between risk aversion and preventative health behaviors, evidence from developing countries is rare and mixed. Using measures utilized in earlier work in developed countries (Dohmen et al., 2011b), and validated on data from Thailand by Hardeweg et al. (2013), Herberholz (2020) find risk averse individuals are more likely to be obese. They attribute the contrary result to different cultural considerations in developed and developing world contexts. In Thailand, obesity may be taken as an indicator of financial well being and abundance, rather than an indicator of at-risk health (Hughes et al., 2010; Tovar and Must, 2014). In this context, being overweight may be protection against future risks and uncertainty, and risk averse individuals may be more likely to be overweight as a protection against undernourishment.[11]

Further evidence using incentivized experiments in Peru (Castillo et al., 2018) and Senegal (Lépine and Treibich, 2020) suggest that risk averse individuals are less likely to engage in risky health behaviors (e.g., smoking, drinking, unprotected sex). In contrast, a small number of studies have found no relationship between risk and health behavior. They show little or no association of risk aversion measures and actual behavior related to smoking, drinking, seat belt use and sexual practices in South Africa (Harrison et al., 2018; Szrek et al., 2012). While low statistical power may be a relevant concern in these studies, the authors do not believe a lack of understanding to be an issue. Despite the interest in this question, most of the literature struggles in identifying causality. Rieger (2015) explore

[11] In an earlier study, Gao and Shen (2017) find similar results from a sample of 1014 adults in China, albeit using an invalidated survey measure.

the relationship between parental risk aversion and child health in an attempt to remove concerns of reverse causality - though other sources of possible spurious correlations may remain. They find children of risk averse parents are more likely to be well-fed, taller, and heavier (Rieger, 2015).

3.4 Other Domains

Risk preferences are relevant in a variety of other decision-making domains relevant to the developing world, such as gender, adherence to laws, and the decision to migrate. For instance, risk preferences may influence compliance with government mandates, with the risk averse more likely to follow government regulations (Brick et al., 2012). In this subsection we summarise a two of these additional domains.

One large body of work is the literature studying gender differences in risk. Evidence from both the developed and developing world indicates that women are typically more risk averse than men, and that these differences may lead to men and women making different decisions faced with the same circumstances (Croson and Gneezy, 2009; Dohmen et al., 2011b; Brick et al., 2012; Turner et al., 2014; Jin et al., 2017). For instance, differences in risk preferences among men and women may explain why we find gender differences in choice of occupation, financial and human capital investment, and marriage market and fertility decisions.

In the context of migration, Goldbach and Schlüter (2018) argue that risk and time preferences can play an important role in the decision to migrate. While other work has attempted to empirically estimate the link between risk preferences and migration using survey data (Jaeger et al., 2010; Williams and Balàz, 2014), Goldbach and Schlüter (2018) complement survey data with measures of risk preferences from incentivized experiments with coastal communities in India and Ghana. Their findings imply that migration is a highly selective process and risk averse individuals are less likely to migrate. Risk and time preferences, along with other factors commonly considered by migration theories and policies, such as

networks, education, or employment status, have substantial explanatory power in their sample. These findings are in line with recent evidence that variability in potential outcomes act as a barrier to internal migration in Bangladesh (Bryan et al., 2014) and China (Dustmann et al., 2020).

3.5 Stability of Risk Preferences

In much of the literature discussed above, there is an implicit assumption that risk preferences are stable (i.e., they do not change over time). Leaning on this assumption, economic theory typically seeks to explain changes in individual behavior through changes in prices and constraints rather than changes in preferences. However, there is a growing literature exploring the possibility that preferences change over time (Schildberg-Hörisch, 2018; Stigler and Becker, 1977; Salamanca et al., 2021; Golsteyn and Schildberg-Hörisch, 2017; Dohmen et al., 2017). Understanding the stability of preferences may be particularly important in developing countries because it is not uncommon for policies to encourage individuals to take greater risks, such as by promoting different forms of entrepreneurship or altering farmers' agricultural practices. Interventions that target risk may not be effective if risk preferences are unstable and change especially in the short term.

Determining the stability of risk preferences is mainly an empirical question. The most widely used method to study it is by estimating the correlation of risk preferences over time for the same individual. Risk preferences with a high correlation are considered to be stable. This correlation ranges between 0.05 to 0.42 in developing countries which is lower than that found in developed countries (which range from 0.13 to 0.68 (see Meier and Sprenger (2015), Chuang and Schechter (2015) and Schildberg-Hörisch (2018)). The empirical findings in the literature on the stability of risk preferences are generally mixed with some research suggesting they are stable (Harrison et al., 2005; Dasgupta et al., 2017).[12] While another

[12]For instance, Dasgupta et al. (2017) study stability of risk preferences in the presence of an experimentally controlled state space and show that risk preferences are temporally stable

(generally smaller) set of studies suggest that they vary over time (Lönnqvist et al., 2015; Menkhoff and Sakha, 2016)). Chuang and Schechter (2015) provide a useful overview of the existing literature in developing countries. Despite this growing literature, existing estimates should be interpreted cautiously as they often rely on small non representative samples with estimates that potentially suffer from measurement error.

More recently, Salamanca et al. (2021) have overcome some of these issues by developing a model to study the dynamics of risk preferences in developed and developing countries using representative data. The authors find that risk preferences are far from stable in developing countries, with idiosyncratic shocks being an important source of variation.[13] They argue that low income security and the lack of access to adequate social protection may play a role in determining the stability of risk preferences. This suggests that especially in developing countries, policies that target risk preferences may be problematic in the longer term. [14]

3.6 Factors influencing risk behavior

If preferences change, then a key question is to understand the factors that are correlated with changes in risk taking (Dohmen et al., 2017; Grubb et al., 2016; Schildberg-Hörisch, 2018). One possibility is through a shock or a explicit government policy. Theoretically, each individual has their own risk preference that will be dependent on factors like background risk (Cameron et al., 2013). A "shock" or new information about the state of the world contains new information about background risk leading to a potential change in the willingness to take more or less risk. The possibility to change risk behavior and subsequently understanding how policies (either intentionally or unintentionally) impact risk is of interest to researchers and policy makers. For instance, Cameron et al. (2013) use an incentivized investment game to study change in preferences in adults born immediately before and after China's one child policy (OCP). They find adults born after the OCP are systematically

[13] In contrast they find that preferences are largely stable in the set of developed countries under study.

[14] Harrison et al. (2020) also utilise a model that aims to account for endogenous sample selection and attrition. They show that in developed countries risk preferences are temporally stable.

more risk averse in incentivized experiments, they are also less likely to be altruistic and less trusting of others, implying long lasting impacts on the Chinese society.

Natural disasters such as floods to droughts are another shock. Cameron and Shah (2015) examine the impact of exposure to a natural disaster on the risk attitudes of people in Indonesia. They find that individuals who recently suffered a flood or earthquake are more risk-averse. The authors argue that exposure to a natural disaster increases peoples belief about the possibility of a natural disaster in the future (thus increasing background risk). Similarly, results from incentivized experiments with survivors of one of the most devastating floods in the Pakistan's history indicate that individuals who suffered from higher losses are more risk taking after the shock (Said et al., 2015b). Beine et al. (2020) study the effects of two earthquakes in Albania on risk preferences of those affected. They report that individuals are significantly more risk averse following the first shock and that the second earthquake amplified the effect of the first. This suggests risk preferences may be more malleable than assumed. Exposure to conflict has also been shown to change risk behavior. Voors et al. (2012) find that participants in incentivized experiments were more risk seeking, several years after experiencing civil conflict and violence, suggesting that preferences can undergo persistent change even after the initial shock from the event has worn off. However, the implications of extreme events for preferences can be context and event specific. Callen et al. (2014) highlight another type of shock: the susceptibility of traumatized individuals to temporary primes. Individuals who were administered primes to induce fear or anxiety were significantly more risk tolerant under uncertainty, suggesting policy makers and others interacting with traumatized individuals may trigger specific behavior.

4 Conclusion

Risk preferences are one of the cornerstones of economic and psychological theories of choice. There is now growing evidence that risk preferences are particularly important in developing

countries. Individuals in this setting are more prone to experience shocks such as natural disasters and many important decisions require undertaking choices under risk.

In this book chapter we summarise the recent literature studying risk preferences in developing countries. We start by discussing a theoretical framework behind the examination of risk followed by a summary of common methods to measure risk. We then discuss the research investigating the influence of risk in the context of agriculture, health and education. These are three commonly studied areas in the context of developing countries.

These results highlight the importance of risk preferences in developing countries. We report evidence that particular survey questions of risk attitudes may be useful for measuring risk preferences. We also show that risk preferences are important for agricultural decisions. For instance, a decrease in weather risk can have large impacts on wealth. The importance of risk in agriculture has led to the developed of numerous policies that aim to reduce the cost of risky behavior. These policies have mixed results; especially worrying is the low take up of these products such as agriculture insurance. Further research is needed to understand this "last mile problem". The last mile problem is a significant challenge in development economics, as it can hinder progress and perpetuate poverty in isolated communities.

We show that risk preferences of the parents can determine their investment on the education and health of their children. Resource-constrained risk averse household can be less likely to invest in their children's education – with returns to education being uncertain and, in the future — choosing to send them to work today. Similarly, risk averse parents may be more likely to invest more in the health of their children to reduce the risk of ill-health in the future, but 'appropriate' levels of investment can be highly context specific. These studies suggest that risk preferences should be an important consideration when designing policies to encourage investment in human capital.

The discussion in this chapter also highlights several unresolved issues in the developing world context that provide directions for future research. For instance, the success of a

policy in mitigating costly decisions when faced by risk may vary by whether the individuals are considering potential gains and loss to self, or to others who depend on them. Existing evidence on the interaction of who the individual is making decisions in a particular domain for, with gain or loss considerations is weak.

Another potential concern is the measurement of risk preferences which can lead to varying estimates of individual risk preferences (e.g., see Pedroni et al. (2017)). In a recent paper, Holzmeister and Stefan (2021) use a more nuanced approach and find that subjects are well aware of the variation in their decisions across different tasks. Their results imply that the apparent heterogeneity in decisions reflect domain-specific preferences. However, literature reconciling differences in estimates in developing world contexts is sparse, where lack of literacy and numeracy can also obfuscate consistency of preferences (Dave et al., 2010). This provides an additional justification for using a simpler risk measure, such as Eckel ad Grossman and the Bomb Risk Elicitation Task; unfortunately, we could only locate one working paper that uses the BRET task. Botchway and Filippin (2022) use BRET to measure the impact on farmers' risk preferences of persistent flooding risk in Ghana. This suggests a potential area for future research in the field.

More recent research has also suggested that risk preferences in developing countries are not stable. This result suggests that the effectiveness of development programs may vary over time, especially if exposed to large shocks. Similarly, welfare calculations, many of which implicitly assume preference stability, are likely to be misleading in developing countries. However, the implications of unstable risk preferences are largely unstudied. Future work is needed to understand potential implications on development programs over the medium to longer term. Unstable risk preferences also suggest that researchers should be frequently *measuring* and monitoring risk preferences. If risk preferences cannot be treated as stable in developing countries, repeated measurement will help program designers implement incentive-compatible and welfare-increasing interventions in these populations.

Finally, the novel Coronovirus disease (COVID-19) resulting in a global pandemic has had a significant impact on the well being of people in developing countries both directly through contact with the virus and indirectly through government policies and changes in the economy (Brodeur et al., 2021; Gupta et al., 2021). People have faced an increased degree of uncertainty and a wider array of potentially risky decisions in the pandemic than before, from business investments, typical household activities, and unusually volatile capital markets. While research is highly dynamic in this area, there is little existing research studying the relationship between COVID-19 and risk preferences in developing countries especially over the medium to longer term. This is despite the possibility that an individual's risk preferences may be correlated with exposure to the virus or similarly the impact of COVID-19 on welfare. There are two relevant exceptions Adema et al. (2022) and Chan et al. (2020). The first directly assesses the stability of risk preferences in Czechia, India, Mexico, and Spain, but only in student samples in these four countries. The second has a more representative sample, but primarily focuses on how risk preferences drive mobility behavior during the pandemic, rather than considering how preferences have changed. One interesting question to consider for future research is that it is difficult to predict how changes in behavior, particularly those that are driven by risk aversion, will persist over time. It is possible that some of the changes in behavior that have occurred as a result of the COVID-19 pandemic will become permanent habits, while others may be temporary and disappear once the pandemic subsides. Future research will be able to provide more insights into this question by examining how individuals' risk preferences and behaviors change over time and under varying circumstances.

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Appendix

A Theoretical Models

For the interested reader, this Appendix contains an overview of the theoretical models. We begin with a summary of the Expected Utility (EU) model. Under the standard EU model, an individuals' evaluation of a lottery, X, is a weighted average of utility from each possible outcome, x_n, where the weight of each outcome is defined by the probability of an outcome occurring, p_n. Outcomes are typically expressed in monetary terms and add to existing wealth, w. Given a choice set $\mathbf{X}$, an individual will select lottery X that maximises Expected Utility:

$$EU(X) = \sum_{n=1}^{n} p_n u(w + x_n) \tag{A1}$$

where u is a utility function capturing an individual's preference towards prior wealth (w) and risk. Preferences under risk can vary because of different, subjective beliefs of an outcome occurring and the shape of the utility function. Assumptions about the shape of the utility function are therefore key to understanding risk preferences under the EU framework. For instance, when deciding between a certain payment (certainty equivalent or CE) and a risky lottery with the same expected payoff, individuals with a concave utility function, will be willing to accept a CE that is strictly less than the expected payoff from the lottery, rather than participating in the lottery. This is because the uncertainty associated with the risky payoff reduces their overall utility. For example, if the expected value of a lottery is \$100, an individual with a concave utility function might be willing to accept a CE of \$90 rather than participate in the lottery. This is because the certain payment of \$90 gives them more utility than the uncertain outcome of the lottery, even though the expected value of the lottery is higher. These individuals are risk averse. Individuals with a convex utility function, on the other hand, will be willing to accept the lottery even when the certain alternative CE is more than the expected payoff from the lottery, and are risk loving. Finally, risk-neutral individuals can be considered to have a linear utility function, willing to pay up to the

expected payoff from the lottery.

The main objective, therefore, is to estimate the utility function. The most common forms are Constant Absolute Risk Aversion (CARA) and the Constant Relative Risk Aversion (CRRA). Under CARA, the utility function takes on the form such that prior wealth is irrelevant to an individual's level of risk aversion. That is, risk aversion does not decrease (increase) as an individual becomes wealthier (poorer). Under CRRA, individuals have a decreasing absolute risk aversion. The coefficient of relative risk aversion can be estimated by observing individual choices in gambles or using certainty equivalents. However, this model requires existing wealth as an input – which can be difficult to measure accurately in the real world (Barseghyan et al., 2018).

The popular CRRA family of models assume the same utility function can be used to model risk aversion in different circumstances and choices, which means that if an individual accepts (rejects) a 50-50 gamble at very low stakes, she must also accept (reject) a 50-50 gamble with moderate or high stakes. However, in real life, people can be very risk averse on small stake gambles, at the same time that they are moderately risk averse on large stake gambles – the EU model is unable to model both behaviors within the same risk aversion parameter. This issue was formalized by Rabin (2000).

An alternate model – the Rank Dependent Expected Utility (RDEU) framework (Quiggin, 1982) – attempts to explain risk preferences for both small and large-stake risks. Under the RDEU, individuals not only vary in subjective beliefs about probability of an event, but also the 'favorability' of that event compared to others (Diecidue and Wakker, 2001). The intuition being that individuals rank outcomes from most to least preferred and weigh outcomes differently. Pessimistic individuals may believe unfavorable outcomes are more likely to occur and 'overweigh' the worse outcomes. Optimistic individuals may unrealistically over weigh favorable outcomes and give insufficient weight to less favorable outcomes. Empirical literature suggests a S-shaped probability weighting function which is concave over small

stakes and convex over moderate or large stakes. Karmarkar (1978); Lattimore et al. (1992) and Prelec (1998) are prominent functional forms for estimating risk aversion levels under this framework.

The Cumulative Prospect Theory, derived from Tversky and Kahneman (1992) Prospect Theory, combines loss-aversion with the RDEU. Utility is derived from gains or losses relative to a reference point, not from final wealth as under the EU framework (Barseghyan et al., 2018). The Tversky and Kahneman (1992) functional form allows individuals to be simultaneously risk averse (for gains) and risk seeking (for losses). The framework requires specifying a reference point: in lab experiments, this is often the experiment endowment, but it can be difficult to pin down in field experiments and natural settings.