Accounting for farmers' risk preferences in investigating land allocation decisions in marginal environments: a test of various elicitation measures in an application from Vietnam

Alwin Keil* and Thea Nielsen

University of Hohenheim, Department of Agricultural Economics and Social Sciences in the Tropics and Subtropics (490a). Wollgrasweg 43, D-70593 Stuttgart, Germany.

***Corresponding author: E-mail: alwin.keil@uni-hohenheim.de**
Tel.: +49-711-459-23301; Fax: +49-711-459-23934

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Abstract

Smallholder farmers' land allocation decisions in marginal areas of developing countries typically involve a substantial element of risk, especially when they concern input intensive cash crops. Hence, apart from farmers' resource endowment, their individual level of risk aversion is a potentially important determinant of such decisions. However, in microeconometric models a measure of individuals' risk preferences is usually lacking. We address this shortcoming by testing the explanatory power of a wide range of risk preference measures based on hypothetical and non-hypothetical elicitation methods in a model explaining land allocation to commercial hybrid maize production in a fragile upland area of Vietnam. Based on data collected in a random sample of 300 households, we find that the poorest farmers are particularly specialized in commercial maize production, but they are highly dependent on relatively disadvantageous input supply and marketing arrangements offered by maize traders, making this specialization particularly risky. Our study confirms the relevance of decision-makers' risk preferences in addition to their asset endowment in the land allocation decision. The inclusion of risk preference measures as explanatory variables is found to not cause any significant endogeneity bias. However, only risk preference measures that are based on hypothetical maize related scenarios have explanatory power. We conclude that (1) risk preferences are to a certain extent decision domain specific and (2) hypothetical scenarios that are closely related to farmers' real-life decisions may produce more reliable results than unfamiliar, non-agricultural scenarios or lottery-based methods, which may be difficult to grasp for respondents with limited formal education.

Key words

Risk preference elicitation, commercial maize production, marginal uplands, tobit regression, Vietnam

JEL classification

C93, D81

1 Introduction

Risk is an integral part of decision making processes, especially in smallholder agriculture in developing countries. While income growth and urbanization have enlarged markets for high-value agricultural commodities, offering opportunities for poverty alleviation in rural areas if farmers are linked to such markets (World Bank 2007: 124), there are concerns that commercialization exposes farm households to market related risks and increases their dependence on purchased food (Pingali and Rosegrant, 1995). This is aggravated by the fact that commercialization often entails farm-level specialization (ibid.). Depending on the variability of the output and input prices, the prices of food, and the security of access to food markets, a high degree of specialization in one commercial farming activity may constitute a relatively risky livelihood strategy. Furthermore, intensive commercial agriculture may entail long-term risks threatening farmers' livelihoods through natural resource degradation (World Bank 2007: 180). On the other hand, lacking access to assets, infrastructure, and institutions may limit the ability of the poor to participate in and benefit from input intensive commercial agricultural activities in the first place (von Braun, 1995; Barrett et al., 2001; Minot et al., 2006; World Bank, 2007). Hence, farmers' decision to what degree to engage in commercial agricultural activities will depend on their asset base – including access to relevant infrastructure and institutions – and on their risk preferences, since typically substantial elements of risk will be involved, as outlined above. However, in microeconometric models on smallholder farmers' land use decisions a measure of risk preferences is usually lacking.

There is no consensus in the literature whether individuals' socio-economic characteristics influence their risk preferences, which would lead to endogeneity bias if both were included in a regression model as explanatory factors. While some studies find, for example, that risk preferences differ significantly based on gender (e.g. Gilliam et al., 2010; Gloede et al., 2011 for Thai respondents), education (e.g., Harrison et al., 2007), age (e.g., Tanaka et al., 2010), and/or income (Cohen and Einav, 2007), others find no significant relationship (e.g., Harrison et al., 2007 for gender; Anderson and Mellor, 2009 for education; Holt and Laury, 2002 for age; Tanaka et al., 2010 for income). What studies that regress easily observable respondent characteristics on measures of risk preferences have in common is a low level of explanatory power of the estimated models; this is a clear indication that other factors, such as innate personality traits and prior experiences which are difficult to assess using survey methods, are of greater importance in determining risk preferences (cf. Mishra and Lalumière, 2011). Consequently, an inclusion of risk preference measures as explanatory variables in regression

models seems justified. We address the lack of consideration of decision-makers risk preferences in microeconometric models by including quantitative risk preference measures in a model explaining farmers' land allocation to commercial hybrid maize production in a fragile upland area of Vietnam, which constitutes a relatively risky activity.

While many methods to elicit risk preferences have been developed since the seminal paper by Binswanger (1980), there remains a research gap on the comparison of different elicitation methods – particularly from data collected in developing countries among resource poor farmers. In general, hypothetical and non-hypothetical methods can be used to assess risk preferences. A lottery choice based measure, i.e., a non-hypothetical measure involving actual payouts, called the multiple price list technique (hereafter MPL) is now the gold standard to assess risk preferences. MPL was popularized by Holt and Laury (2002) and has subsequently been used in a number of studies (e.g., Anderson and Mellor, 2009; Harrison et al., 2007; Andersen et al., 2006). Widely used hypothetical risk preference assessment methods comprise the Survey of Consumer Finances risk tolerance question (e.g., Chang et al., 2004; Grable and Lytton, 2001; hereafter SCF), a self-assessment scale based on the German Socio-Economic Panel Study (e.g., Caliendo et al., 2009; Fietze et al., 2010; Gloede et al., 2011; hereafter self-assessment), and hypothetical scenarios involving income and inheritance gambles (Anderson and Mellor, 2009; hereafter income and inheritance series).

The objectives of this study are threefold: (1) to investigate the extent to which smallholder farm households in a marginal upland environment of Vietnam are engaged in commercial hybrid maize production; hereby, we are particularly interested in differences between wealth groups; (2) to identify determinants of the scale of hybrid maize adoption using regression analysis, accounting for farmers' risk preferences and assessing potential endogeneity bias; and (3) to compare risk preference measures based on a wide range of elicitation methods, especially with respect to their explanatory power in the regression model.

The study contributes to the literature in two aspects: (1) by comparing risk preferences elicited from a wide range of methods, namely the MPL, SCF, self-assessment, income and inheritance series, as well as hypothetical scenarios related to yields and prices of maize and rice. To the best of our knowledge, no such comparison exists so far, and there is a particular lack of comparative studies in a developing country context; and (2) by explicitly accounting for farmers' risk preferences in a microeconometric model explaining a risky land use

decision, whereby we test the explanatory power of the full range of risk preference assessment methods listed above.

The remainder of the paper is structured as follows: some background information on commercial maize production in the northern uplands of Vietnam and a brief description of the research area is provided in Section 2; Section 3 describes the methodology applied; our findings are presented in Section 4 and discussed in Section 5; finally, our conclusions are summarized and recommendations are derived in Section 6.

2 Commercial maize production in the northern upland region of Vietnam

In Vietnam, rapid economic growth and urbanisation in the past 15 years have led to a diversification of diets and, hence, to an increased demand for meat, eggs, and dairy products (Minot et al., 2006). Rising from 16.0 to 40.7 kg, annual per-capita meat consumption increased by more than 150% between 1990 and 2007 (FAOSTAT, 2011). Maize (*Zea mays* L.) is the primary source of feed for Vietnam's rapidly growing livestock and poultry industry. Therefore, the demand for maize has grown dramatically and is expected to further increase in the future (Dao et al., 2002; Thanh Ha et al., 2004; Thanh and Neefjes, 2005). Consequently, maize production increased from 671,000 metric tons in 1990 to 4,381,800 metric tons in 2009 – an increase by 553% - which was achieved by the combined effect of higher-yielding varieties and area expansion: mean yields increased by 159% from 1.55 Mg ha^{-1} in 1990 to 4.03 Mg ha^{-1} in 2009 while the area harvested grew by 152% from 431,800 ha to 1,086,800 ha during the same period (FAOSTAT, 2011).

The area expansion and intensification of maize production has been particularly pronounced in the uplands of north-western Vietnam, where maize production almost quadrupled between 1990 and 2000, growing from 53,600 to 211,800 metric tons (Dao et al., 2002). Yen Chau is a mountainous district in Son La province in north-western Vietnam, which is one of the poorest provinces in the country (Minot et al., 2006). Only patches of natural forest remain, mostly on mountain tops above 1,000 m a.s.l. Lowland villages benefit from easy access to infrastructure, such as markets, paved roads, and irrigation systems, and are relatively better-off than villages located at higher elevations. Farmers nowadays cultivate two main crops: rice, which is grown on irrigated paddy fields in the lowlands mainly for own consumption, and maize, which is grown in the uplands as a cash crop. Maize production in Yen Chau is input intensive, using exclusively hybrid varieties and substantial amounts of mineral fertilizer, which are mostly financed on credit. Recent years have seen substantial fluctuations

of input and output prices. Maize is mainly grown on sloping land, and field measurements indicate a high degree of soil erosion with annual soil loss rates ranging from 21 to 132 Mg ha^{-1} (Tuan et al., 2010), implying a high level of long-term risk through soil degradation (Wezel et al., 2002). While substantial efforts have been made since the mid 1990s to promote soil conservation technologies in the area (van der Poel, 1996; UNDP, 2000), adoption rates have remained low (Wezel et al., 2002; Saint-Macary et al., 2010), whereby a major reason is the fear of adverse effects on maize production through competition for land, sunlight, and nutrients (Saint-Macary et al., 2010). Because of the short-term and long-term risks involved in maize production, it is reasonable to assume that – apart from asset base related factors – the decision about land allocation to maize is influenced by farmers' risk preferences.

3 Methodology

3.1 Risk preference assessment

Multiple price list

In the MPL, respondents made ten consecutive choices between two options – a safer option (Option A) and a riskier option (Option B) – in which each have two possible payouts with different probabilities of each payout being realized (see Table 1). Expected values were not shown to respondents. The payouts in the safer option have a lower variance than those in the riskier option. With each choice, the expected value of the safer option decreases while the expected value of the riskier option increases. Risk preferences are based on the point at which respondents switch from the safer option to the riskier option.

The payout amounts are based on Holt and Laury (2002); the same percentage of contribution of the payouts towards the U.S. average daily per capita expenditure in 2002 was used for this study. For example, in their scenario in which payouts were fifty times that of their base scenario[1] (hereafter, referred to as the 50x scenario), the highest payout amount was equivalent to approximately 432% of the U.S. average daily per capita expenditure in 2002. Therefore, the highest payout amount in our scenario was calculated to be equivalent to 432% of the daily per capita expenditure for our sample, amounting to 79,000 VND[2]. Table 1 shows the low and high payout amounts in each scenario. The payouts were based on the 50x

[1] Holt and Laury (2002) gave respondents multiple sets of these ten choices which were scaled-up by 20x, 50x, and 90x the baseline scenario.

[2] At the time of the survey, the exchange rate was approximately 20,830 VND per 1 USD.

scenario due to budgetary constraints on the one hand, and the desire for the highest payout amount to be significant for the respondents on the other.

Table 1. Choices in the multiple price list (MPL)

Choice (row)	Probability of high and low payouts		Payouts in the safe Option A ('000 VND)			Payouts in the risky Option B ('000 VND)				Risk preference if switched to Option B in row…**
	Low	High	Low	High	E(A)*	Low	High	E(B)*	E(A)-E(B)	
1	0.90	0.10	33	41	33.8	2	79	9.7	24.1	Extremely risk loving
2	0.80	0.20	33	41	34.6	2	79	17.4	17.2	Highly risk loving
3	0.70	0.30	33	41	35.4	2	79	25.1	10.3	Very risk loving
4	0.60	0.40	33	41	36.4	2	79	32.8	3.4	Risk loving
5	0.50	0.50	33	41	37.0	2	79	40.5	-3.5	Approximately risk neutral
6	0.40	0.60	33	41	37.8	2	79	48.2	-10.4	Slightly risk averse
7	0.30	0.70	33	41	38.6	2	79	55.9	-17.3	Risk averse
8	0.20	0.80	33	41	39.4	2	79	63.6	-24.2	Very risk averse
9	0.10	0.90	33	41	40.2	2	79	71.3	-31.1	Highly risk averse
10	0	1.0	33	41	41.0	2	79	79.0	-38.0	Extremely risk averse

* Expected values were not shown to respondents and choices were shown one at a time with visuals.

** This assumes that the respondent did not switch back to the safe option again after already having chosen a risky option.

Enumerators carefully explained the decision between Option A and Option B before respondents made their choice. Respondents were aware that one of the ten choices would be randomly selected by the toss of a ten-sided die, and that another toss of the die would then determine the amount to be paid out. Similar to Holt and Laury (2002), we base our risk preference measure on the total number of safe options chosen by the respondent.

Self-assessment questions

The SCF and self-assessment questions allow respondents to identify the level of risk they are willing to take. The SCF question has been widely used to gauge respondents' risk preferences (e.g., Chang et al., 2004; Grable and Lytton, 2001). Respondents are asked about the level of financial risk they are willing to take: (1) substantial financial risks, expecting to earn substantial returns; (2) above average financial risks, expecting to earn above average returns; (3) average financial risks, expecting to earn average returns; or (4) not willing to take any financial risks. The self-assessment question is based on the German Socio-Economic Panel Study (SOEP) and has also been widely used to analyze risk preferences

(e.g., Caliendo et al., 2009; Fietze et al., 2010; Gloede et al., 2011). Respondents are asked, "How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please rank yourself on a scale of 0 to 10 with 0 meaning fully avoiding risks and 10 meaning fully prepared to take risks." Responses are rescaled so that 0 represents the most risk preferring and 10 the most risk averse to align with the coding of the other assessment techniques where increasing values are associated with increasing risk aversion.

Income and inheritance series

In the income and inheritance series respondents are presented hypothetical scenarios and asked how they would respond. The income and inheritance series is based on Anderson and Mellor (2009) and originates from the Health and Retirement Study conducted by the University of Michigan. In the income series, subjects are presented with two possibilities, a job with a certain outcome or a riskier job with two possible outcomes, each occurring with a probability of 50%. There are five questions in the income series; in the risky choice, one outcome always involves a doubling of the current income while the other is a decrease of the current income by 75%, 55%, 33%, 20%, or 10%.

Respondents were asked a similar set of questions related to the timing of sale of an inheritance: the safe option was selling the inheritance immediately for a certain amount and the riskier option was waiting a month and selling the inheritance for either twice as much or for a loss of varying amounts (75%, 55%, 33%, 20%, or 10%) with a 50% probability of each event occurring. Since respondents may differ in their choices based on the frame of reference – income versus an inheritance, the latter representing a windfall gain – we analyze responses to each series separately. Classifications of risk aversion from the income and inheritance series are categorical indicators based on Anderson and Mellor (2009). The degrees of risk aversion range from 1, representing the least risk averse, to 6, representing the most risk averse.

Agriculture related scenarios

We developed hypothetical scenarios based on the yields and output prices of maize, the dominant cash crop in the research area, and rice, the primary food crop. The reasoning behind this was to present respondents hypothetical scenarios that are more closely related to their real-life decisions than the literature-based self-assessment questions or income and inheritance scenarios described above. For example, respondents were asked which of the following maize yield scenarios they preferred (assuming constant output prices): (1) a

constant yield of 6.8 Mg ha^{-1} (the median yield of dry maize seeds based on our survey data); (2) a yield of either 5.8 or 8.8 Mg ha^{-1}, each occurring with a probability of 50% (this scenario represents a 15% decrease and 30% increase compared to the safe option, respectively); (3) a 50/50 chance of either 4.8 or 10.9 Mg ha^{-1} (-30% and +60%, respectively); and (4) a 50/50 chance of either 3.7 or 12.9 Mg ha^{-1} (-45% and +90%, respectively). The yield intervals were chosen in this way to ensure that increasing risk, i.e., yield variability, was associated with increasing expected returns while yield levels stayed within a realistic range. For data analysis, the scale of 1 to 4 was reversed to ensure that, as in the other elicitation methods, values increase with increasing risk aversion, i.e., a value of 1 represents the lowest and a value of 4 the highest degree of risk aversion. Similar scenarios were developed for maize prices (assuming constant yields) and, analogically, for rice yields and prices.

3.2 Classification of households into wealth groups

To analyze differences between wealth groups regarding their engagement in commercial hybrid maize production as well as their asset endowment and risk preferences, which we hypothesize to influence the area allocation to maize (see Section 3.3), we classify households into wealth groups using a linear composite index which measures the relative wealth status of a household within our sample. It is constructed by principal component analysis (cf. Dunteman, 1994) from a range of indicator variables capturing multiple dimensions of poverty. The application of principal component analysis for this purpose is described in detail by Zeller et al. (2006). The index represents the households' scores on the first principal component extracted, which follows a standard normal distribution. Based on this index we create wealth terciles, i.e., groups representing the poorest, middle, and wealthiest thirds of the sample households for our further analyses.

3.3 Determinants of the scale of hybrid maize adoption

In their seminal paper on the adoption of agricultural innovations Feder et al. (1985) review the literature on factors that have frequently been found to influence adoption. These are (1) farm size, (2) risk exposure, (3) human capital, (4) labor availability, (5) credit access, (6) tenure security, and (7) access to commodity markets. Based on this review and drawing on the concept of livelihood resources as laid out in the sustainable livelihoods framework (Chambers and Conway, 1992; Scoones, 1998), we hypothesize the scale of hybrid maize adoption to be determined by households' asset base and risk preferences. The asset base includes access to relevant services and commodity markets and is subsumed under four types of capital, namely (1) natural capital, (2) human capital, (3) financial capital, and (4) market

access/infrastructure. Natural capital is reflected by the characteristics of the households' land endowment and a proxy of local climatic conditions. The variables capturing human capital are related to characteristics of the household head, ethnicity, and household demography. Economic and financial capital is reflected by off-farm income and credit access. Market access and infrastructural conditions are captured by input and output prices, the physical distance to the nearest paved road and the closest fertilizer outlet, and perceived access to agricultural extension. Risk preferences are assessed using the different methods outlined in Section 3.1, whereby they were elicited separately for the household head and spouse. The regression model uses the risk preferences of the main decision maker in maize production[3]. Brief definitions and summary statistics of all variables in our regression model are provided in Table 3 (section 4).

3.4 The regression model employed

We measure the scale of hybrid maize adoption by the area share devoted to the crop at a particular point in time, which is appropriate in the case of a divisible technology (Feder et al., 1985). This share is bound between 0 and 100%, and both limit values are observed in eight and six cases (2.9 and 2.2%), respectively. Hence, the distribution of the dependent variable *Maize share* is censored at its minimum and maximum limit values, which has to be accounted for by the regression model employed. Due to the censored nature of the dependent variable an ordinary least squares (OLS) regression would yield biased estimates. Therefore, a model proposed by Tobin (1958) is employed which accounts for the qualitative difference between limit and non-limit observations and uses the maximum likelihood (ML) method for parameter estimation.

The Tobit regression model expresses the observed outcome, *Maize share*, in terms of an underlying latent variable as follows:

[3] In cases of reported "joint decision making" of household head and spouse the mean of the two risk preference measures was used.

$$y_i^* = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ji} + \varepsilon_i \qquad (1)$$

Maize share = max (0, y_i*) and min (y_i*, 100), respectively (2)

where

y^* = Latent dependent variable

i = Household index (i = 1,…, N)

x_j = Vector of explanatory variables (j = 1,…, k), as outlined in the previous section

β = Vector of parameters to be estimated

ε = N (0, σ^2) distributed random error term

Maize share = Observed dependent variable

The latent dependent variable y^* in equation (1) satisfies the classical linear model assumptions; in particular, it has a normal, homoskedastic distribution with a linear conditional mean (Wooldridge, 2006: 596). Equation (2) states that the observed dependent variable, *Maize share*, equals y^* if $0 \leq y^* \leq 100$, but it equals 0 if $y^* < 0$ and 100 if $y^* > 100$. As a remedial measure for potential heteroskedasticity in the Tobit model, we compute the heteroskedasticity-consistent standard errors proposed by White (1980). Furthermore, these robust standard errors are adjusted to account for the cluster sampling procedure applied in selecting the farm households (cf. Deaton, 1997: 51-56).

3.5 Sampling procedure and data collection

Data were collected in from 300 randomly selected households in Yen Chau district in several rounds of survey between July 2007 and May 2011. A cluster sampling procedure was followed in which in a first step a village-level sampling frame was constructed encompassing all villages of the district[4], including information on the number of resident households. Next, 20 villages were randomly selected using the Probability Proportionate to Size (PPS) method (Carletto, 1999). In a second step, 15 households were randomly selected in each of these villages using updated village-level household lists as sampling frames. Since the PPS method accounts for differences in the number of resident households between villages in the first stage, this sampling procedure results in a self-weighing sample (Carletto, 1999). A team of local enumerators collected the data in structured interviews using a carefully tested questionnaire.

[4] Except for the villages in four sub-districts bordering Laos, for which research permits are very difficult to obtain.

4 Results

4.1 Comparing risk preferences elicited via different methods

Although all assessment methods provide evidence that respondents are, on average, risk averse, there are clear differences in the degree of risk aversion between the various assessment methods. The MPL, the only non-hypothetical technique used, found more risk aversion than the other methods. The mean number of times the safe option was chosen is 6.43 (s.d. = 1.973) on a scale from 0 to 10, which, according to the classification by Holt and Laury (2002) indicates that respondents are risk averse to very risk averse.

Deviating from the MPL, the mean response in the self-assessment question was 5.58 (s.d. = 2.366) on a scale from 0 to 10, and responses to the SCF about the willingness to take financial risks are also centered around the response indicating an "average" level of risk aversion, with 51% of respondents choosing the "average" category. Respondents also indicated a higher willingness to take risks in the SCF compared to the MPL. One-third of respondents stated that they are willing to take above average or substantial financial risk in the SCF, whereas only 6% are classified as risk preferring according to the MPL measure.

Unlike the self-assessment questions, the income and inheritance series lack an "average" or "middle" response category. If we group together respondents who preferred the riskier option only when the possible loss was 33% or lower as being risk averse, 85% and 83% of respondents are classified as risk averse in the job series and the inheritance series, respectively. This matches well with the classification from the MPL, in which 84% of respondents are classified as risk averse to some degree.

The agriculture related scenarios use a coarse ordinal scale from 1 (= least risk averse) to 4 (= most risk averse). The share of respondents preferring the certain outcome ranges from 29% in the maize price scenarios to 50% in the rice price scenarios. If one groups together respondents preferring either option (1) or (2) as being risk averse (cf. Section 3.1), the share ranges from 71% in the maize price scenarios to 81% in the rice price scenarios. Between 8% of respondents (rice price scenarios) and 17% (maize price scenarios) preferred the riskiest option.

Correlations between the different risk preference measures are shown in Table 2. Correlations ≥ 0.25 are in bold to illustrate that there two clusters of relatively strong correlations. The first cluster comprises the hypothetical income and inheritance series as well

as the SCF question and the self-assessment, whereby the strongest correlation (0.73) is found between the last two measures, which are both self-assessment based. The second cluster comprises the agriculture related hypothetical scenarios. Correlations between the two clusters are weak to very weak, amounting to 0.18 at the most. The correlations between the self-assessment based measures and the agriculture related measures are all statistically insignificant. With correlations ranging from 0.13 to 0.23 the non-hypothetical MPL measure is only relatively weakly correlated with the first cluster, while correlations with the second cluster even turn negative.

Table 2. Correlations between risk preference measures (≥ 0.25 in bold)

	MPL	SCF	Self-assess.	Income series	Inherit. series	Maize yield	Maize price	Rice yield
MPL		0.13**	0.23***	0.17***	0.20***	-0.14**	-0.15**	-0.11*
SCF	0.13**		**0.73*** **	**0.31*** **	**0.33*** **	0.04	0.04	0.05
Self-assess.	0.23***	**0.73*** **		**0.27*** **	**0.35*** **	0.02	0.04	0.05
Income ser.	0.17***	**0.31*** **	**0.27*** **		**0.47*** **	0.11*	0.18***	0.18***
Inherit. ser.	0.20***	**0.33*** **	**0.35*** **	**0.47*** **		0.04	0.14**	0.08
Maize yield	-0.14**	0.04	0.02	0.11*	0.04		**0.51*** **	**0.68*** **
Maize price	-0.15**	0.04	0.04	0.18***	0.14**	**0.51*** **		**0.48*** **
Rice yield	-0.11*	0.05	0.05	0.18***	0.08	**0.68*** **	**0.48*** **	
Rice price	0.07	0.05	0.09	0.11*	-0.04	**0.35*** **	**0.29*** **	**0.40*** **

Notes: Correlations are based on 272 households with complete data sets that could be used for the regression analysis. Due to their ordinal measurement scale, Spearman rank correlation coefficients are reported for all combinations apart from the MPL x self-assessment scale, where the Pearson correlation coefficient is shown. *(**)[***] denotes statistical significance at the 10% (5%) [1%] level of alpha error probability.

4.2 Classification of households into wealth terciles

Based on indicators related to households' asset endowment, housing condition, demography, consumption expenditures, and the official poverty classification in 2006[5] we construct a relative wealth index by principal component analysis. All signs of the component loadings conform to our theoretical expectations. Only indicators with an absolute loading greater than 0.4 are retained in the final model, as suggested by Stevens (2002: 394). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is larger than 0.5 for all individual variables, as recommended by Field (2005: 642). Overall, the KMO statistic yields a value of 0.876, indicating a very distinct and reliable first principal component (Field, 2005: 640).The eigenvalues of two principal components extracted exceed the value of one and can therefore be considered meaningful (Kaiser, 1960). Since the first principal component yields a much

[5] Once a year, the local government classifies households into poor (i.e., below the official rural poverty line) and non-poor based on a set of criteria developed by the Ministry of Labor, Invalids, and Social Affairs (MOLISA).

larger eigenvalue than the second (5.01 versus 1.36), explains a far greater share of variance in the data (41.7% versus 11.3%), and shows consistency in the signs of all component loadings we conclude that this is the component that reflects households' wealth status. Hence, the households' scores on this factor are used as the relative wealth index on which the classification of households into wealth terciles for the following analyses is based.

4.3 Sources and diversity of cash income and land allocation to crops

With an overall cash income share from farming of approximately 83% households in Yen Chau are highly dependent on their own agricultural production. This applies to all wealth groups. With an overall share of 65% of total household cash income (and 78% of cash income from farming), maize is by far the most important source of cash earnings. Hereby, a differentiation by wealth terciles reveals that at 73% the poorest third of households obtain a particularly large share of their cash earnings from maize. The share is significantly lower at 64% ($P < 0.10$) and 58% ($P < 0.01$) in the medium and wealthiest terciles, respectively. In the main cropping season of 2007, 97% of the sample households grew maize. With an overall share of 73% of the cultivable area, maize clearly dominated land use in the area. At 76%, the share of maize was significantly larger in the poorest tercile than in the wealthiest tercile (69%, $P < 0.10$). Farmers sold 95% of their maize harvest, on average, whereby there is no difference between wealth groups. The median share of maize sold is 100% in all wealth groups. Hence, the poorest tercile also grow maize almost exclusively as a cash crop.

4.4 Determinants of land allocation to maize

The factors hypothesized to influence the area share of maize, which serve as explanatory variables in our regression model, are summarized in Table 3. Since we are particularly interested in differences between wealth groups regarding these factors, apart from listing the overall mean of each variable the table also contains their means in the poorest and the wealthiest terciles and tests the difference in means for statistical significance. It is important to note that while most asset related variables differ between the two groups there is no statistically significant difference in any of the risk preference measures between all three wealth groups.

Table 3. Hypothesized influencing factors of the farm area share allocated to maize production (hypothesized direction of relationship in parentheses), and their means, differentiated by wealth group[1]

Variable description			Mean values			
			Whole sample	Poorest tercile[2]	Richest tercile	Stat. sig.
Dependent variable			**(N=272)**	(N=88)	(N=97)	
Maize share	=	Share of the cultivable area that was devoted to maize in the main growing season 2007 (%)	**73.29**	76.20	69.17	**[/a]
Natural capital						
Land availability (+)	=	Per capita cultivable area in the main growing season 2007 (hectares)	**0.35**	0.31	0.40	***[/a]
Upland share (+)	=	Share of land officially classified as 'upland' within the total cultivable area (%)	**77.50**	82.27	73.70	***[/a]
Upland distance (+)	=	Mean distance between homestead and upland plots (walking minutes)	**39.28**	50.93	36.24	n.s.[/a]
Paddy share (-)	=	Share of paddy land within the total cultivable area (%)	**12.28**	9.84	13.56	***[/a]
Red Book share (?)	=	Share of total cultivable area under a formal land use certificate ('Red Book') (%)	**72.97**	59.11	84.07	***[/a]
Elevation (?)	=	Elevation of the village centre above sea level ('00 m)	**5.19**	6.71	4.35	***[/a]
Human capital						
Age HH head (?)	=	Age of the household head	**43.22**	38.54	46.62	***[/a]
Literacy HH head (+)	=	Dummy, = 1 if HH head is literate, 0 otherwise	**0.77**	0.55	0.94	***[/b]
Sex HH head (?)	=	Dummy, = 1 if HH head is female, 0 otherwise	**0.08**	0.09	0.03	*[/b]
H'mong (?)	=	Dummy, = 1 if HH head belongs to the ethnic group of the H'mong, 0 otherwise	**0.15**	0.44	0.00	***[/b]
Kinh (?)	=	Dummy, = 1 if HH head belongs to the ethnic group of the Kinh, 0 otherwise	**0.08**	0.08	0.06	n.s.[/b]
Dependency ratio (-)	=	Number of HH members aged < 18 and/or > 64 relative to total number of members	**0.41**	0.52	0.31	***[/c]
Financial capital						
Off-farm income (+) / - squared (-)	=	Share of off-farm income in total HH income in the past 12 months (%)	**15.83**	16.26	18.73	n.s.[/a]
Credit limit (+)	=	Logged maximum amount of credit available to the HH (million VND)[3]	**42.67**	20.68	69.35	***[/a]
Market access/infrastructure						
Maize price (+)	=	Maize price received in 2006 ('000 VND kg^{-1})	**2.10**	2.03	2.14	***[/a]
Urea price (-)	=	Mean village level price of urea in the cropping season 2007 ('000 VND kg^{-1})	**5.08**	5.28	4.99	***[/a]
Input distance (-)	=	Distance to the closest fertilizer store (km)	**0.71**	1.08	0.45	**[/a]
Road distance (-)	=	Distance to the next paved road (walking minutes)	**16.00**	23.45	11.30	**[/a]
Good extension access (+)	=	Dummy, = 1 if perceived access to agr. extension on a scale from 1 (= very poor) to 5 (= very good) is above the median score of 3	**0.41**	0.39	0.46	n.s.[/b]

(continued)

Table 3 (continued)

Risk preferences[4] (one variable at a time included in the regression model)						
MPL (-)	=	Total number of safe options chosen in the multiple price list (0 to 10)	**6.35**	6.31	6.39	n.s.[/a]
SCF (-)	=	Survey of Consumer Finances financial risk tolerance question (ordinal scale from 1 to 4)	**2.74**	2.78	2.74	n.s.[/b]
Self-assessment (-)	=	German Socio-Economic Panel Study self-assessment question (scale from 0 to 10)	**5.19**	5.61	5.00	n.s.[/b]
Income series (-)	=	Hypothetical income scenarios (ordinal scale from 1 to 6)	**2.88**	3.11	2.71	n.s.[/b]
Inheritance series (-)	=	Hypothetical inheritance scenarios (ordinal scale from 1 to 6)	**2.70**	3.17	2.48	n.s.[/b]
Maize yield series (-)	=	Hypothetical maize yield scenarios (ordinal scale from 1 to 4)	**2.92**	2.90	2.82	n.s.[/b]
Maize price series (-)	=	Hypothetical maize price scenarios (ordinal scale from 1 to 4)	**2.85**	2.94	2.75	n.s.[/b]
Rice yield series (-)	=	Hypothetical rice yield scenarios (ordinal scale from 1 to 4)	**3.01**	2.99	3.04	n.s.[/b]
Rice price series (-)	=	Hypothetical rice price scenarios (ordinal scale from 1 to 4)	**3.24**	3.24	3.22	n.s.[/b]
Maize yield dummy (+)	=	Dummy, = 1 if riskiest maize yield scenario is preferred, 0 otherwise	**0.15**	0.14	0.18	n.s.[/b]
Maize price dummy (+)	=	Dummy, = 1 if riskiest maize price scenario is preferred, 0 otherwise	**0.14**	0.15	0.15	n.s.[/b]

*(**)[***] Difference between means in the poorest and wealthiest terciles statistically significant at the 10% (5%) [1%] level of alpha error probability based on [/a] Mann-Whitney test, [/b] Chi-square test, [/c] t-test.

[1] Means are based on a total of 272 cases without missing values for any of the variables.

[2] Based on the relative wealth index described in Section 3.2.

[3] Vietnamese Dong. 1 US$ = 16,000 VND (June 2007). For ease of interpretation, means are given for the unlogged variable.

[4] In all risk preference measures (apart from the deduced dummy variables), larger values are associated with a higher degree of risk aversion.

Table 4 presents the regression results from four model specifications[6]. The base model (1) does not include any risk preference measure. Model (2) includes the MPL measure based on the only non-hypothetical elicitation method involving actual payouts. Models (3) and (4) include those risk preference measures which are found to have explanatory power. These are dummy variables based on the two maize related hypothetical scenarios[7].

[6] The remaining models are not show for space reasons, but results are available on request.

[7] The ordinal scaled maize related risk preference measures yield statistically significant regression coefficients but do not permit an interpretation in terms of marginal effects.

Table 4. Tobit estimates of determinants of the farm area share allocated to maize, testing the explanatory power of risk preference measures based on different elicitation methods (N = 272)

Variable	(1) Model without risk preference measure	(2) Model with lottery choice based risk preference measure (MPL)	(3) Model with maize price based risk preference measure	(4) Model with maize yield based risk preference measure
Constant	**20.244**	**20.219**	**19.185**	**25.168**
	(30.489)	(30.338)	(30.575)	(28.710)
Land availability	**10.400**	**10.398**	**9.795**	**9.933**
	(6.813)	(6.775)	(6.740)	(6.589)
Upland share	**0.434*** **	**0.434*** **	**0.433*** **	**0.427*** **
	(0.060)	(0.061)	(0.059)	(0.060)
Upland distance	**0.017*** **	**0.017*** **	**0.018*** **	**0.018*** **
	(0.004)	(0.004)	(0.004)	(0.004)
Paddy share	**- 0.449*** **	**- 0.449*** **	**- 0.452*** **	**- 0.458*** **
	(0.096)	(0.097)	(0.092)	(0.092)
Red Book share	**- 2.124**	**- 2.124**	**- 1.994**	**- 2.330**
	(3.000)	(2.994)	(2.955)	(2.874)
Elevation	**- 0.281**	**- 0.280**	**- 0.165**	**- 0.171**
	(0.681)	(0.673)	(0.674)	(0.643)
Age HH head	**- 0.072**	**- 0.073**	**- 0.068**	**- 0.068**
	(0.066)	(0.071)	(0.068)	(0.066)
Literacy HH head	**- 7.119*** **	**- 7.119*** **	**- 7.328*** **	**- 7.610*** **
	(2.055)	(2.043)	(2.111)	(2.108)
Sex HH head	**13.595** **	**13.593** **	**13.630** **	**12.605** **
	(5.429)	(5.433)	(5.322)	(5.328)
H'mong	**- 14.999*** **	**- 15.001*** **	**- 15.659*** **	**- 16.118*** **
	(4.641)	(4.703)	(4.616)	(4.595)
Kinh	**15.585*** **	**15.581*** **	**15.619*** **	**14.958*** **
	(4.888)	(4.843)	(4.788)	(5.175)
Dependency ratio	**- 9.936**	**- 9.935**	**- 10.448**	**- 10.055**
	(7.226)	(7.250)	(7.144)	(7.267)
Off-farm income	**0.307*** **	**0.307*** **	**0.333*** **	**0.325*** **
	(0.119)	(0.122)	(0.117)	(0.123)
Off inc. squared	**- 0.006*** **	**- 0.006*** **	**- 0.006*** **	**- 0.006*** **
	(0.002)	(0.002)	(0.002)	(0.002)
Credit limit	**4.469** **	**4.469** **	**4.412** **	**4.239** **
	(2.237)	(2.237)	(2.216)	(2.154)
Credit limit x poor	**0.750** **	**0.750** **	**0.763*** **	**0.737** **
	(0.292)	(0.292)	(0.294)	(0.293)
Credit limit x wealthy	**- 0.231**	**- 0.231**	**- 0.231**	**- 0.236**
	(0.237)	(0.237)	(0.243)	(0.247)
Maize price	**3.670**	**3.672**	**4.014**	**3.845**
	(4.646)	(4.616)	(4.652)	(4.609)
Urea price	**- 4.988*** **	**- 4.988*** **	**- 4.962*** **	**- 5.593*** **
	(1.547)	(1.548)	(1.561)	(1.511)
Input distance	**- 0.417**	**- 0.417**	**- 0.316**	**- 0.438**
	(0.375)	(0.376)	(0.364)	(0.362)
Road distance	**0.296*** **	**0.296*** **	**0.299*** **	**0.303*** **
	(0.041)	(0.041)	(0.043)	(0.044)
Good extension access	**3.120** **	**3.121** **	**3.048** **	**3.043** **
	(1.443)	(1.447)	(1.429)	(1.400)
MPL	-	**0.005**	-	-
		(0.478)		
Preference of riskiest scenario	-	-	**3.541** **	**5.933*** **
			(1.489)	(2.074)
	Log likelihood = -1087.43 Pseudo R^2 = 0.083	Log likelihood = -1087.43 Pseudo R^2 = 0.083	Log likelihood = -1086.56 Pseudo R^2 = 0.084	Log likelihood = -1085.11 Pseudo R^2 = 0.085

% censored obs. at 0 = 2.9; % censored obs. at 100 = 2.2

Notes to Table 4: Dependent variable: Maize share. Coefficients are marginal effects on the latent (uncensored) dependent variable. Values in parentheses are heteroskedasticity-consistent standard errors (White, 1980) that account for the cluster sampling procedure applied in selecting the farm households. *(**)[***] denotes statistical significance at the 10% (5%) [1%] level of alpha error probability.

We test for possible multicollinearity among the explanatory variables in the models by producing variance inflation factors (VIF). Naturally, the VIF are quite large for the variables *Off-farm income* and its squared term. Apart from these, with a maximum VIF of 4.24 for the variable *H'mong* in model (2) and a maximum average VIF of 2.42 in this model, there is no cause for concern with regard to multicollinearity. The risk preference measures yield VIF of 1.12 in model (2) and 1.08 in the other two specifications. Myers (1990) suggests that a value of 10 should not be exceeded.

We explore potential endogeneity with respect to the risk preference measures by regressing all remaining explanatory variables in the model on the respective risk preference measure and assessing the explanatory power of these models[8]. We find that the adjusted R-squared in an Ordinary Least Squares regression on MPL amounts to merely 0.025, and that probit models on the maize scenario related measures lack predictive power: while 232 out of 233 cases (99.6%) of observed zeros (= respondent does not prefer the riskiest scenario) are correctly predicted in the case of the *Maize yield dummy* (cf. Table 3), only one out of 39 cases (2.6%) of observed ones (= respondent prefers the riskiest scenario) is correctly predicted. Hence, the model is not capable of differentiating the most risk taking from the remaining respondents. The same is true for the probit regression on the *Maize price dummy*, in which only 1 out of 42 cases of observed ones (2.4%) is correctly predicted.

5 Discussion

We find that the poorest tercile are particularly specialized in hybrid maize production. Since farmers in all wealth groups grow maize almost exclusively as a cash crop there is no indication that the poorer households are less commercially oriented than the wealthier ones, which is contrary to the findings of Minot et al. (2006). However, the authors observed that households in all income categories had shifted toward commercial production over the

[8] Due to lacking instruments, it was not possible to conduct a formal Hausman test on endogeneity of the risk preference measure. A suitable instrument would have to be strongly correlated with the level of risk aversion, but uncorrelated to the other, asset related explanatory variables in the model.

period 1993 to 2002. Hence, while the poorer households may initially have lagged behind they may well have caught up over time.

Regarding the modeling of the land allocation decision to commercial maize production, our study confirms the relevance of decision-makers' risk preferences in addition to their asset endowment. The literature offers conflicting evidence about whether or not and how individuals' observable characteristics affect risk preferences, creating potential endogeneity bias if measures of individuals' level of risk aversion are used as explanatory variables in regression models, along with variables reflecting their socio-economic characteristics. We find that asset base related factors have only minimal predictive power regarding the risk preference measures that we test. Furthermore, the comparison of the regression results of model specifications (2) to (4) with the base model (1) shows that the asset related regression coefficients remain very similar, indicating that endogeneity bias – if it exists – is negligible. Finally, also the fact that no statistically significant difference between wealth groups was found for any of the risk preference measures (cf. Table 3) indicates that risk preferences are mostly determined by factors other than the asset base as captured by the regression models. These are likely to be innate or acquired personality traits, which are difficult to assess using survey methods, such as a person's degree of impulsivity, sensation-seeking, and self-control, for example (Mishra and Lalumière, 2011).

Only the risk preference measures that are based on the hypothetical maize yield and maize price scenarios are found to have explanatory power in our model, indicating that persons who preferred the riskiest scenario allocated an additional area share of 5.9 and 3.5 percentage points to maize, respectively. The difference between the two estimates is not statistically significant. Interestingly, risk preferences elicited from very similar scenarios related to rice are far from showing a statistically significant effect in the model, yielding alpha error probabilities of 27% and 43% in the yield and price related scenarios, respectively. The correlations between the agriculture related risk preference measures and the other measures are surprisingly weak (cf. Table 2). This may be due to a lacking applicability of some of the other measures, such as the income and inheritance series, to real life decisions of smallholder farmers in developing countries. Especially the applicability of the SCF question to respondents in developing countries who have little investment opportunities is highly questionable. Regarding the MPL method, there is evidence that the lottery choice task was not taken seriously be some respondents and/or that the procedure was not well understood; in

22 out of 272 cases (8.1%) that could be used for the regression analysis, respondents switched back to the safe Option A at least once after having moved to the riskier Option B. Hence, our study indicates that hypothetical scenarios that are closely related to farmers' real-life decisions may produce more reliable results than unfamiliar and non-applicable scenarios or complex, costly methods involving real payouts.

Regarding the role of households' asset base, we find that the endowment with natural capital, both 'upland' and paddy area, has a highly significant influence on the area allocation to maize. Across all model specifications, a one-percentage-point increase in *Upland share* entails an increase in *Maize share* by 0.43 percentage points. On the other hand, if *Paddy share* increases by one percentage point, *Maize share* is reduced by 0.45 to 0.46 percentage points. The magnitude and high level of statistical significance of the negative coefficient on *Paddy share* shows that, although maize has become a very profitable cash crop, farmers continue to have a clear priority to use irrigable land not for maize but for the cultivation of rice. This suggests that they view relying on rice markets as too risky for the acquisition of their major food crop and are willing to pay a considerable risk premium (in terms of foregone gross margin on the more lucrative crop maize) for ensuring food security through home-produced rice. The statistically highly significant differences in *Upland share* and *Paddy share* between the poorest and the wealthiest tercile of farm households (Table 2) clearly work towards the poorest allocating a larger portion of land to maize.

Concerning human capital, the model results confirm that the characteristics of the household head have important implications on the area allocation to maize. Contrary to our expectation, literacy of the household head reduces the area allocated to maize by 7.1 to 7.6 percentage points, which could be an indication that literate household heads are more aware of the phyto-sanitary need to diversify cropping patterns and/or that they are more aware of beneficial alternative crops. The statistically highly significant difference in the literacy rate between the poorest and the wealthiest tercile (55% versus 94%, Table 3) means that the poorest are more likely to allocate a larger share of their area to maize. Surprisingly, we find that the portion of land devoted to maize is 13.6 percentage points larger if the household head is female (model (4): 12.6). This may be explained by differences in land endowment: first, the total cultivable area available to female-headed households is significantly smaller than that of male-headed households (0.97 ha versus 1.63 ha, Mann-Whitney test significant at $P < 0.01$); and, second, female-headed households are less endowed with irrigable land

allowing them to grow rice for home consumption (269 versus 382 m^2 per person, Mann-Whitney test significant at $P < 0.1$). Both factors indicate that the need to allocate land to a profitable cash crop is particularly pronounced for female-headed households.

Regarding the endowment with financial capital, the regression coefficient on *Off-farm income* is positive (0.31 to 0.33) and that on its squared term is negative (- 0.006). In combination, these coefficients imply that up to a share of approximately 50% there is a positive but decreasing effect of off-farm income on the portion of land allocated to maize; beyond this threshold the effect becomes increasingly negative. This means that, if off-farm income is only supplementary, farm households are likely to use it to finance agricultural inputs, in our case hybrid maize seed and mineral fertilizers. If, however, off-farm income accounts for a major share of total income, households may prefer to devote a larger share of their cultivable area to food crops for home consumption to reduce their exposure to market related risks or to crops with particularly low labor requirements to free up labor resources to engage in their off-farm activities.

As expected, *Credit limit* yields a positive regression coefficient. Since this variable enters the model in its logged form, we conclude that a one *percent* increase in credit access leads to an expansion of the area share devoted to maize by 4.2 to 4.5 percentage points. We allow the marginal effect to vary between wealth groups by interacting *Credit limit* with dummy variables for the poorest and wealthiest terciles; *Credit limit* alone thus indicates the marginal effect on the middle tercile. *Credit limit x poor* yields a positive and statistically significant regression coefficient, showing that, at 5.0 to 5.2 percentage points, the marginal effect of a one percent increase in credit access on *Maize share* is approximately 17% larger for the poorest tercile than for the middle tercile. The sign of the coefficient on *Credit limit x wealthy* is negative, as would be expected, but not statistically significantly different from zero. Furthermore, it is important to note that producers – especially the poor – rely on credit from informal lenders such as shopkeepers or traders, which is typically supplied at comparatively high interest rates: while the interest rates paid by the wealthiest tercile of households average 0.93% per month, they amount to 1.64% in the poorest tercile. Hence, for the poorest tercile credit is on the average 76% more expensive (Mann-Whitney test statistically significant at $P < 0.001$).

Our findings regarding the influence of output and input prices on the area allocation to maize are mixed. The regression coefficient on the maize price received in the cropping season 2006 carries the expected positive sign but is not significantly different from zero. This may be due to a lack of alternative cash crops that are able to compete with maize, even though the price received in a particular location and under a specific marketing arrangement (see below) may be comparatively low. We do find a statistically significant negative influence of the urea price on the area allocation to maize, however: for a urea price increase of 1,000 VND per kg our model predicts a decrease in *Maize share* of 5.0 percentage points (model (4): 5.6). Hence, based on the means of the two variables (cf. Table 3), a 20% increase in the price of urea would entail a 6.8% reduction in maize area (elasticity = - 0.34), indicating that farmers do respond to input price signals.

With respect to physical input and output market access, an influence of the distance to the closest fertilizer outlet is not supported by our data. Contrary to our expectation the portion of land devoted to the cash crop maize *increases* with increasing distance to the nearest paved road, by 0.3 percentage points for an increase by one walking minute, which is statistically highly significant. Both findings can be explained by the fact that many villages have established marketing contracts with maize traders who collect the produce at the farm gate. These traders also supply the farmers with the necessary inputs. Especially in remote locations maize may be the only cash crop to grow because the transaction costs involved in cultivating and marketing alternative crops, such as fruits or vegetables, may be prohibitive. The marketing arrangements with maize traders come at a cost, however: in the two most remote research villages that rely on such arrangements the maize price received was 23 and 28% lower than in the remaining villages in 2006 and 2007, respectively (Mann-Whitney test significant at $P < 0.001$). Moreover, as mentioned above, especially the poor receive in-kind credit in the form of seeds and fertilizers from these traders at comparatively high interest rates, which is reflected by the significantly lower output price that the poorest tercile receive and the significantly higher price they have to pay for urea (Table 3). Finally, maize, as the dominant crop in the area, is also the main focus of agricultural extension activities. Consequently, *Good extension access* is found to increase the area share devoted to maize by 3.0 to 3.1 percentage points. Since 41% of households enjoy good extension access by our definition, one can conclude that there is scope for the agricultural extension service to influence land use decisions in the area.

6 Conclusions and recommendations

In summary, we find that hybrid maize is by far the most important cash crop in Yen Chau district, covering most of the uplands and generating the lion's share of households' cash income. The poorest households allocate a particularly large portion of their land to maize which they use almost exclusively as a cash crop, as do the wealthier households. Apart from the availability of upland area, farmers' area allocation to maize is mainly determined by the households' endowment with human and financial capital. Infrastructural conditions, such as easy access to paved roads and markets, are found to not play a significant role, which is probably due to marketing and input supply arrangements with maize traders who collect the produce in more remote villages. Our first main conclusion, therefore, is that maize is attractive to farmers from all social strata, notably the poor. Not only are there no barriers preventing the poorest households from participating in commercial maize production, but this group is even particularly specialized in this enterprise.

Furthermore, we find that an increase in credit access has a particularly large effect on the area allocation to maize in the poorest tercile. Although it is comparatively easy for them to obtain in-kind credit in the form of seed and fertilizer from maize traders, the cost of these arrangements manifests itself in significantly higher input and lower output prices as compared to the wealthiest tercile of farmers. We therefore conclude that the enhancement of the poor's access to low-interest formal rural credit may promote their specialization on maize even further, which would enhance the profitability of maize production in this stratum and therefore contribute to poverty alleviation. Moreover, through moderate interest rates, the risk of becoming indebted and caught in a poverty trap would be reduced. This risk is considerable given the extremely high shares of maize in overall production and cash income, coupled with input and output price fluctuations as well as possible yield depressions due to maize pests, maize diseases, adverse climatic conditions, and soil degradation.

Due to the trade-off between short-term profitability of maize production and lacking longer-term sustainability we propose a two-pronged rural development policy approach: on the one hand, the potential of maize production to alleviate poverty should be harnessed. This means that the poor should become less dependent on the relatively disadvantageous input supply and marketing arrangements offered by maize traders who service remote villages. Appropriate policy measures would encompass public investments in the rural road network, maize storage facilities, and a price information system, as well as enhancing the access of the

poor to formal credit at moderate interest rates. On the other hand it is crucial to make maize production in the uplands ecologically more sustainable, and it is desirable to foster a diversification of land use and income sources in the longer run to reduce the risks associated with the specialization in maize.

Regarding the modeling of land allocation decisions, our study confirms the relevance of decision-makers' risk preferences in addition to their asset endowment. We add a quantitative measure of the degree of risk aversion as an explanatory variable to a regression model on land allocation to maize, along with commonly used asset related variables. While we test a wide range of measures derived from different elicitation methods – among them a lottery choice based method with actual payouts - only the risk preference measures that are based on hypothetical maize related scenarios are found to have explanatory power in the model, whereby the effect is quite considerable. Interestingly, risk preferences elicited from very similar scenarios related to the major food crop, rice, are far from being statistically significant in this cash crop related model. Hence, regarding the empirical elicitation of farmers' risk preferences in developing countries our study yields evidence that (1) risk preferences are to a certain extent decision domain specific, e.g. farmers' degree of risk aversion may deviate between cash crops and food crops, and (2) hypothetical scenarios that are closely related to farmers' real-life decisions may produce more reliable results than unfamiliar, non-agricultural scenarios or lottery-based methods, which can be difficult to grasp for respondents with limited formal education and mathematical understanding, and/or may not be taken seriously. However, this result should be viewed as being exploratory and needs to be followed-up by studies that use risk preference elicitation techniques that are more related to respondents' own life conditions and studies which are able to more rigorously assess the level of risk involved in a portfolio of income generating activities, ideally based on panel data from which the variances and co-variances of returns over time can be calculated.

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