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DO CASTE AND SOCIAL INTERACTIONS AFFECT RISK ATTITUDES AND ADOPTION OF MICROINSURANCE? EVIDENCE FROM RAINFALL INSURANCE ADOPTION IN GUJARAT, INDIA[1]

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ABSTRACT

In this paper, we argue that for an improved understanding of the market for microinsurance, it is necessary to understand the social context within which risk attitudes are formed and participation decisions are made. Given the scarcity of empirical evidence on the relationship between social affiliation, social interaction, risk attitudes and market participation in the context of microinsurance, we estimate the impact of caste affiliation and social interaction on farmers' risk attitudes using microdata of rural farm households from the Indian state of Gujarat. Both, caste affiliation and social interaction are found to significantly affect the risk attitudes of farmers. Farmers belonging to the Scheduled Caste (SC) and the Other Backward Classes (OBC) categories are 13 and 10 per cent more likely to be risk averse than the Other Castes (OC) farmers, respectively. Also, farmers who reported getting agricultural information from friends in the same or other villages are 27 per cent less likely to be risk averse than the farmers who do not engage in such interactions. Our analysis of the effects of caste affiliation and social interaction on adoption of an innovative microinsurance product, rainfall insurance also reveals a significant influence of social interaction on adoption. Farmers who get agriculture related information from friends in the same or other villages are 29 per cent more likely to participate in the market for rainfall insurance than those who do not. Important policy implications for the development of microinsurance follow from our findings.

1. INTRODUCTION

Agriculture is a risky enterprise and farmers' risk bearing capacity as well as their risk management strategies are determined by their risk preferences or risk attitudes to a large extent (Binswanger, 1978; Binswanger and Sillers, 1983; Eswaran and Kotwal, 1990; Knight et al., 2003). Risk preferences of the farmers are central to agricultural decision making in the context of adoption of new technology and agricultural innovations. Risk factors are also critical in determining the consequences of risk on household welfare (Gaurav, 2012). Having acknowledged the importance of risk attitude of farmers, an improved understanding of the determinants of their risk attitudes appears non trivial. In this context a question that emerges is: does an individual's cultural and social affiliation shape his (her) risk attitude?

The effect of social and cultural affiliation on individual risk attitudes is well established throughout the world. There is a strand of literature that identifies the differences in risk attitudes of individuals from different ethnic groups, nationalities and religious affiliations. For example, Brimmer (1988) finds African Americans in the US to be exhibiting risk aversion behaviour by investing in low risk and low return assets compared to white communities. Halek and Eisenhauer (2001) find African Americans and Hispanics to be more risk tolerant than Whites in the US, while Brumagim and Wu (2005) find Chinese individuals to be more risk seeking than their US counterparts. Zinkhan and Karande (1991) find evidence on cross-cultural differences in risk attitudes, with Spanish students demonstrating more risk aversion than students of other nationalities. Bartke and Schwarze (2008) find individuals with a religious affiliation to be significantly less risk tolerant than atheists, and Muslims and Protestants to be relatively more risk averse.[5]

Though the above mentioned studies are confined to individuals in the developed world, an important question that remains to be answered is the role of socio-cultural affiliation in the context of the developing world. Using a sample of small scale farmers in Chile and Tanzania, Heinrich and

1 We would like to acknowledge the research grant from ILO Microinsurance Innovation Facility for taking up this study. Thanks are in place to Tatiana Goetghebuer of FUNDP, Namur for facilitating the study. We are thankful to Natu Macwana of Sajjata Sangh and staff at the field offices (SSKK, Khambha and Daheda Sangh, Khambhat) for collaborating with us. Ilesh Shah provided excellent survey assistance. We also acknowledge the organizational assistance from the Centre for Microfinance, IFMR, Chennai, India. We are thankful to two anonymous referees for their insightful comments.

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5 Strictly speaking, risk attitude, risk tolerance and risk appetite are not the same. While risk attitudes comprise of risk aversion, risk neutrality and risk seeking behaviour; risk tolerance pertains to the acceptable and unacceptable deviations from the expected payoffs. Risk appetite on the other hand, consists of the quantum or the degree of risk an individual is willing to take.

McElreath (2002) find that, while sex, age, land holdings and income do not predict risk preferences of small-scale farmers in Chile and Tanzania, cultural group affiliation seems to predict their risk preferences.

Furthermore, the literature on innovation adoption by farmers (e.g., see Feder, Just and Zilberman (1985) and Besley and Case (1993) for an excellent review of literature) has also identified the effect of social networks on attitudes towards new technologies, and in turn their adoption. There have been numerous studies on the role of social networks, especially social learning (e.g. Banerjee, 1992; Bhikachandani, Hirshleifer and Welch, 1992), social networks (e.g. Manski, 1993; Bertrand, Luttmer and Mullainathan, 2000) and experimentation by individuals (e.g. Besley and Case, 1994) in technology diffusion. For example, Bandeira and Rasul (2003) show how Mozambiquan farmers' decisions to adopt a new crop (sunfl ower) relate to the adoption choices of farmers in their social network of family and friends. Three important results of their work suggest the relevance of social networks in farmers' adoption process. First, they provide evidence of an 'inverted-U' shaped relationship, indicating social eff ects to be positive when there are few adopters in the network, and negative when there are many. Second, they demonstrate that the adoption decisions of farmers with better information about a new crop are less sensitive to the adoption choices of others. Third, they show that adoption decisions are more correlated within the network of family and friends than within religion networks, which show no correlation in adoption decisions of farmers.

On a similar note, Conley and Udry (2001; 2010) develop the notion of 'information neighbourhoods' to establish a positive effect of social learning through informational linkages on technology adoption by pineapple farmers in Ghana. Moser and Barrett (2003) also find social learning from others as a significant variable in determining modern rice technology adoption among rice farmers in Madagascar. In the context of risk management and insurance, Vanderpuye-Orgle and Barrett (2005) find that the people left out of social networks are relatively less insured than people with strong social networks.

In the Indian context, Foster and Rosenzweig (1995) look at the adoption of high yielding varieties (HYVs) and find social learning to be relevant and that the farmers with more experienced neighbours earn higher profits. Munshi (2004) finds significant heterogeneity in the modern technology adoption decisions of Indian farmers. He provides evidence that wheat growers respond strongly to their neighbours' experiences while rice farmers experiment.

Maertens (2012) identifies three distinct channels through which social networks influence adoption of 'Bt cotton' in India: social learning, social pressures and imitation. Her results suggest that the importance of knowledge about profitability of the new technology is established through experimentation, observing and learning from experiences of other farmers and discussing the technology with others. She also finds evidence of imitation: adopting a new technology without observing the outcomes of other farmers. Further, she argues that social pressures could be inhibiting the technology adoption process. In the context of 'Bt cotton' in India, Gaurav and Mishra (2012a) also suspect social networks to have played an important role in its remarkable diffusion over the past decade.

Though there are a few studies which have investigated the impact of social affiliation and interaction on the risk attitudes of farmers in the developing world, a literature search on the subject failed to result in any study which has rigorously investigated the same relationship for India.[6] Today, India is one of the fastest growing economies of the world, with a substantial rural and agricultural sector; but the share of agriculture in India is shrinking at an enormous pace. Also, there has been a crisis in the Indian agriculture as well as the agrarian society, which has been associated with a spate of farmers' suicides and falling agricultural productivity in different parts of the country (Reddy and Mishra, 2009). Mishra (2008) and Gaurav and Mishra (2012) suggest an improved understanding of risk and uncertainty issues in the midst of such an unprecedented crisis. Given the limited evidence on the determinants of risk attitudes of Indian farmers, particularly on the role of caste and social interactions, we in this paper, investigate the possible determinants of risk attitudes of a sample of Indian farmers with a special focus on social affiliation and social interaction. We measure social affiliation by a farmer's caste affiliation and social interaction by the information on whether a farmer gets agriculture related information from his (her) friends: in his (her) own villages or other villages.

We measure risk attitude using hypothetical questions on a farmer's selection criteria while adopting new agriculture innovations under conditions of risk and uncertainty. As the discussion on social affiliation, social interaction and risk attitude will be incomplete without understanding how these factors affect adoption of innovations, we further investigate the effects of caste affiliation, social interaction and risk

6 Binswanger (1981) investigated the effect of caste on risk aversion and failed to find any significance between a farmer's caste ranking (relative position in a caste hierarchy as well as relative population share of the caste the farmer belonged to) and risk aversion However, the study doesn't take into account the role of social interaction in shaping the risk attitude of farmers and further, it is more than two decades old.

aversion of farmers on their adoption of a relatively new innovation – rainfall insurance.[7] For the first stage of the analysis (effect of caste affiliation and social interaction on risk attitudes), we use a rich micro dataset comprising of 800 farmers in two-agro ecological zones in the state of Gujarat, India. In the second stage we study the role of caste affiliation and social interaction in explaining rainfall insurance adoption. For this purpose, we use a subsample of 400 farmers from one of the agro ecological zones (of the above dataset) where rainfall insurance was offered.

We find that caste affiliation significantly affects the risk aversion of farmers; with farmers belonging to the Scheduled Castes (SC) and the Other Backward Classes (OBC) category being 13 per cent and 10 per cent, respectively, more likely to be risk averse than the Other Castes (OC) farmers. We also find social interactions to have a significant effect on risk aversion in the sense that farmers with social interaction are 27 per cent less likely to be risk averse than farmers who do not get agriculture related information from village friends or friends from other villages. Further, we find that farmers' social interaction significantly encourages their adoption of rainfall insurance. Our point estimates indicate that farmers who get agriculture related information from friends within their village as well as other villages are 29 per cent more likely to adopt rainfall insurance than those who do not.

The paper is structured as follows. The next section describes some salient features of caste affiliation, social interaction, risk attitude and rainfall insurance in India. It is followed by a section providing details of the survey and the data used in this study. Estimation and Results follow the discussion on survey and data. The last section concludes our study along with providing some policy implications.

2. CASTE AFFILIATION, SOCIAL INTERACTION, RISK ATTITUDE AND RAINFALL INSURANCE

We take caste affiliation as a measure of social affiliation as caste forms the social fabric of India (Deshpande, 2011).[8] We have reasons to believe that taste affiliation is likely to shape the risk attitude of Indian farmers. Our conjecture that caste background of farmers might shape their risk attitudes and also influence the adoption of rainfall insurance is grounded in the following reasons.

First, it is well established that individuals belonging to some castes in India, to be specific, Scheduled Castes (SC) have historically suffered from severe exclusion from social activities and public resources like water wells, public grounds and access to markets (Shah et al. 2006; Deshpande 2011 and the references therein). Similarly, individuals belonging to Scheduled Tribes (ST) category have suffered from substantial physical and social isolation (Das et al. 2010). Together they (SCs and STs) are considered to be the lowest in the social hierarchy. They are followed by individuals belonging to Other Backward Classes (OBC) which are considered above the Scheduled groups in the social hierarchy but below individuals belonging to the General/Upper/Other castes (OC) category (Deshpande 2001; Shah et al. 2006).

Social exclusion is common in villages and also translates into active discrimination in access to different governmental and non-governmental services including credit and agriculture markets (Shah et al. 2006). Shah et al. (2006) relates low productivity (and therefore low income) for the SC farmers to discrimination in access to factor input market which results in higher prices for the factor inputs (vis-a-vis

7 See Manuamorn (2007) for the development of index based weather insurance in the form of rainfall insurance in India.

8 Castes in the Indian context are related to 'Jatis' (and 'upajatis' or subcastes) and 'Varna'. The ancient Varna system divided the Hindu society into initially four, later five, distinct 'Varnas' or castes that are mutually exclusive, hereditary, endogamous, and occupation specific. These castes are the Brahmins (priests), Kshatriyas (warriors), Vaisyas (traders and merchants), and Sudras (those engaged in menial jobs) and those doing the most despicable menial jobs – the Ati-Sudras or Antajyas, the former untouchables (those belonging to the fifth group are also commonly referred to as the 'Dalits'). However, the operative category that determines the contemporary social code is the 'Jati'. Jatis are also castes (and share the basic characteristics of the Varna), with individuals of different jatis lying at different levels of development and welfare (Deshpande, 2000, 2001, p. 131). There has been sufficient evidence of some Jatis having suffered severe discrimination and atrocities on the hand of upper castes of Indian society. The Constitution of India abolished the practice of untouchability and prohibits any discrimination on the basis of caste. The Government of India imbibes the principle of social equality and implements affirmative policies in terms of positive discrimination (compensatory discrimination) favoring the lower castes (SC, ST and OBC) and categorizes the different Jatis into four caste categories, namely, SC, ST, Other Backward Classes (OBC), and Other Castes (OC). The social and economic condition of SC/STs has been historically poorest in India followed by OBCs whose conditions were poorer than the OCs (other castes or upper castes) (Singh 2011, p. 106).

market prices) for the SC farmers. The study also reports about restrictions on selling of produce by the SC farmers, which results in lower selling prices (than market prices) and loss of income. Using data from the northern parts of the state of Gujarat (same as our study state), Dubash (2002) finds that the lower caste farmers are excluded from the benefits of groundwater exploitation in the study regions owing to their limited access to land and credit. The benefits of the deeper tube wells (which require high investments) are also cornered mainly by the land owning castes, such as 'Patels' (one of the upper/other castes (OC) in the state of Gujarat), further centralising control over water and widening the gap between the lower and the Other Castes (OC) farmers.[9] Anderson (2011) offers additional evidence on the restriction on access to important markets like groundwater (for irrigation) for farmers belonging to lower caste categories. The study's results suggest that the OC households do not easily trade water with the SC and the OBC households.[10] Also, the SC and the OBC farmers have better access to irrigation through private groundwater markets in the SC and the OBC dominated villages compared to villages dominated by the OCs.[11]

Moreover, Singh (2011) provides evidence on lower annual net farm returns for the SC/ST and the OBC farmers compared to farmers belonging to the OC category. Due to social isolation, absence of strong social support systems and restriction in access to different markets (especially credit markets), the risk attitude and risk management behaviour of SC, ST and OBC farmers could be hypothesized to be significantly different or could have evolved differentially from that of farmers belonging to the Other Castes/Upper Castes (OC) categories. To be specific, there is every possibility that famers belonging to the SC category might show different (more) risk aversion than farmers belonging the OC category.[12]

Moscardi and Janvry (1977) can also be referred to in this regard. This study which is based on the farmers of Mexico, finds that access to public institutions significantly reduces the risk aversion of farm households. Given the nature of caste based differences (discrimination) in access to public institutions in India, there is every possibility that farmers of different caste groups exhibit different levels of risk aversion. Added support for the caste based diversity in risk behaviour of farmers comes from the findings of Eswaran and Kotwal (1990), who argue that the differences in risk behaviour of farmers arise from differences in the ability to smoothen consumption through risk pooling mechanisms like credit and money transfers from friends and relatives.[13]

Second, the relationship between individual risk attitude and social affiliation along with the fact that caste forms the social fabric of Indian populace lend support to our hypothesis of caste affiliation contributing to the risk attitude of Indian farmers.

Third, caste affiliation could influence risk attitude through its influence on awareness level of farmers. For example, Bonte and Filipiak (2011) find that the SC/ST populations residing in regions with a large fraction of SC and ST population have a lower probability of being aware of various financial instruments. Whereas, Knight et al. (2003) find that awareness affects risk aversion, as it is likely to lower risk aversion. Taken together, these two studies support our belief that caste affiliation can shape up the risk attitudes of farmers.[14]

Finally, since caste affiliation can influence the formation of risk attitudes which influence adoption of innovations like rainfall insurance, caste can potentially affect the adoption of these innovations.[15] Caste affiliation can also influence rainfall adoption through the awareness channel. Moreover, Bonte and Filipiak (2011) find some empirical evidence of a direct effect of caste affiliation on investment behaviour.

The significance of social interaction in risk attitude formation and adoption of innovations has already been discussed. Furthermore, the literature on social networks identifies that different factors like kinship,

9 Chen (1991) can also be seen in this regard.

10 Anderson (2011) does not have ST households in the study villages.

11 Dominant caste group in a village is the caste group which owns the majority of the land in the village.

12 The same may not be true for the ST farmers because their day to day life involves more hardships and risk taking decisions than any other caste categories and therefore they might show higher risk taking behaviour than non-ST categories including OCs.

13 As risk behaviour can be linked to risk attitude, we are using Eswaran and Kotwal (1990) in support of our argument which mainly deals with caste based diversity in risk attitudes (or risk aversion).

14 Clearly, here we are identifying two channels through which caste affiliation can affect the risk attitudes of farmers. First is the direct channel which is nothing but the caste based discrimination in access to different markets and social support whereas, second is the indirect channel, where caste affiliation affects other factors (for example, awareness levels) which in turn affect the risk attitudes. In our estimation we don't segregate the effects of direct and indirect channels but capture the overall effect of caste affiliation on risk attitudes and adoption of rainfall insurance.

15 For the relationship between risk aversion and adoption of innovations, see Knight et al. (2003). For a systematic analysis of the relationship between risk aversion and insurance adoption, Galarza (2009) can also be referred.

geographical proximity, the number of common friends, clan membership, religious affiliation and wealth determines the membership in a social network (De Weerdt, 2002; De Weerdt and Dercon 2006; Fafchamps and Gubert, 2007). Though caste affiliation could be a significant variable determining the membership in a social network, other variables might also play a role in determining social interactions. So, we include social network (or social interaction) variable as a separate factor in our analysis.

As our focus is on the determinants of adoption of rainfall insurance or alternatively, participation in the market for rainfall insurance, it is worthwhile to describe rainfall insurance, its importance and patterns of its adoption in India.

Rainfall insurance is a very popular version of index-based weather insurance which emerged in response to the need of insuring farmers against weather induced variations in income. The market for these products developed in response to the drawbacks of the traditional multi-peril crop insurance schemes and promised to facilitate market-based risk management by enhancing risk sharing and risk transfer opportunities (Skees, 1999).[16] It should be borne in mind that, index-based weather insurance products emerged as a promising financial innovation to 'weather-proof' farm based livelihoods and appear as a natural candidate for weather based microinsurance in the developing world given their product design and potential to insure poor farmers against rainfall shocks (Gaurav, 2012).

Of late, rainfall insurance has been introduced in many parts of India, Africa, and several countries in East Asia.[17] However, its adoption is apparently low in India. This apparently slow adoption of rainfall insurance in India has puzzled researchers and policy-makers, and various explanations for the inertia to adoption among farmers have been provided in the emerging literature on barriers to rural households' risk management (Alderman and Haque, 2007; Cole, Tobacman and Topalova, 2008; Cole et al., 2009; Cole et al., 2010; Hill, Hoddinott and Kumar, 2011).

A plausible reason behind slow adoption of rainfall insurance could be the inability of farmers to observe payout frequencies which makes them consider the premium paid as a waste of money in years when no payout is made (Cole et al., 2009). Issues of trust could also influence the demand for rainfall insurance (Gine et al., 2007). Further, it has also been argued that there are wide gaps in intelligently communicating the details of such complex financial products to people with low 'financial literacy'. Low or no prior financial experience and limited ability to process financial information also impede adoption. Gaurav, Cole and Tobacman (2010; 2011) find that randomly assigned financially literacy sessions and subtle marketing treatments had significant positive effects on adoption of rainfall insurance among farmers in the Indian state of Gujarat. Gaurav and Singh (2012) provide evidence of poor financial literacy and cognitive abilities among the same set of farmers and argue that inability to process the product attributes of financial instruments could affect farmers' understanding, and hence adoption of rainfall insurance products.

Clarke (2011) raises questions about the quality of weather insurance products itself and argues that weather derivatives being marketed to poor farmers in the developing world may in fact be suffering from the problem of 'contractual non-performance', especially 'basis risk'.[18] In this context, Binswanger-Mkhize (2012) argues that those farmers who may be effectively insured via informal mechanisms like income diversification, own assets and social networks, may achieve profit-maximising portfolios without formal insurance.[19]

In a recent paper, Mobarak and Rosenzweig (2012) study the demand for, and effects of offering rainfall insurance through a randomized experiment (with randomized insurance offer and rain gauge location) in a setting where the focus is on informal risk sharing network – subcastes in rural India. Their analysis allows for both individual level and aggregate risks and shows that informal networks lower the demand for formal insurance only if the networks provide

16 For a recent discussion of index-based insurance, see IFAD (2010). Hazell and Skees (2005), Manuamorn (2007) and Barrett et al. (2007) have an excellent discussion on the emergence of rainfall insurance in different parts of the world and associated challenges with scale-up.

17 The first rainfall insurance contract in the world was introduced in India in 2003-04. The rainfall risk of 148 farmers of BASIX (a livelihoods promotion company) in Mahabubnagar district in the Indian state of Andhra Pradesh was underwritten by ICICI Lombard General Insurance Company with technical assistance from the World Bank.

18 Basis risk is the mismatch between payouts and actual losses due to the distance between the farmer's plot and location of weather station; or mismatch between experienced loss and measured loss, which could affect the payout probability.

19 According to Binswanger-Mkhize (2012) farmers would be interested in such contracts only if these products reliably reduce their exposure to risk at lower costs than their self-insurance. Raising serious doubts on the scalability of rainfall insurance, he comments that the standard ways suggested for improving the adoption of index insurance, such as reducing basis risks, educating farmers and improving weather data, do not improve the ability of small farmers to purchase insurance and may not improve product design sufficiently to be competitive with self-insurance for whom self-insurance is effective.

protection against aggregate risk, but not if their primary role is to insure against farmer-specific or idiosyncratic losses.[20]

Given the low adoption of rainfall insurance in India, our analysis which investigates the major determinants of rainfall insurance adoption (in addition to examining the determinants of risk attitudes/aversion) identifies the factors which encourage the adoption of rainfall insurance and therefore has potential policy value

3. SURVEY AND DATA DESCRIPTION

We conducted a baseline survey of 800 farmers in two agro-ecological zones in the Indian state of Gujarat. The baseline survey was conducted in the pre production period of the major agricultural season (Kharif) of 2011-12 which begins with the onset of the Indian monsoon. An endline survey of the same 800 farmers was conducted in the post harvest period, six months later. The baseline survey gathered detailed information on household demographics, financial savings, credit, consumption, income sources, farm characteristics and risk attitudes, while the endline survey collected information on crop production, rainfall experience and rainfall insurance adoption. It may be noted that there was no attrition in our sample over the short period between the two surveys.

The choice of study regions was influenced by our main objective which was to study insurance adoption decisions under different agroclimatic conditions and variable social systems. We decided to focus on Paddy farmers in eight villages of Khambhat 'taluka' in Anand district and Cotton farmers in eight villages of Khambha 'taluka' in Amreli district (see Appendix 1 for a map of Gujarat and our study districts), for whom rainfall insurance was being marketed that season by our field partners: Development Support Centre and Sajjata Sangh.

The villages were selected to meet our twin selection criteria: (i) the village should be within 30 kilometres of the certified reference weather station (RWS) which is specified in the rainfall insurance contract (to control for variations in basis risk); and (ii) the villages should provide substantial caste based heterogeneity, but be more or less representative of other villages in the district. Since one of our major objectives was to study the caste based variations in market participation (adoption of rainfall insurance), we chose villages which have sizable proportions of farmers from each of the four caste categories (SC, ST, OBC and OC).

From each study village, 50 farmers were randomly sampled from a sampling frame comprising of all land holding farmers in the study villages. The rich set of information on caste affiliation along with other socioeconomic and demographic attributes at the household and individual (respondent) level enables us to investigate the role of caste in determining risk attitudes and market participation.

3.1 RAINFALL INSURANCE – PRODUCT INFORMATION

The rainfall insurance product marketed in our study regions was underwritten by the world's largest agricultural insurer, the Agricultural Insurance Company of India (AICIL). In Khambhat taluka, the rainfall insurance product provided insurance for Paddy crop, against deficit rainfall and excess rainfall during the harvest period. The coverage period started from June 10, 2011 and lasted till October 15, 2011. The coverage for deficit rainfall and excess rainfall was provided over two distinct phases and the total sum insured were INR 2250 and INR 2000, respectively.[21] The premium for this product, inclusive of service taxes was 14.92 per cent of the total sum insured (INR 4250).

In Khambha taluka also, a rainfall insurance product was designed for the major cash crop - Cotton and provided insurance against deficit rainfall, deficit in number of rainy days and excess rainfall during the harvest period. However, due to some confusion prevailing in the taluka, the adoption of this product was negligible.

It is worthwhile to mention here that data from both the talukas is used in the investigation on the effects of caste affiliation and social interaction on risk attitude but due to the negligible take up of rainfall insurance in the Khambha taluka (less than 1 per cent), we include only Khambhat taluka in the analysis of the determinants of rainfall insurance adoption (take up in Khambhat taluka was substantial, about 55 per cent).[22]

3.2. RAINFALL INSURANCE ADOPTION AND RISK ATTITUDE – DEFINITIONS AND MEASUREMENTS

The primary outcome of interest in our study is rainfall insurance adoption at the individual level, which we

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20 The study shows that in the presence of basis risk, informal risk sharing which covers idiosyncratic losses enhances the benefits of index insurance. In terms of the impact of index insurance, the study finds evidence on insurance enabling households to take more risk even in the presence of informal insurance.

21 INR stands for Indian Rupees (Rs.)

22 Subsequent inquiries in Khambha taluka about possible reasons for such low take up rates, revealed past experiences with rainfall insurance (introduced in 2009), high premium and basis risk as the most plausible explanations.

measure using the information on purchase of rainfall insurance by the respondents (from the endline survey). It is coded as '1' if a respondent has purchased rainfall insurance, '0' otherwise.

Risk attitude of farmers is measured using a module on self reported risk assessment which contains hypothetical questions for measuring risk behaviour. Every farmer (respondent) was asked the question - 'In choosing a new technology, farming practice or new agriculture related product what motivates your decision the most?' If the farmer chose 'risk protection' as the answer, then he is considered to be risk averse (coded as '1'); non-risk averse (coded as '0'), otherwise (other options were 'expected profit', 'price to cost ratio' etc.). So our risk attitude variable – hence forth referred as risk averse is dichotomous: it takes a value of '1' if a farmer is risk averse, '0' otherwise.

Before the risk assessment question was asked, the respondents were informed about the contextual relevance of the risk assessment question and different risk scenarios were explained to them. It may be noted that there are inherent problems in any individual risk attitude measurement because risk attitudes are unobservable and inferring true risk attitudes through observed portfolio choices are problematic (e.g. Watson and McNaughton, 2007). Even self reported risk attitude assessments are not free from problems on account of measurement errors due to the respondents' lack of understanding of the questions. These limitations notwithstanding, the use of hypothetical questions to assess risk attitudes has gained wide acceptability in the literature (see Hill 2006 for details) and even large scale studies like the US Survey of Consumer Finances and German Socioeconomic Panel have used questions on an individual's willingness to take a risk. Moreover, we preferred this methodology to experimental methods of risk attitudes elicitation (e.g., Binswanger, 1981) due to budgetary constraints and the limitations of experimental studies with modest payoffs in approximating true risk preferences in the real world settings (e.g. North, 2003). Also, Reynaud and Couture (2010) find a high correlation between self-reported risk evaluation measures and choices in the lottery experiments and conclude that the self-reported measures can be used as a meaningful measure of risk attitudes. .

3.3. CASTE AFFILIATION, SOCIAL INTERACTION AND OTHER SOCIOECONOMIC CHARACTERISTICS

Caste affiliation relates to the caste group to which a respondent belongs. Every respondent in our sample belongs to either of the four caste groups: Scheduled Castes (SC), Scheduled Tribes (ST), Other Backward Classes (OBC) and Upper/General/Other Castes (OC). This is based on Government of India's classification scheme and the classification on the basis of which individuals provide their caste affiliation details (supported by a caste certificate) in applications for access to various governmental and non-governmental services and benefits (Singh, 2012).

The social interaction variable is constructed on the basis of whether a respondent gets agriculture related information from his (her) friends in his (her) own village or other villages and is taken as '1' if he (she) indeed gets agriculture related information from his (her) friends from the aforementioned villages; '0' otherwise. Though this is a limited measure of social interaction given the more sophisticated frameworks developed in the literature which rely on complex social network mappings and information flows within and between networks (e.g. Conley and Udry, 2010) we rely on this measure due to the absence of alternative indicators of a farmer's social interactions in our surveys. Moreover, similar measures of social interaction are common in literature; for example, Bonte and Filipiak (2011) use a dummy variable 'friends' to measure social interaction which takes a value of one if a respondent's first answer to the question 'Did you consult anybody outside your household before making savings decisions?' is that she or he consults friends/peer group, and zero otherwise.

In our analysis, we also use information on various other household and respondent level socioeconomic and demographic factors such as household size, land holdings, education, age and sex of respondents. In addition, we use information on financial assets and liabilities of the sampled households.

3.4. SAMPLE DESCRIPTION

The average farmer in our total sample is forty-five year old male; has a family of four, and earns INR1, 36,000 (annually) from own cultivation which is the major income source of the household. The average household in our sample has a monthly per capita consumption expenditure (MPCE) of INR1550. In terms of financial assets and liabilities, a third of the farmers in our sample have outstanding crop loans and the average amount of their formal savings (deposits in banks, post-offices and other financial institutions) is nearly INR 5151- a very small fraction of their annual household income.

As far as the educational attainment in the sample is concerned, nearly three-fourth of the farmers have completed primary (more than five years of) schooling, which is better than the national average. In addition, more than 90 per cent of the respondents can read and write Gujarati language In our sample, about 37 per cent of the farmers are risk averse. With respect to the caste composition; farmers belonging to OC category form nearly 34.5 per cent of the sample whereas SC and ST farmers constitute 28.5 per cent and 14.5 per cent of the sample, respectively. The remaining farmers in the sample belong to the OBC category.

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Table 1 Sample Statistics

	Mean/Proportion	Standard Deviation	N
Household Characteristics			
Household Size	4.44	1.25	800
Household Head's Year of Schooling	8.13	3.31	800
Household Head's Father's Years of Schooling	5.98	4.41	800
Household head's Mother's Years of Schooling	3.01	3.42	800
Caste - Others (OC)	34.54		800
Caste - Scheduled Castes (SC)	28.54		800
Caste - Scheduled Tribes (ST)	14.52		800
Caste - Other Backward Classes (OBC)	22.40		800
Social Interaction	62.45		800
Respondent's Characteristics			
Age	45.09	8.71	800
No Formal Schooling	1.00		800
Schooling: < =5 Years	24.66		800
Schooling: >5 and < = 10 Years	61.08		800
Schooling: > 10 Years	13.27		800
Able to Read Gujarati	93.11		800
Able to Write Gujarati	90.34		800
Risk Averse	36.92		800
Household Assets and Income (INR)			
Annual Income from Own Cultivation	135774.2	104495.5	800
Annual Income from Agricultural Labor	12550.85	15686.66	800
Annual Income from Farm Enterprise	23306.51	16947.81	800
Per Capita Consumption Expenditure (INR)	1553.13	581.69	800
Total Land Holding (Acre)	6.41	7.62	800
Percentage of Irrigated Land	66.06	38.81	800
Have Outstanding Crop Loans	34.04		800
Formal Savings (Rs)	5151.34	10569.1	800

4. ESTIMATION AND RESULTS

4.1. EFFECTS OF CASTE AFFILIATION AND SOCIAL INTERACTION ON RISK ATTITUDES

Since we are interested in understanding the relationship between a farmer's risk aversion and caste and social interaction, we estimate the effect of caste affiliation and social interaction on the risk aversion of farmers using the following model. Let *i* (= 1,..., *n*) index a particular farmer. Whether a farmer is risk averse or not, is hypothesized to depend on his caste affiliation, social interaction and a host of other socioeconomic (individual and household level) characteristics. Formally,

$$R_i = f(C_i, S_i, X_i, u_i) \qquad (1)$$

where, R_i =1 if the ith farmer is risk averse and '0' otherwise. C_i is caste affiliation of the farmer; Si is social interaction variable of the farmer; X_i is a vector of socioeconomic characteristics that characterize the ith farmer; and u_i is a random error term.

Assuming that this relationship has a linear form, we get:

$$R_i = \alpha C_i + \beta S_i + X_i \gamma + u_i \qquad (2)$$

where, α , β and γ (vector) are the regression coefficients (parameters to be estimated). We estimate equation (2) using OLS estimation, which in our case becomes linear probability estimation (LPM) as the dependent variable takes a value of '1' or '0'.[23]

The details of the variables used in the estimation procedure are as follows: Caste – categorical variable (OC, SC, ST and OBC; OC as the reference category); Social Interaction – dichotomous variable (= '1' if farmer gets agriculture related information from friends; '0' otherwise); The vector of socioeconomic characteristics includes education (categorical – no formal schooling, schooling up to primary (5 years), schooling more than primary but up to secondary (10 years), schooling more than secondary; no formal schooling as the reference category), age (in years), squared age, household size (continuous variable), agricultural land owned (in acres), and outstanding crop loans (dichotomous, = '1' if farmer has an outstanding crop loan; '0' otherwise).[24]

Table 2 reports the distribution of risk aversion by the explanatory variables included in equation (2). The OCs are the least risk averse group on an average whereas SC farmers are the most risk averse, with the maximum proportion of farmers demonstrating risk aversion belonging to this category. The proportion of risk averse farmers is also more in the case of ST and OBC categories compared to that of the OC category. A striking finding from the table is that, on an average farmers who get agriculture related information from friends are half less risk averse than those who do not. Surprisingly, there is no clear pattern in the distribution of risk aversion by education, household size and land holdings. However, prevalence of risk aversion seems to be increasing with age initially and then decreasing. Also, the prevalence of risk aversion is marginally more among the farmers having an outstanding crop loan.

23 Though we have used linear probability modelling for the estimation, we also ran probit and logistic models for risk aversion and the nature of results do not change. Therefore, our results are robust to these alternative specifications. See appendix 2 for details.

24 The socioeconomic factors are included in equation (2) after a systematic review of literature on determinants of risk attitudes and taking into consideration the Indian context. For example, Moscardi and Janvry (1977), find increase in risk aversion of farmers with age but decrease in risk aversion with education, family size, off-farm income and land under control. Following the existing literature on the effect of social interaction on risk aversion and adoption of innovations (references already provided), we have taken social interaction as exogenous in equation (2). Further, one cannot change his (her) caste in India and therefore caste affiliation can also be safely taken as exogenous in equation (2). In this regard, Deshpande (2001, 2011) can be referred for greater details. Moreover given the inclusion of an exhaustive set of socioeconomic characteristics in our model, it is unlikely that our estimations suffer from any severe omitted variable bias.

Table 2 Distribution of Risk Aversion by Caste Affiliation, Social Interaction and Other Socioeconomic Variables

	Risk Aversion (%)
Caste	
Other Castes (OC)	31.9
Scheduled Castes (SC)	41.2
Scheduled Tribes (ST)	36.2
Other Backward Classes (OBC)	39.7
Social Interaction	
Yes	24.9
No	57.0
Education	
No formal schooling	37.5
Schooling up to primary	17.8
Schooling up to secondary	48.0
Schooling more than secondary	21.7
Age	
>=20 years and < 30 years	16.7
>=30 years and < 40 years	38.4
>=40 years and < 50 years	43.2
>50 years	25.1
Household Size	
<=3	27.0
>3 and <=6	39.3
>6	21.6
Land Holdings (Quartiles)	
1 (Lowest)	46.9
2	23.4
3	26.3
4 (Highest)	47.3
Has outstanding crop loan	
Yes	38.6
No	36.1

The results of the regression (LPM) of risk aversion on caste affiliation, social interaction and other socioeconomic factors are presented in Table 3. Here we have estimated a series of models; first we regress risk aversion on caste affiliation only (model 1); then we regress risk aversion on social interaction only (model 2); in the third model, we regress risk aversion on caste affiliation and social interaction (model 3); and finally we regress risk aversion on caste affiliation, social interaction and the full set of controls (model 4 – full model).

Our results clearly indicate that caste affiliation and social interaction have a significant impact on risk attitudes (aversion) of farmers. In model (1) (caste affiliation only) the risk aversion of SC and OBC farmers comes out to be significantly higher (9 per cent and 8 per cent higher chance of being risk averse, respectively) than that of the OC farmers. Similarly, model (2) (social interaction only) indicates that farmers who get agriculture related information from friends (within or other villages) are 32 per cent less likely to be risk averse compared to those farmers who do not (significant at the 1 per cent level). Results reported for model (3) (caste affiliation and social interaction only) are consistent with those in the last two models and show that both caste affiliation and social interaction significantly predict the risk aversion of farmers. Also, the effect of caste gets magnified by the introduction of social interaction variable, both, in terms of value as well as the significance. Finally, we introduce the full set of controls in the model (model 4) which further enhances the effect of caste on risk aversion. We now focus on the results of our full model (model 4) and describe them in detail.

Farmers belonging to the SC and the OBC categories are 13 per cent (significant at the 1 per cent level) and 10 per cent (significant at the 5 per cent level), respectively, more likely to be risk averse as compared to those belonging to the OC category. However, there is no significant difference between OC and ST farmers as far as risk aversion is concerned. This is an important finding for farmers in the Indian context as Binswanger's (1981) study based on experimental gambles failed to find any significance between a farmer's caste ranking (relative position in a caste hierarchy as well as relative population share of the caste the farmer belonged to) and his measure of risk aversion.

We find that a farmer's social interaction also affects risk aversion significantly. A farmer who gets agriculture related information from friends is 27 per cent (significant at the 1 per cent level) less likely to be risk averse than other farmers who do not get any agriculture related information from friends.

Further, risk aversion seems to be following an 'inverted – U' type relationship (significant at the 5 per cent level) with a farmer's age. This implies risk aversion is low when a farmer is young; it increases as the farmer grows old, peaks at a particular age and then falls as the farmer becomes older. This is consonance with the findings in other studies where relationship between age and risk aversion is not linear: risk aversion has been shown to be low in an age group while rise in another (Bellante and Saba, 1986; Halek and Eisenhauer, 2001).

Land holding, which is the best indicator of a farmer's wealth (asset), appear to be positively associated with risk aversion, but the point estimate is very low and it is significant only at the 10 per cent level.

Table 3 Linear Probability Estimates of Risk Aversion (Risk Aversion = 1 if farmer is risk averse; 0 otherwise)

Dependent Variable:	Risk Aversion (1)	Risk Aversion (2)	Risk Aversion (3)	Risk Aversion (4)
Caste (reference: OC)				
Scheduled Castes (SC)	0.093***		0.106***	0.133***
	(0.043)		(0.040)	(0.040)
Scheduled Tribes (ST)	0.043		0.081	0.069
	(0.053)		(0.051)	(0.048)
Other Backward Classes (OBC)	0.078*		0.097**	0.099**
	(0.046)		(0.045)	(0.045)
Social Interaction (reference: no)		-0.322***	-0.327***	-0.273***
		(0.035)	(0.034)	(0.037)
Household Size				-0.001
				(0.013)
Education (reference: no schooling)				
Schooling up to primary				-0.131
				(0.200)
Schooling up to secondary				0.067
				(0.199)
Schooling more than secondary				-0.155
				(0.203)
Age				0.029**
				(0.014)
Age squared				-0.000**
				(0.000)
Land holdings				0.004**
				(0.002)
Have outstanding crop loans (reference: no)				0.044
				(0.035)
Intercept	0.319***	0.570***	0.509***	-0.184
	(0.028)	(0.029)	(0.036)	(0.426)
R-squared	0.017	0.104	0.114	0.176
N	800	800	800	800

4.2. DETERMINANTS OF RAINFALL INSURANCE ADOPTION – ROLE OF CASTE AFFILIATION AND SOCIAL INTERACTION

Based on theory, earlier literature and our own discussion so far we estimate the effect of caste affiliation and social interaction on the rainfall adoption of farmers using the following model. Once again, let i (= 1,... , n) index a particular farmer. Whether a farmer adopts rainfall insurance, is hypothesized to depend on his caste affiliation, social interaction, risk aversion and a host of other socioeconomic (individual and household level) characteristics. Formally,

$$A_i = f(C_i, S_i, R_i, X_i, v_i) \qquad (3)$$

where, A_i =1 if the i^{th} farmer purchased rainfall insurance and '0' otherwise. As before C_i is caste affiliation of the farmer; S_i is social interaction variable of the farmer; R_i is the risk aversion of the farmer; and X_i is a vector of socioeconomic characteristics that characterize the i^{th} farmer; and v_i is a random error term.

Assuming that this relationship has a linear form, we get:

$$A_i = aC_i + bS_i + \delta R_i + X_i\lambda + v_i \qquad (4)$$

where, C_i, S_i, R_i *and* X_i are as defined earlier (X_i includes the same socioeconomic characteristics as in (2); a, b, δ and λ (vector) are the regression coefficients (or the parameters to be estimated); and v_i stands for the random error term in the rainfall insurance adoption model.

As we have shown that risk aversion itself can be affected by caste affiliation, social interaction, and other socioeconomic characteristics as well as random factors; therefore, by substituting (1) in (3), we get:

$$A_i = f(C_i, S_i, R(C_i, S_i, X_i, u_i), X_i, v_i) \qquad (5)$$

Taking its linear form or substituting (2) that is, $R_i = \alpha C_i + \beta S_i + X_i\gamma + u_i$, in (4) we obtain the reduced form of rainfall insurance adoption:

$$A_i = (a + \delta\alpha)C_i + (b + \delta\beta)S_i + X_i(\lambda + \delta\gamma) + (v_i + \delta u_i) \qquad (6)$$

Equation (6) can again be estimated using OLS (linear probability estimation (LPM) as the adoption of rainfall insurance takes a value of '1' or '0') as[25]

$$A_i = \rho C_i + \omega S_i + X_i\psi + \varepsilon_i \qquad (7)$$

where, $\rho = a + \delta\alpha$, $\omega = b + \delta\beta$, $\psi = \lambda + \delta\gamma$, and $\varepsilon_i = v_i + \delta u_i$

Clearly equation (4) (or the full system (4) and (2)) suffers from the problem of endogeneity and needs to be treated with appropriate econometric techniques. However, estimation of the reduced form equation (7) is sufficient if we want to estimate the overall effects of caste affiliation and social interaction (plus a host of other socioeconomic characteristics) on the rainfall insurance adoption; and it eliminates the need for worrying about the econometric endogeneity in equation (4) or the full system equation (4) and equation (2).[26]

Ideally, we should estimate the full system (4) and (2), because it will help us in segregating the overall effect of caste affiliation and social interaction on rainfall insurance adoption into direct and indirect effect (effect on rainfall insurance adoption through the influence on risk aversion) components. But, the cross-sectional nature of our data and the general absence of satisfactory instruments do not allow us to go for the estimation of the full system and therefore, we only estimate the overall effects of caste affiliation and social interaction (and the relevant socioeconomic characteristics) on rainfall insurance adoption (which is precisely our objective); and cannot inform about the extent of it due to a direct effect and the extent due to an indirect effect through the influence on risk aversion.

Table 4 presents the main descriptive statistics of the sample used for analyzing the effects of caste affiliation and social interaction on rainfall insurance adoption. As noted earlier, the data for this exercise comes from only one taluka – Khambhat, as rainfall insurance was satisfactorily taken up only in Khambhat.

25 The nature of results does not change if we use logit or probit estimations. See appendix 3 for details.

26 For a similar kind of situation, approach and treatment, see Bourguignon et al. (2007) and Ferreira and Gignoux (2008). Though, the context of the studies and the outcome of interests are different, Bourguignon et al. (2007) and Ferreira and Gignoux (2008) face a similar situation and use the same approach as we are adopting here.

Table 4 Descriptive Statistics: Analysis of Determinants of Rainfall Insurance Adoption

	Sample Statistics (Mean/ Proportion (%))	Adoption of rainfall Insurance (%)
Caste		
Other Castes (OC)	30.83	53.66
Scheduled Castes (SC)	37.34	53.02
Scheduled Tribes (ST)	9.27	64.86
Other Backward Classes (OBC)	22.56	53.33
Social Interaction		
Yes	56.14	68.30
No	43.86	36.57
Education		
No formal schooling	0.75	66.67
Schooling up to primary	26.07	60.58
Schooling up to secondary	56.89	46.70
Schooling more than secondary	16.29	70.77
Age		
>=20 years and < 30 years	1.5	100
>=30 years and < 40 years	33.58	57.46
>=40 years and < 50 years	40.6	49.38
>50 years	24.31	55.67
Mean Age (years)	45.59	
Household Size		
<=3	11.78	70.21
>3 and <=6	83.71	51.50
>6	4.51	66.67
Mean Household Size	4.46	
Land Holdings (Quartiles)		
1 (Lowest)	25.06	53.00
2	24.56	57.14
3	13.28	62.26
4 (Highest)	37.09	50.68
Mean Land Holding (acres)	8.27	
Has outstanding crop loan		
Yes	23.56	62.32
No	76.44	50.19
No. of Observations	400	400

It may be noted that the sample of Khambhat is similar to the overall sample as far as distribution of major socioeconomic characteristics is concerned. In Khambhat also the average farmer is nearly forty-five years old and has a family of four. Further, the distribution of education is similar. The proportion of the SCs in the Khambhat sample is more than that of the total sample. The proportion of OBC farmers is similar to that of the total sample, whereas the proportion of the OC and ST farmers is lower than that of the total sample. The average land holding by farmers is slightly more and is about 8 acres. The proportion of farmers who get agriculture related information from friends from the same village or other villages (56.1 per cent) is lower. The proportion of farmers having outstanding crop loan (23.6 per cent) is also lower than that of the total sample (34 per cent).

The percentage adoption of rainfall insurance by caste affiliation, social interaction and other socioeconomic variables is also presented in Table 4. It can be seen from the table that SC farmers have the lowest adoption (53 per cent) followed by the OBC and OC farmers, whereas ST farmers have the highest (64.8 per cent). It is striking to find that percentage adoption among farmers who get agriculture related information from friends is nearly twice of that among farmers who do not get the same information from friends.

There is no clear pattern in adoption percentage by education as well as land holdings of farmers. However, it can be said that the adoption percentage is higher among the farmers in the two youngest age groups (20-30 and 31-40 years). Adoption percentage is also highest in households with up to 3 members only. It is worthwhile to mention here that both age and household size have been taken as continuous variables in the multivariate analysis of rainfall insurance adoption.

Table 5 presents the linear probability estimates of the rainfall insurance adoption. Before elaborating upon the results of our full model, we first discuss the results of two models (1 and 2) – first, model (1) with caste affiliation and other socioeconomic characteristics (but no social interaction variable) and second, model (2) with social interaction variable and other socioeconomic characteristics (but no caste affiliation variable). It is clear from model (1) that the probability of adoption of rainfall insurance is significantly higher among ST farmers (about 15 per cent) compared to the OC farmers. Whereas, model (2) shows that social interaction significantly increases (by 29 per cent) the probability of adoption of rainfall insurance. The results of our main model of rainfall insurance adoption (model 3; full set of variables) show that the effects of caste affiliation and social interaction do not change when both caste affiliation and social interaction are included in the estimation along with the other socioeconomic characteristics. This justifies the inclusion of the social interaction variable in addition to the social affiliation (captured by caste affiliation) variable in our model of adoption of rainfall insurance. Results indicate that, in terms of caste affiliation, only the probability of adoption of rainfall insurance of the farmers of the ST caste group (as in the case of model 1) is significantly different from that of the farmers belonging to the OC caste group. Being an ST farmer, the likelihood of adoption goes up by 15 per cent compared to OC farmers. In conjunction with the results reported in Table 2, it could be possible that the STs who have a higher level of risk aversion (but not significantly different from the OCs) could be given targeted marketing by the NGOs who are working for the promotion of livelihoods of STs in the region.
Also, our estimates indicate that farmers with social interaction are 29 per cent more likely (p-value of 0.000) to participate in the market for rainfall insurance compared to those who do not interact with friends regarding agriculture related information. The nature of the social interaction variable could explain this result. Drawing from the extensive literature on the role of social networks and social learning on adoption of agricultural innovations, which we reviewed earlier, it is likely that farmers who talk with friends from within and outside their village could be evaluating the prospects of rainfall insurance and learning from the decisions of those who are experienced users. In the absence of more detailed mappings of such social interactions, we cannot comment on whether the farmers in our sample follow progressive farmers (early adopters from their or other villages) or observe the outcomes for those who have experience with adoption.

Further, the probability of rainfall adoption significantly decreases with the increase in household size. For every one person increase in the household size, the probability of rainfall adoption decrease by 4 per cent (significant at the 10 per cent level). This could be attributed to the higher probability of reliance of large households on informal risk management strategies, such as, off farm labour, crop diversification activity and nonfarm enterprises on account of more individuals in the household. An alternative factor impeding demand for rainfall insurance among large households could be their need to protect their family's subsistence consumption requirements, given a level of income. The rainfall insurance premium in the region was around half of the monthly per capita expenditure (MPCE) making it a costly expense. In the event of the farmers' apprehending a loss of the premium amount in a scenario with no payout and poor crop outcomes, the risk averse farmers might fall below their safety thresholds. It may be noted that this argument is in line with Scot's (1977) subsistence ethics; Roy's (1952) safety first principle; and Roumasset's (1976) 'disaster avoidance rule'.

Moreover, farmers' age also significantly influences participation in the market for rainfall insurance. In contrast with the case of risk aversion; where risk aversion had an 'inverted U' (first increasing and then decreasing) kind of relationship with age of farmers, probability of rainfall adoption has a 'U' kind of relationship (first decreasing and then increasing) with the age.

However, education categories do not have any significance on the probability to adopt rainfall insurance. Furthermore, land and outstanding crop loans have no significant effect on the likelihood of rainfall insurance adoption, though their positive signs suggest that the probability of adoption might go up marginally with every acre increase in land owned or if there is a crop loan outstanding.

Table 5 Linear Probability Model Estimates of Rainfall Insurance Adoption (Rainfall Adoption = 1 if farmer purchased rainfall insurance; 0 otherwise)

Dependent Variable:	Rainfall Insurance Adoption (1)	Rainfall Insurance Adoption (2)	Rainfall Insurance Adoption (3)
Caste (reference: OC)			
Scheduled Castes (SC)	-0.024		-0.009
	(0.061)		(0.059)
ST (Scheduled Tribes)	0.152*		0.149*
	(0.091)		(0.087)
OBC (Other Backward Classes)	-0.016		-0.010
	(0.070)		(0.067)
Social Interaction (reference: no social interaction)		0.287***	0.285***
		(0.051)	(0.051)
Household Size	-0.038	-0.041*	-0.039*
	(0.024)	(0.022)	(0.023)
Education (reference: no formal schooling)			
Schooling up to primary	-0.082	-0.206	-0.210
	(0.273)	(0.249)	(0.249)
Schooling up to secondary	-0.199	-0.213	-0.230
	(0.268)	(0.243)	(0.243)
Schooling more than secondary	-0.007	-0.103	-0.109
	(0.273)	(0.249)	(0.249)
Age	-0.068***	-0.056***	-0.057***
	(0.019)	(0.017)	(0.018)
Age squared	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Land holdings	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)
Have outstanding crop loans (reference: no crop loans)	0.050	0.030	0.036
	(0.060)	(0.057)	(0.059)
Intercept	2.358	1.995	2.034***
	(0.533)	(0.503)	(0.514)
R-squared	0.078	0.140	0.148
N	400	400	400

5. CONCLUSIONS

In this paper, we study the relationship between social affiliation, social interactions, risk attitudes and market participation in the context of rainfall insurance adoption by farmers in India. Using micro-data of rural farm households from the Indian state of Gujarat, we first estimate the impact of caste affiliation and social interaction on farmers' risk attitudes. Our findings indicate that caste affiliation and social interaction are significantly associated with the risk attitudes of the farmers. We find that farmers belonging to the Scheduled Caste (SC) and the Other Backward Classes (OBC) category are 13 and 10 percent, respectively, more likely to be risk averse than the Other Castes (OC) farmers. This finding contributes to an improved understanding of the role of caste affiliation in determining attitudes and behaviours – factors which play an important role in the participation of various groups in the market for formal insurance. Especially, from the context of microinsurance; if we have reasons to believe that individuals belonging to a particular caste group are more likely to be poor or more vulnerable, then policy makers should design policies and products that are more sensitive to the heterogeneity in attitudes which are caste dependent.

In addition, our finding that farmers who reported having specific social interactions in the form of getting agricultural information from village friends or friends from other villages being 27 per cent less likely to be risk averse than farmers who do not engage in such interactions, has a strong policy implications. As evident from Gaurav, Cole and Tobacman (2011), financial literacy and subtle marketing treatments can influence participation in the market for rainfall insurance. A potential channel through which the costs of such interventions could be brought down is by banking on the externalities generated from such initiatives. When farmers are actively interacting with each other on agriculture and related topics, the cost of information dissemination comes down drastically. In this context, our findings also support the lessons from information and communication technology (ICT) initiatives like ITC's 'e-choupal' (Prahalad, 2004) in India, which provides a low cost information dissemination and knowledge enhancing platform for thousands of farmers. Furthermore, as discussed in our paper, it is imperative to identify the exact channel through which such social interactions influence attitudes and behaviour and this can be taken up as future research.

Our point estimates from the model of determinants of rainfall insurance adoption show that caste affiliation and social interaction also influence rainfall insurance adoption. A limited measure of social interaction significantly encourages farmers to adopt rainfall insurance, with farmers who get agriculture related information from friends within their village as well as other villages being 29 per cent more likely to participate in the market for rainfall insurance than those who do not. This again supports our earlier claim that social interaction might lower the needs of financial literacy and subtle marketing treatments which can influence participation in the market for rainfall insurance, thus reducing the cost of facilitating the adoption process. As we have found that social interaction lowers risk aversion and earlier studies (Knight *et al.*, 2003) have found that decrease in risk aversion increases adoption of innovations, social interaction clearly looks to be facilitating the adoption of rainfall insurance through the risk attitude channel, that is by lowering the risk aversion of farmers.

For a more systematic analysis of the adoption of rainfall insurance, one should try to control for informal risk management strategies which could compete with formal insurance as well as the presence of other uninsured risk which could lower the demand for formal insurance (Gaurav, 2012). However, these limitations notwithstanding, the findings of our study could be considered as an important contribution to understanding the role of socio-institutional factors on risk attitudes and some missing dimensions in the analysis of microinsurance adoption. In doing so, we have also contributed to the literature on the barriers to household management of risk and participation in formal markets.

The lesson from this study could play an important role in our understanding of pathways to develop the market for microinsurance in the developing world. Mainly because of following reasons: First, influencing a decision maker's behaviour and risk attitudes could be instrumental in the determination of technology adoption and the overall diffusion of new technology, such as, microinsurance innovations. Differences in risk attitudes, which might in turn lead to disparities in technology adoption process, could potentially worsen the existing inequalities between different sections (or socioeconomic groups) of the farming community within a population resulting in drastic welfare consequences.

Second, an individual's social affiliation could also determine the socio-institutional context within which risk perceptions and risk management strategies evolve and articulation of risk takes place (Carter, 1997). Identifying the institutional context within which risk and risk management strategies are formed could play a critical role in the success of market based risk management strategies in a setting where informal risk management strategies are in place.

Third, technology adoption being a dynamic process, it could be perceived as a process in which an individual adjusts to a new equilibrium by learning and experimenting with a new technology, whose introduction results in a period of disequilibrium (Schultz, 1975). The social environment provides the most natural setting under which such adjustments play out and interact with one another. These arguments and the findings of our paper necessitates further inquiries into the role of social and cultural factors in influencing risk attitudes and innovation adoption decisions, particularly in India. Moreover, given the dynamic nature of the adoption process, efforts to collect panel data from varied socio-institutional contexts should be taken up.

Another important aspect is the welfare of the 'socially isolated' communities in the region. Our research finds that the people who do not indulge in social interactions are less likely to adopt the rainfall insurance products. Given the findings by previous research that ascertains that they are also less likely to be insured through informal methods (Vanderpuye and Barrett, 2006), policy needs to focus on reducing the vulnerability of these farmers to different shocks. Given that these farmers have different risk attitudes, some thoughts need to go into incentivising them to adopt innovations and making them aware of the consequences of usage of such innovations.

Last but not the least; appropriate marketing strategies and policy designs could also be developed keeping the sensitivity to social affiliation in mind – caste affiliation in case of India. As our research shows, one size does not indeed fit all given the complex social fabric of India. The diffusion and effectiveness of microinsurance products should be tailored keeping this idiosyncrasy of the rural society in mind. It is also imperative to understand that the targeting efforts involve costs to the intermediaries and future research could focus on the estimated benefits of such targeted marketing and communication efforts and evaluate them against their implementation costs and potential or realized benefits.

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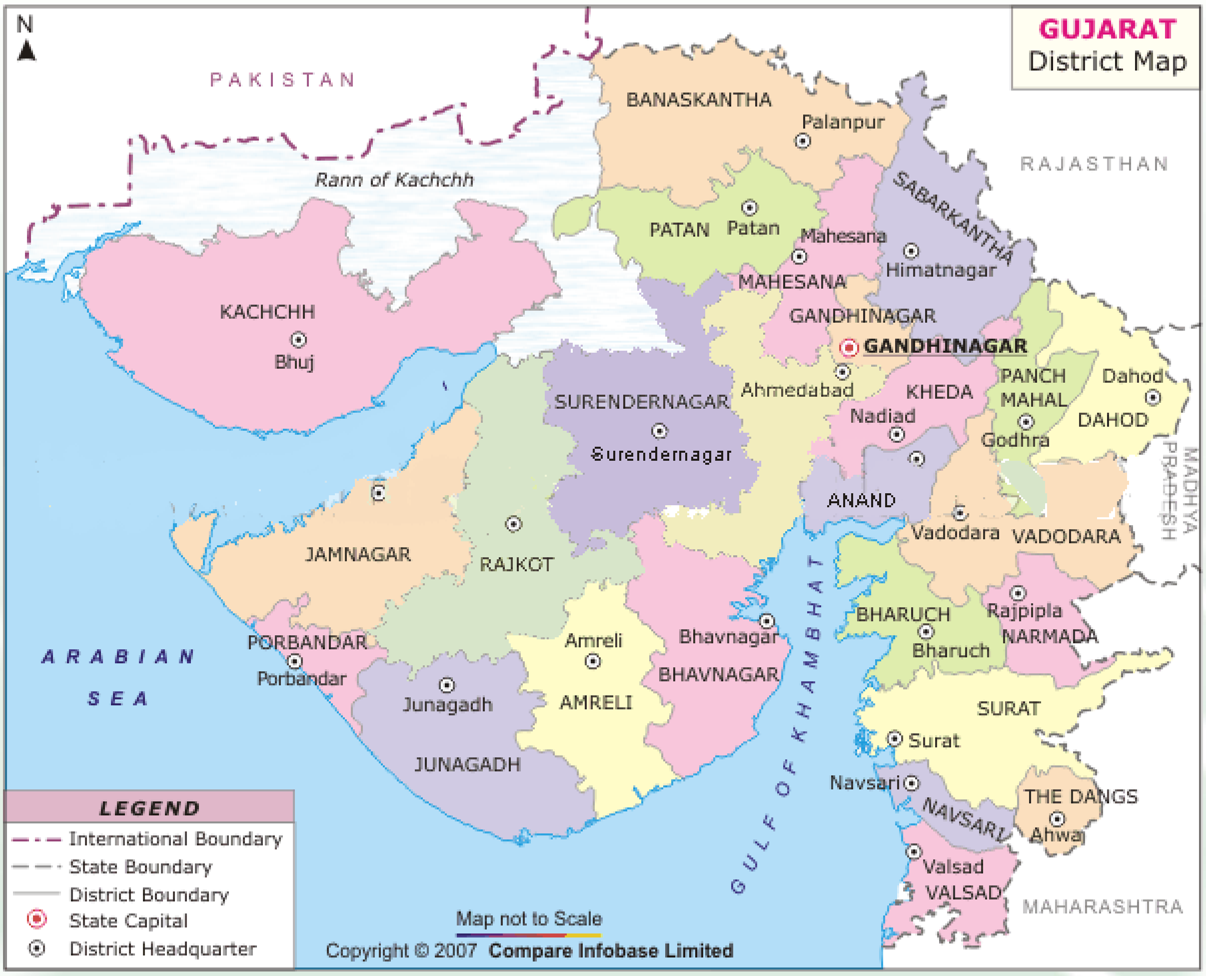
ANNEX 1

Map of Gujarat indicating our Study Districts



Note: The solid dots indicate the approximate location of our study talukas: Khambhat in Anand district and Khambha in Amreli district.
Source: India Meteorology Department (www.imd.gov.in)

ANNEX 2

Logit and Probit Estimates of Risk Aversion (Risk Aversion = 1 if farmer is risk averse; 0 otherwise)

	Logit Estimates (Odds ratios)	Probit Estimates
Caste (reference: OC)		
Scheduled Castes (SC)	1.959***	0.397***
	(0.416)	(0.125)
Scheduled Tribes (ST)	1.408	0.191
	(0.353)	(0.150)
Other Backward Classes (OBC)	1.645**	0.287**
	(0.383)	(0.136)
Social Interaction (reference: no social interaction)	0.291***	-0.753***
	(0.051)	(0.105)
Household Size	1.014	0.010
	(0.083)	(0.047)
Education (reference: no formal schooling)		
Schooling up to primary	0.493	-0.490
	(0.546)	(0.575)
Schooling up to secondary	1.371	0.128
	(1.496)	(0.567)
Schooling more than secondary	0.465	-0.546
	(0.528)	(0.587)
Age	1.248**	0.117**
	(0.142)	(0.058)
Age squared	0.997**	-0.001**
	(0.001)	(0.001)
Land holdings	1.021*	0.012*
	(0.012)	(0.007)
Have outstanding crop loans (reference: no)	1.262	0.138
	(0.225)	(0.105)
Intercept		-2.617*
		(1.516)
Prob > chi^2	0.000	0.000
Pseudo R^2	0.145	0.145
N	800	800

Notes: Figures in parenthesis are robust standard errors. An odds ratio of greater (less) than one shows a positive (negative) relationship. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

ANNEX 3

Logistic and Probit Estimates of Rainfall Insurance Adoption (Rainfall Adoption = 1 if farmer purchased rainfall insurance; 0 otherwise)

	Logit Estimates (Odds Ratios)	Probit Estimates
Caste (reference: OC)		
Scheduled Castes (SC)	0.970	-0.012
	(0.267)	(0.166)
Scheduled Tribes (ST)	2.009*	0.439*
	(0.831)	(0.249)
Other Backward Classes (OBC)	0.979	-0.005
	(0.300)	(0.186)
Social Interaction (reference: no social interaction)	3.448***	0.765***
	(0.795)	(0.140)
Household Size	0.803*	-0.133*
	(0.098)	(0.072)
Education (reference: no formal schooling)		
Schooling up to primary	0.378	-0.634
	(0.440)	(0.731)
Schooling up to secondary	0.355	-0.663
	(0.404)	(0.718)
Schooling more than secondary	0.595	-0.341
	(0.695)	(0.736)
Age	0.721***	-0.200***
	(0.081)	(0.067)
Age squared	1.004***	0.002***
	(0.001)	(0.001)
Land holdings	1.012	0.007
	(0.010)	(0.006)
Have outstanding crop loans (reference: no)	1.180	0.100
	(0.324)	(0.164)
Intercept		5.289***
		(1.809)
Prob > Chi^2	0.000	0.000
Pseudo R^2	0.115	0.116
N	400	400

Notes: Figures in parenthesis are robust standard errors. An odds ratio of greater (less) than one shows a positive (negative) relationship. ***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level.

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Housed at the International Labour Organization's Social Finance Programme, the Microinsurance Innovation Facility seeks to increase the availability of quality insurance for the developing world's low income families to help them guard against risk and overcome poverty. The Facility was launched in 2008 with generous support from the Bill & Melinda Gates Foundation to learn and promote how to extend better insurance to the working poor. Additional funding has gratefully been received from several donors, including the Z Zurich Foundation and AusAID.