Regional Climate Extremes and Farmer's Perception: Impact on Acceptance of Environmentally-Friendly Rubber Plantations in Southwest China

by Shaoze Jin, Lijuang Zhang, and Shi Min

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ABSTRACT

Climate extremes fail agricultural production and threaten smallholder farmers' livelihood and food security. We provide new insights into the shaping of farmers' perception of climate extremes and its impact on their acceptance of sustainable agriculture. The study takes environmentally-friendly rubber plantations (EFRP) with 611 smallholder farmers in Xishuangbanna Dai Autonomous Prefecture, Southwest China. The research focus is on the ex-ante experience of climate extremes and income volatility that influence farmers' perception of climate extremes as well as acceptance of EFRP. We develop two models: (i) an endogenous switching methodology allows indirectly link experience of climate extremes and income volatility to EFRP acceptance, intermediated by the perception; and (ii) an OLS and a seemingly unrelated regression models to assess the direct effects of the experience and income volatility on the acceptance. Interestingly, the results show the heterogeneous effects of farmers' perception and experience of climate extremes. While the experience provides a strong motive for the acceptance, farmers who perceived increases in regional climate extremes are unlikely to accept EFRP. This asymmetry attributes to farmers' limited adaptation capability and cognitive bias subject to income volatility. The empirical lesson underpins the opposite effects of farmers' climate change experience and perception on their adaptive intentions.

***Keywords**:* Perception; Income Volatility; Experience; Climate Extremes; Environmentally Friendly Rubber Plantation.

***JEL codes**:* Q01, Q54, Q15.

1 Introduction

Adapting to and coping with the threat and impacts of climate change have become a consensus of scholars and policymakers around the globe (World Bank, 2010; IPCC, 2014; Reser and Swim, 2011). This is especially urgent for farmers in developing countries who are exposed to the brunt of the downsides of climate change and climate variability (Huang et al., 2015). Farmers' perception of the regional climate events reflects their judgments and awareness of climate change and may further influence their adaptation activities (Hou et al., 2015). Hence, the first step in the process of improving adaptation is to understand how farmers' perception of climate change is shaped (Shi, Visschers, and Siegrist, 2015; Hou et al., 2017).

However, the dilemma "perceived but not accepted" is one of the critical barriers in the adaptation to climate change. This is being observed because climate change and its consequences can hardly raise enough concerns and evoke visceral adaptation reactions in society (Weber, 2006). Scholars have already shed light on the psychological and behavioural interpretations of this phenomenon. For example, adaptation to climate change is limited by individual cognition and behaviour, perceived risks, non-rational judgments and beliefs, and psychological distance (e.g., Weber and Stern, 2011; Gifford, 2011; Spence et al., 2012; Zaval and Cornwell, 2016).

Farmers' subjective perception of climate change is not always in line with the meteorological record data (Maddison, 2007; Lee et al., 2015; Brüssow et al., 2019; Nguyen and Nguyen, 2020). This inconsistency may lead to inappropriate adaptations (Dawson et al., 2011). The adaptation decisions based on such perception, therefore, remain controversial. Mainly in two ways, the empirical literature for rural households shed light on the adaptation asymmetry. One is to estimate the correlations between perception and adaptation willingness or actions, while findings are quite mixed (e.g., Mertz et al., 2009; Abid et al., 2015). Another is to assess the effects of the specific experience of climate shocks on adaptations (e.g., Leiserowitz, 2006; Whitmarsh, 2008; Bryan et al., 2009; Spence et al., 2011). Determinants (or constraints) in adaptation to deal with climate hazards are simply identified as adaptive capacity, insufficient intra-household endowments, external forces, and under-developed conditions (e.g., Khanal et al., 2018; Trinh et al., 2018; Brüssow et al., 2019). The gaps of research are twofold: (i) the absence of a convincing framework to outline the rationale as to how farmers perceive climate change and its connection with adaptation, and (ii) methodologically, few studies account for the potential endogeneity and sample selection bias of the perception, which may lead to misleading results.

Regional climate patterns are closely associated with land-use change and the resulting alterations in landscapes (Dale, 1997; Pielke, 2005). A typical case is the expansion of rubber plantation in Xishuangbanna Dai Autonomous Prefecture (XSBN) of Southwest China. Driven by continuous increases in rubber prices over decades, rapid transitions of the landscape have been ongoing, from the ecologically valuable indigenous forest and traditionally managed field crops to the large-scale rubber monoculture (Häuser et al., 2015). The transitions resulted in the rising vulnerability of agricultural sectors to regional climate extremes of XSBN, such as wind-, temperature- and precipitation-extremes, and their corresponding events like storms, frosts, droughts, floods and landslides (Liu et al., 2005; Nong et al., 2012). Hence, more sustainable management of rubber-dominated land use is urgently needed to improve its ecosystem services in coping with climate risks.

A program called Environmentally Friendly Rubber Plantation (EFRP) was announced by the local Government of XSBN in 2009, while the doable implementation guidelines of the program were formulated until 2013 (XSBN Biological Industry Office, 2013). This program aims to mitigate the negatives caused by the unrestricted expansion of rubber monoculture and help smallholder farmers adapt to regional climate change (Min et al., 2018). The core content includes: (i) the modification of the existing rubber systems by introducing ecosystem-service-based land use plans and standards, such as restoring the lands in unsuitable conditions for rubber plantations to forests and other crops cultivation; (ii) the introduction of rubber intercropping systems to promote land use diversification. One of its main objectives is to increase smallholder rubber farmers' livelihood resilience to climate uncertainties that threaten the sustainability of rubber plantations. To date, the implementation of EFRP was solely carried out through the conceptual introductions to agricultural extension personnel and village leaders, and the establishment of pilot projects in selected villages. In practice, a broader knowledge extension and adoption of EFRP by smallholder rubber farmers are not yet observed in XSBN.

Given the importance of farmers' perception of climate change on their adaptive actions, the paper relates to the following questions: (i) how smallholder rubber farmers' perception of regional climate extremes is shaped, and (ii) to what extent the perception can affect their acceptance of a sustainable land use program (i.e., EFRP) to cope with climate risks in XSBN.

We begin the study by establishing two hypotheses. First, farmers' perception or belief of climate extremes is shaped though both climate risk appraisal and adaptation risk appraisal, and then affect their intentions to adaptation. Notably, two risk appraisals are denoted by the ex-ante experience of climate extremes and income volatility. The second hypothesis refers to the direct impact of farmers' experience of climate extremes and income volatility on EFRP acceptance. Empirically, we specify two models: an endogenous switching approach to test the indirect channel of decision-making, and an OLS and a seemingly unrelated regression models to estimate the direct channel.

Results confirm that a knowledge of the increasing occurrences of climate extreme will result in a reduction of farmers' acceptance of EFRP. Such phenomenon derives from their limited adaptation capability and cognitive bias following their adaptation risk appraisal. Besides, the experience of climate extremes depicts a direct and strong impact on the acceptance.

The study gives new evidence shedding light on the dilemma "perceive but not accept" in climate change adaptation. On the one hand, it advances the understanding farmers' perception of climate change and their acceptance of adaptive actions in the rubber planting areas in Southwest China. The findings of this study, on the other hand, can provide empirical insights on the implementation of the EFRP practices and its obstacles.

The rest of this paper is organized as follows. Section 2 introduces the theoretical framework. Section 3 describes the survey site, including the rubber cultivation in XSBN as the basis, and the data collection procedures. Section 4 presents the analysis of descriptive statistics. Sections 5 and 6 specify the model estimations and discuss results, respectively. Section 7 concludes.

2 Theoretical framework

2.1 Conceptual model

In this section, we conceptualize rubber farmers' acceptance of sustainable land management to offset the risks of regional climate extremes. In some earlier classic theories, the use of agricultural innovations (e.g., sustainable land management) is described as a learning process (e.g., Feder and O'Mara, 1982; Just and Zilberman, 1983). We employ a model developed by Tsur, Sternberg, and Hochman (1990, hereafter TSH) designed as a stochastic optimization process under risk and uncertainty. The TSH model demonstrates the plausibility of Bayesian learning as the underlying dynamic process. The decision-makers collect and process information, and the effect of learning on the diffusion of new technology varies according to their cognitive capability. We adjust the TSH model by emphasizing farmers' expectations on the future returns of land-use innovations built upon their own information sets. The model can be specified as one dynamic optimization task[1]:

$$\text{Max}\, J = \int_0^{\infty} e^{-\gamma t}[\Pi_t(\Omega_t) - 0.5\lambda e^{-\gamma t}\sigma_t^2(\Omega_t)]dt \tag{2.1}$$

$$\text{Subject to: } \underline{B}_t \leq \Delta l_t \leq \overline{B}_t \tag{2.2}$$

where Π_t and σ_t^2 is defined as the mean and the variance of total return at time *t*, respectively, which are determined by the individual information sets Ω_t. Notably, λ is the absolute risk aversion coefficient. γ is an exponential structure of a discount rate. Δl_t is the area of rubber lands transferred from the existed to the land-use innovations to adapt to regional climate extremes. Regarding the physical and economic constraints, the adaptive activities Δl_t are bounded between certain levels of land area $[\underline{B}_t, \overline{B}_t]$. Following the Euler conditions for the optimality of the most rapid approach path, we obtain the optimal area l_t^* which can be given as a reduced-form function $f(\cdot)$ with respect to the information set Ω_t:

$$l_t^* = f(\Omega_t). \tag{2.3}$$

2.2 The decision-making process of adaptation

This section introduces a framework to outline the decision-making process conditional on the individual information set Ω based on the results of Eq. (2.3). Our framework helps explain why some farmers likely to take adaptive actions while others give evasive responses to climate change. As shown in Figure 1, farmers make adaption decisions based on two mechanisms of risk appraisals: (i) *climate risk appraisal* and (ii) *adaptation risk appraisal*. Since perception is not necessarily founded strictly on

[1] Proof procedure can be found in the Appendix.

experience, we consider farmers' judgement on the probability and severity of climate extremes as well as their adaptive capacity indicated by efficacy and costs that involved.

<Figure 1>

In the process of decision-making, farmers face a trade-off between the two risk appraisals. That is, on the one hand, if farmers anticipate higher costs from the adaptation than taking no action, they are likely to choose an evasive response (e.g., perceived but not accept) to the climate extremes. On the other hand, if the losses from climate extremes are higher than the costs in the adaptation, farmers may adopt agricultural innovations (e.g., sustainable land management).

In the *climate risk appraisal*, farmers' judgement of the probability and severity of climate change mainly depends on ex-ante losses or damages experienced as a consequence of climate extremes. Farmers who experienced the shocks of climate extremes expect the occurrence of shocks in the future (Lerserowitz, 2006; Whitmarsh, 2008; Akerlof et al., 2012). And those who perceive themselves to be more affected by climate extremes are expected to more readily adapt (Hou et al., 2017). Given a high-risk appraisal of climate extremes, farmers' adaptive intentions may not necessarily lead to actions of adaptation. Farmers may somehow adopt evasive responses by applying agricultural innovations to climate risks.

Moreover, the decision-making process is subject to farmers' limited adaptive capability and cognitive bais in the *adaptation risk appraisal*. The former (adaptive capability) relates to insufficient access to resources such as time, money, knowledge, entitlements, social interactions, and supports of institutional arrangements (Brüssow et al., 2019). The latter (cognitive bias) is considered as some behavioural and psychological barriers that may play a role in the long-term planning of adaptation. Cognitive bias and irrational judgment may inhibit people from accurately observing the future benefits of immediate costs for adapting to climate change (e.g., Zaval and Cornwell, 2016). The prospect theory may help to understand such cognitive bias. According to the prospect theory (Kahneman and Tversky, 1979), there are two possibilities as to how individuals' conditions can influence their climate change perception. The first is loss-aversion that people present higher sensitivity on losses than gains (Tversky and Kahneman, 1991). In light of climate change, those who encountered worse physical or economic conditions are more likely to perceive climate risk and uncertainty. The second possibility draws on the concept of reference-dependent preferences, which indicates that people's behaviours respond to some specific reference points (Camerer et al., 1997; Farber, 2005, 2008; Köszegi and Robin, 2007). People are more sensitive to climate risks below some reference points (e.g., expected or targeted incomes) than those above it. For example, farmers who suffered losses in income compared to their previous income levels are more likely to perceive the risks of climate change. Therefore, a better understanding of the decision-making process of adaption calls for the identification of both climate and adaptation risk appraisals. At the same time, the regional heterogeneity in terms of the economic and natural conditions should be considered.

As a strategy of identification, we propose to use the ex-ante experience of climate extremes and income volatility. To detect *climate risk appraisal*, the previous experience of climate extremes is a key factor that can influence farmers' judgement or belief on the probability and severity of climate extremes. Notably, there are two channels (i.e., indirect and direct channels) that the experience relates to the adaptation. First, the experience shapes the perception of climate extremes, and further influence their adaptation intention and behaviours (e.g., Mertz et al., 2009; Akerlof et al., 2013; Niles and Mueller, 2016). Second, the experience can directly influence the adaption[2] (e.g., Lerserowitz, 2006; Whitmarsh, 2008; Akerlof et al., 2012). For the identification of *adaptation risk appraisal*, we use the ex-ante income volatility to capture the household adaptive capability and individual cognitive bias. It is plausible that farmers who experience income losses compared to the income level in the past are supposed to endowed with lower objective capability in the adaptation and thus are not likely to take positive activities. Moreover, losses in income may lead to behavioural and psychological barriers related to the cognitive bias, as a result of loss-aversion and reference-dependent preferences. All else equal, we expect the existence of both indirect and direct channels in the adaptive decision-making process.

Based on this problem analysis, in combination with our conceptual framework, we establish hypotheses as follows:

[2] A major obstacle to motivating action on climate change is the fact that for people the phenomenon appears personally distant in space and in time (Weber and Stern, 2011; Weber, 2015). Weber (2016) pointed out the phenomenon attributes to a pattern of "seeing-is-believing". It indicates that belief in climate change increases when people personally experiences climate change manifestations. Stronger beliefs in the presence of climate change may make it more likely that people will look for adaptive actions.

Hypothesis 1 *(indirect channel). Farmers' perception of climate extremes that affected by ex-ante experience and income volatility can shape their acceptance of sustainable land management to adapt to climate extremes.*

Hypothesis 2 *(direct channel). Farmers' ex-ante experience and income volatility can directly affect their acceptance of sustainable land management.*

In the next chapters, we describe the database and the methods used to test these hypotheses.

3 Survey sites and data

3.1 Rubber expansion and climate change in XSBN

Xishuangbanna Dai Autonomous Prefecture (see Figure 2) is located in the mountainous region of the upper Great Mekong, harbours a wealth of natural resources, and is widely known for its indigenous tropical rainforests, rich biodiversity, and the headwaters of major rivers (Zhu et al., 2006). As the home of rich ethnic minorities, farmers enjoy the unique, long-standing agricultural traditions in practising diverse land-use systems, highly in line with the sustainable and environmentally friendly principle (Ziegler et al., 2011). Introduction of natural rubber plantations in XSBN dates back to the late 1950s. Over the decades, the traditional shifting cultivation together with local tropical rainforest has been replaced by more intensive agricultural systems, in particular by large-scale rubber monoculture. Facilitated by the rising rubber prices and liberal land policy of local Government, XSBN experienced dramatic land-use transformations. By 2010s, the area of rubber plantations rose to 424,000 ha (i.e., 22% of total landscape), mainly operated by smallholder farmers in XSBN (Xu et al., 2014).

<Figure 2>

The expansion of rubber plantations resulted in significant socioeconomic and ecological impacts in XSBN. The growth in rubber-dominated agriculture was once regarded as a reliable source of income to reduce poverty in rural XSBN (Min et al., 2017). However, a slowdown in global demand of natural rubber combined with growing stocks due to widespread rubber expansions has led to sharp declines in rubber prices by over 70% since the 2010s (Ahrends et al., 2015). Concerns arise from several matters, such as rubber price fluctuations, narrowing income sources, threats to food security, vulnerability, and high dependency on the global market (Fu et al., 2010). Moreover, the rubber expansion gave rise to the destruction of ecologically valuable indigenous forest areas and the negative implications for biodiversity, water resources, carbon sequestration, soil productivity, and other ecosystem services in XSBN (de Blécourt et al., 2013).

Although studies over climate variability are limited, some researchers map a clear tendency of climate change in XSBN. For example, Yu et al. (2008) observe an increasing annual temperature of 0.262 ˚C per 10 years, as well as yearly a decreasing precipitation of -20.72 mm per 10 years on average since the 1960s. Ahrends et al. (2015) find that region- and geographic-specific effects of climate change likely increase climate uncertainty and occurrence of climate extremes that resulted in crop failure among the major rubber producing countries in the Great Mekong. In particular, rubber plantation is sensible to the climate extremes in XSBN, such as cyclones, frosts, droughts, floods, and landslides, due to the problems of ecosystem services that it triggered.

On the other hand, land use and cover play roles in determining current climate conditions, as well as the impact of climate change and environmental variability on ecological systems (Pielke, 2005). In XSBN, the rapid transition of land cover led to deforestation and environmental degradation. Human activities related to rubber management, land use and land cover change deteriorate the local micro-climate conditions and increase farmers' vulnerability to climate extremes. For example, it resulted in an averagely annual increase in temperature of 0.09 ˚C per 10 years in the 1980s when the most significant land-use change occurred (Nong et al., 2012). Hence, sustainable land use should be adjusted to climate change in coping with potential climate hazards (Dale, 1997).

3.2 Data source

The empirical basis of the study is a cross-sectional dataset consists of a sample of 611 smallholder rubber farmers collected from a follow-up household survey in XSBN carried out in March 2015. The first round of the survey was conducted in March 2013. Based on a stratified random sampling approach, we obtained a representative sample of rubber farmers in XSBN. The sample was selected in the three-step process, including all three counties (i.e., Jinghong, Menghai, and Mengla), eight townships, and forty-two villages. It considers the size of rubber area per capita and the distribution of rubber planting areas in each county, being well able to picture the smallholder rubber farming in XSBN. Besides, our samples depict the geographical features and multi-ethnicity in XSBN. The sample households, most living in the mountainous regions, are broadly ranging from 540 and 1500 meters over sea level. Around 58% of samples are Dai households who are dominated by population in XSBN, followed by the Hani, Yi, Bulang, etc. Only 5% of respondents are Han ethnicity who are the ethnic majority in China but can be considered as migrants in XSBN.

The survey instruments included household and village questionnaires. The household dataset consists of socioeconomic information of all family members, including all income-generating activities, such as crop and livestock production, as well as off-farm and non-farm activities. The household questionnaire also included a detailed module on rubber production to capture the labour input, material use, and outputs. Moreover, the household questionnaire includes household assets and consumption, experienced shocks, and expected future risks. Notably, we also designed a section to survey the regional climate change and farmers' mitigation behaviours. Within the modules, we recorded farmers' perceptions of trends in temperature, rainfall, climate extremes in the past 15 years, the impacts of these changes on rubber farming, and farmers' mitigation behaviours related to these changes. The village questionnaire, which was administered with the head, included demographic conditions, infrastructure, and institutions in the villages.

4 Descriptive statistics

This section reports the results of descriptive statistics. First, we show the self-reported experience of regional climate extremes in XSBN. Second, in line with the theoretical framework, we depict the link between farmers' experience and perception of climate extremes as well as the relationship between income volatility and perception. Then, we introduce farmers' acceptance toward the practical items of Environmentally Friendly Rubber Plantations.

4.1 Self-reported experience[3] of climate extremes in XSBN

In Table 1, we report the number and the proportion of households reporting experience of climate extremes in the total sample. We list the climate shocks[4], including three categories of events (i) heavy precipitation (e.g., flood and landslide); (ii) temperature extreme (e.g., heatwave and frost); and (iii) Storm. The most frequent climate extreme is the storm. There are 81 households (13.3% in the total 611 samples) experienced at least one storm which led to damage or losses in their rubber plantations in the reference period. Also, temperature extreme and heavy precipitation commonly occur in XSBN. 63 and 55 households report the experience of the two climate shocks.

<Table 1>

4.2 Relating experience of climate extremes and income volatility to perception

In Figure 3, we show the distribution of farmers' perception and experience of climate extremes, as well as income volatility between 2012 and 2014[5]. Here we define farmers' perception of climate extremes by "*whether the respondent perceived an increasing tendency of occurrences of local climate extremes in 2014, or not*". Also, the income volatility is denoted by an indicator "*whether the household experienced income losses between 2012 and 2014, or not*". Only 26 per cent of the 611 smallholders reported their experience of climate extremes, whereas 51 per cent perceived an increasing trend. Around 50 per cent of households were worse-off and earned lower incomes in 2014 under the rubber price declines, likewise the distribution of farmers' perception of climate extremes.

<Figure 3>

The interrelationships between experience, income volatility, and perception of climate extremes are further shown in Table 2. Farmers who suffer real climate extremes are likely to perceive an increasing tendency of the occurrences of these events. At the same time, farmers who experience declines in household incomes between 2012 and 2014 tend to be sensitive to the changes in climate

[3] The meteorological record data of climate extremes at the household level is not available. Some extreme weathers are idiosyncratic shocks at household level rather than covariate shocks, which are hardly recorded by the officials. Hence, we introduce the household self-reported experience of climate extremes.

[4] Other extreme weather events or disaster such as drought in XSBN are rare. These climate extremes were not observed in our household survey.

[5] Here, we use the historical income data (from the survey in March 2013) as a reference.

extremes. Hence, in principle, both farmers' experience of climate extremes and income volatility may be correlated to their perception.

<Table 2>

4.3 Acceptance of environmentally friendly rubber plantation

To understand smallholders' attitude toward specific items of EFRP, we assess farmers' willingness to accept EFRP practices. In the design of the survey, we referred to the EFRP guideline announced by XSBN Biological Industry Office in 2013. Farmers were asked to rate their score of willingness to accept toward EFRP on a continuous range from "1" to "10", wherein "1" represents "*Not at all willing to accept*" and "10" represents "*Fully willing to accept*" toward specific scientific knowledge items. In Figure 4, seven EFRP practices are grouped as "rubber intercropping system" or "scientifically-based standards of rubber modification"[6]. The average acceptance score for all seven practices is 6.902 (see the red line in Figure 3). All the median values are above the average value. The result suggests a high degree of awareness of EFRP. In terms of the "rubber intercropping system", specifically, the notion of replacing rubber plantations in high elevations (above 900m) seemingly reaches an agreement among farmers. Farmers show narrow knowledge on the practice that rubber trees should not be planted in unsuitable regions, such as land plots on steep-slope, riverbed, roadside, and dyke or edge of fields. Moreover, farmers' acceptance toward the adoption of intercropping with forest trees is somehow higher than those with tree crops.

<Figure 4>

Next, we estimate the Spearman's correlations to test the relation of income volatility, experience and perception of climate extremes to the EFRP acceptance (see Table 3). Smallholders' perception is significantly and negatively associated with their acceptance of EFRP, especially for the practices in terms of rubber intercropping. It implies that the perceived increases in climate extremes may drive farmers to take adaptive actions, such as land-use diversification, to buffer the losses of climate risks.

[6] The establishment of rubber intercropping systems and promotion of the scientifically-based standards of rubber modification are two core issues of EFRP. Consulting with the local officials from XSBN Biological Industry Office who are in charge of the EFRP, we give special attention to these two issues and re-group the practices that suggested by EFRP.

However, the experience implies an inverse relationship[7]. Farmers who suffered any climate extremes are more likely to accept the practices referring to both rubber modification and intercropping. Already having seen the damages caused by climate shocks, these farmers are willing to modify their cropping systems and adopt more diverse land use to achieve better resilience against climate hazards.

<Table 3>

5 Empirical specification

In this section, we specify two approaches to testify the hypotheses (i.e., indirect and direct channels of the adaption decision-making process). First, an endogenous switching regression model to test the roles of experience of climate extremes and income volatility on affecting the perception, and further assess the impact of the perception on farmers' acceptance of EFRP. Second, an OLS and a seemingly unrelated regression model are used to estimate the direct impacts of experience of climate extremes and income volatility on the acceptance.

5.1 The endogenous switching regression model

To test the first hypothesis, we quantify the causality of farmers' perception of climate extremes on their acceptance of EFRP. Two technical problems should be addressed in the estimation: (i) the perception is endogenous in explaining their adaptive behaviours, and (ii) the sample selection bias due to unobserved heterogeneity. An endogenous switching regression approach (ESR) is employed for the model identification, in line with previous empirical studies (Di Falco et al., 2011; Huang et al., 2015; Khanal et al., 2018). Afterwards, a counterfactual analysis is carried out to simulate the average treatment effects. In the ESR model, the variables of experience of climate extremes and income volatility are used to test their correlations with the acceptance of EFRP[8].

[7] Note that the likely inconsistency in the results of Tables 2 and 3. In Table 2, it suggests a positive interrelation between farmers' experience and perception of climate extremes. But in Table 3, the connections of two variables related to farmers' acceptance toward EFRP are inverse. Such an inconsistency is reasonable because the perception would not be entirely determined or caused by the experience (i.e., complete causality), or vice versa. At same time, some unobservable factors can lead to outcomes of correlations. These relationships will be further tested and discussed using proper empirical strategies below.

[8] In existing studies (e.g., Min et al., 2018), the experience of climate extremes is employed as an instrumental variable for the perception of climate change. Adding this variable in the model can avoid the biased estimations in the absence of the potential direct effect of the actual experience.

We consider the perception of increasing occurrences of climate extremes triggers smallholders' adaptive behaviours. The samples are partitioned into two regimes: the farmers who perceived an increase in any climate extremes, and others who did not. We can then represent farmer *i*'s perception by a latent variable I_i^* as:

$$I_i^* = g(EXP, CHG, min\{CHG, 0\}, X, Z, \vartheta) + u_i \qquad I_i = 1[I_i^* > 0] \tag{4.1}$$

where *EXP* and *CHG* represent the experience of climate extremes and income volatility, respectively. *EXP* is defined as a dummy variable that equals one if the farmer experienced any climate extremes, and zero otherwise. *CHG* is defined as a continued variable that indicates the changes in net income between 2012 and 2014. As losses are treated differently than gains in the prospect theory (Kahneman and Tversky, 1979), the particular interest is in the different effects of income gains and losses in shaping farmers' acceptance of EFRP. For comparison, we use $min\{CHG, 0\}$ to measure the income changes relative to zero. Since the changes in income can be positive or negative, the minimum portions of the specification allow those who suffered losses to have different outcomes than those whose incomes increased over time. That is, $min\{CHG, 0\}$ will equal the income changes (i.e., *CHG*) if the farmer encounters an income loss, but it will be zero if the household income increased in 2014.

X is a set of control variables that include the following: (i) characteristics of rubber farming (intensity of rubber plantation in total household farmlands as well as those in harvesting phase, intensity of intercropping, average duration of rubber tapping, decision of rubber tapping based on weather conditions, availability of technical services on rubber farming); (ii) characteristics of respondents (gender, age, educational attainment, off-farm experience, membership of social group); (iii) characteristics of households (household size, ethnicity, elevation, farm size, wealth, livestock, remittance, credit, and land rental); and (iv) county dummies to control for the effects of region-specific factors. The specific definitions and summary of all regressors are shown in Table A1 in the Appendix. Besides, ϑ denotes the vector of parameters to be estimated, and *u* is the error term with mean zero and variance σ_u^2 captures measurement errors and unobservable factors.

The variable *Z* is an instrumental variable for *I* as an explanatory variable in the outcome equations discussed below. The instrument we employed is the variable "*average proportion of other farmers in* *the village who perceived an increasing tendency of the occurrences of any climate extremes*". Typically defined as the mean value of the corresponding variable for peers, the cluster-effect instrument has been used to control for endogeneity (e.g., Benjamin, 1992; Ji et al., 2012). Regarding the interactions of peers on individual perception of climate change (e.g., Stevenson et al., 2016; Valdez et al., 2018), we consider farmers' perception of the local climate extremes is likely to be influenced by their friends, neighbours and other residences living in the same village. The validity test of the instruments is based on the falsification test from Di Falco et al. (2011). Following a valid exclusion restriction frame, the method should significantly affect the selection of a particular perception (i.e., either increase or non-increase) in the selection equation but should not affect the outcome equation of those who believed the occurrences of climate extremes did not increase.

A set of separate outcome equations is specified for the respondent who perceived an increase or a non-increase in any climate extremes, respectively:

Regime 1 (Perceived increase): $y_{1i} = f_1(I, EXP, CHG, min\{CHG, 0\}, X, \eta_1) + \varepsilon_{1i}$ if $I_i = 1$ (4.2a)

Regime 2 (Perceived non-increase): $y_{2i} = f_2(I, EXP, CHG, min\{CHG, 0\}, X, \eta_2) + \varepsilon_{2i}$ if $I_i = 0$ (4.2b)

where y_{1i} and y_{2i} are the outcome variables defined by the acceptance scores of EFRP (i.e., the average score in general, the average score of "rubber intercropping system", and the average score of "scientifically-based standards of rubber modification") in two regimes. The vectors η_1 and η_2 are the parameters to be estimated.

Error terms u, ε_1, and ε_2 in equations (4.1), (4.2a), and (4.2b) are assumed to have a tri-variate normal distribution, with zero mean and the following covariance matrix:

$$\Omega = \begin{bmatrix} \sigma_u^2 & \sigma_{u1} & \sigma_{u2} \\ \sigma_{1u} & \sigma_1^2 & \sigma_{12} \\ \sigma_{2u} & \sigma_{21} & \sigma_2^2 \end{bmatrix} \tag{4.3}$$

where Var(ε_1) = σ_1^2, Var(ε_2) = σ_2^2, Var(u) = σ_u^2, Cov(ε_1, ε_2) = σ_{12}, Cov(ε_1, u) = σ_{1u}, and Cov(ε_2, u) = σ_{2u}. The covariance between ε_1, and ε_2 (i.e., σ_{12} or σ_{21}) is not defined since y_{1i} and y_{2i} are unable to be observed simultaneously. Considering the possibility that the error term of selection equation u might be correlated with the error terms of the outcome equations ε_1, and ε_2, the expected values of ε_1, and ε_2 conditional on the sample selection are nonzero:

$$E[\varepsilon_{1i}|I_i = 1] = E\big(\varepsilon_{1i}|u > -g(EXP,\ CHG, min\{CHG,0\}, X, \boldsymbol{IV}, \vartheta)\big) = \sigma_{1u}\frac{\varphi[g/\sigma]}{\phi[g/\sigma]} \equiv \sigma_{1u}\lambda_{1i} \quad (4.4a)$$

$$E[\varepsilon_{2i}|I_i = 0] = E\big(\varepsilon_{2i}|u \leq -g(EXP, CHG, min\{CHG,0\}, X, \boldsymbol{IV}, \vartheta)\big) = -\sigma_{2u}\frac{\varphi[g/\sigma]}{1-\phi[g/\sigma]} \equiv \sigma_{2u}\lambda_{2i} \quad (4.4b)$$

where $\varphi(\cdot)$ is the standard normal probability density function, and $\phi(\cdot)$ is the standard cumulative distribution function. The terms λ_1 and λ_2 refer to the inverse Mills ratio evaluated at $g(\cdot)$, and are incorporated into equations (4.4a) and (4.4b) to correct the selection bias problem. The ESR model, with the Probit model applied in the first stage, is estimated by the full information maximum likelihood (FIML) method (Lokshin and Sajaia, 2004).

Counterfactual analysis is constructed based on the ESR model. Specifically, we examined the impacts in four scenarios: expected acceptance of (i) the farmers that perceived an increase in climate extremes, for (ii) those perceived a non-increase in climate extremes; in counterfactual, (iii) the farmers that perceived an increase in climate extremes if they would not have done so, and (iv) those perceived a non-increase in climate extremes if they would have perceived an opposite tendency of the occurrences of climate extremes. Respectively, the expected value of outcomes can be given as:

$$E[y_{1i}|I_i = 1] = f_1(I, EXP,\ CHG, min\{CHG,0\}, X, \eta_1) + \sigma_{1u}\lambda_{1i} \quad (4.5a)$$

$$E[y_{2i}|I_i = 0] = f_2(I, EXP,\ CHG, min\{CHG,0\}, X, \eta_2) + \sigma_{2u}\lambda_{2i} \quad (4.5b)$$

$$E[y_{2i}|I_i = 1] = f_2(I, EXP,\ CHG, min\{CHG,0\}, X, \eta_2) + \sigma_{2u}\lambda_{1i} \quad (4.5c)$$

$$E[y_{1i}|I_i = 0] = f_1(I, EXP,\ CHG, min\{CHG,0\}, X, \eta_1) + \sigma_{1u}\lambda_{2i} \quad (4.5d)$$

Average effects of treatment on the treated (ATT) can be computed as the difference between (4.5a) and (4.5c):

$$ATT = E[y_{1i}|I_i = 1] - E[y_{2i}|I_i = 1] = f_1 - f_2 + (\sigma_{1u} - \sigma_{2u})\lambda_{1i} \quad (4.6)$$

Average effects of treatment on the untreated (ATU) can be calculated as the difference between (4.5d) and (4.5b):

$$ATU = E[y_{1i}|I_i = 0] - E[y_{2i}|I_i = 0] = f_1 - f_2 + (\sigma_{1u} - \sigma_{2u})\lambda_{2i} \quad (4.7)$$

5.2 The OLS and seemingly unrelated regression models

To test the second hypothesis, we identify the role of ex-ante experience of climate extremes and income volatility in determining farmers' EFRP acceptance. We separately establish an OLS model to test the effects of experience on the general acceptance of EFRP, and a SUR model to capture the effects on the acceptance in specific contents accounting for the potential unobservable correlations across the error terms of system equations. Therefore, the OLS model can be specified as:

$$y_i = \alpha_0 + \alpha_1 EXP_i^k + \alpha_2 CHG_i + \alpha_3 min\{CHG, 0\} + \alpha_4 X_i + \epsilon_i \tag{4.8}$$

where EXP_i^k (k=1,2,3) denotes (i) whether farmer i experienced any climate extremes, (ii) number of climate extremes, and (iii) number of climate extremes with low, middle, and high impacts on incomes, respectively. Likewise, the dependent variable y_i indicates farmer i's acceptance scores, while controlling for other independent variables X_i that used in the ESR models. Additionally, α denotes the vectors of parameters to be estimated, and ϵ is the error term. Furthermore, the SUR model can be given as:

$$\begin{cases} y_i^{MOD} = \beta_0 + \beta_1 EXP_i^k + \beta_2 CHG_i + \beta_3 min\{CHG, 0\} + \beta_4 X_i + \omega_i \\ y_i^{INT} = \gamma_0 + \gamma_1 EXP_i^k + \gamma_2 CHG_i + \gamma_3 min\{CHG, 0\} + \gamma_4 X_i + \upsilon_i \end{cases} \tag{4.9}$$

where y_i^{MOD} and y_i^{INT} denote farmer i's average acceptance score of "scientifically-based standards of rubber modification" and "rubber intercropping system", respectively. β and γ denote the vectors of parameters to be estimated, and ω and υ are the error terms of each equation.

6 Model results

This section reports the results of the econometric model estimations. It begins with the introduction to the results of the ESR model that test the indirect channel of the adaptive decision-making process in the first hypothesis. We first introduce the determinants of perception of climate extremes base on the results of the selection equation of the ESR model. Next, we show the determinants of acceptance of EFRP using the results of the outcome equation of the ESR model. We then conduct a counterfactual analysis to give an interpretation of perception impacts on acceptance. Finally, to test the second hypothesis that proposes the direct channel of adaptive decision-making, we show the results of the OLS and seemingly unrelated model.

6.1 Determinants of perception of climate extremes

Table 4 reports the estimates of the ESR model, including the results of the selection equation and outcome equations based upon the FIML method. The particular focus is on the estimated coefficients of experience of climate extremes and income volatility.

The results of the validity test of the selected instrument (see Table A2 in the Appendix) suggest that the perception of climate extremes from the peers positively affects the farmers' perception, while unrelated to their EFRP acceptances for those who perceived a non-increase tendency. The results of the falsification test, together with a series of Wald tests on the selection instrument, indicate the validity of estimation.

In the results of the selection equation, the roles of experience of climate extremes and income volatility have been tested (see Table 4). By controlling for covariates, the experience of climate extremes is less likely to affect the perception. And correlations between the experience and acceptance of EFRP are (only) significant in the general case. Different from the effects of experience, interestingly, income volatility significantly influences farmers' perception. The indirect mechanism in the theoretical framework thus is testified: the income volatility can shape their perception of climate extremes. The effects of the gains and losses in household incomes are different. Given gains in income (i.e., $min\{CHG, 0\} = 0$), farmers are less likely to perceive the increases in climate extremes (see, for example, the coefficient -0.0385 in Column 1). But the losses (i.e., $min\{CHG, 0\} = CHG$) can evoke farmers' perception of climate change (see, for example, the coefficient 0.0042 in Column 1[9]).

For other variables, of particular interest is on the characteristics related to the farmers' adaptive capability and cognitive bias in the perception of climate extremes. As shown in Table 4, for example, farmers with high-school attainment level and above, or engaged in off-farm employments less likely

[9] It is computed by -0.0385 + 0.0427.

believe the climate extremes increasingly occurred. Other factors, such as characteristics of farm management wealth and network, present insignificant effects on farmers' climate change perception.

<Table 4>

6.2 Determinants of EFRP acceptance

We now show the results of outcome equations (see also Columns 2 and 3 in Table 4). In the general case, the differences in the coefficients between the farmers that held an increase perception and those who held a non-increase perception indicate the presence of household heterogeneity. Scholars have addressed the role of personal experience of climate change, in particular, extreme weather events in shaping people's perception (e.g., Akerlof et al., 2013; Broomell et al., 2015; Weber, 2016). In line with these findings, the experience of some climate shocks significantly affect farmers' acceptance of EFRP for both groups who perceived either an increase or non-increase of the occurrences of local climate extremes. In addition, the income volatility is less likely to influence farmers' attitude toward EFRP.

Characteristics of farm management and activities are usually included in studies on farmer's perception and adaptation to climate change (e.g., Di Falco et al., 2011; Huang et al., 2015; Hou et al., 2015). In our case of rubber smallholders, interestingly, the characteristics of rubber farming are more likely to influence the acceptance of farmers who did not perceive an increase in climate extremes. Share of the cultivated farm size of rubber does not have a significant correlation with the acceptance of EFRP. Larger percentages of rubber lands in harvesting phases and intercropping are significantly positively correlated with their acceptance. In the same equation, farmers who regularly make the rubber tapping decisions based on weather conditions tend to accept EFRP. Social and institutional interventions from the Government, like expertise, training, and advisory services can tailor to farmers' needs in the adaptations to the climate change (Chen et al., 2014; Hyland et al., 2016).

Underlined by the existing literature (e.g., Huang et al., 2014, 2015), the influences of demographic factors of the respondents and farm households are heterogeneous to the specific context of survey sites. For rubber farmers in XSBN, the schooling attainments are significantly and positively correlated with farmers' acceptance only for those perceived a rising tendency of climate extremes. Farmers with access to off-farm employment are less likely to perceive the increasing trend of the occurrences of climate extremes given slight influences on their household incomes from climate change. Those partially engaged in off-farm works are more likely to accept the EFRP, yet, only for those perceived that the occurrences of climate shocks were not intensified. Better social networks can improve farmers' awareness of climate change and affect their adaptation intentions (Chen et al., 2014; Hou et al., 2015). Surprisingly, the attendance of social groups leads to fewer acceptances of EFRP. This probably because households engaged in better social networking appear to have better resilience to climate uncertainties, and therefore maintain the status quo and take evasive responses. Household assets, including wealth and land endowments, play essential roles in affecting farmers' perception of climate change in the empirical pieces of evidence (e.g., Wang et al., 2014; Huang et al., 2015). But we do not observe any strong effect in determining either rubber farmers' perception of climate change or their attitudes toward the EFRP.

When looking at the results of another two outcome equations (see Table 5), we find similar results in the determination of the acceptances of rubber modification and intercropping with slight differences. The full results of the ESR model estimation for the acceptance of rubber modification and intercropping is available on request.

The estimates presented in the last two columns of Tables 4 and 5 account for the endogenous switching in all equations. The estimated coefficients of the correlation terms ρ are not significantly different from zero in the equations of the acceptance of general content and rubber modification. It implies that the hypothesis of the absence of sample selection bias may not be rejected. But we observe a significant coefficient of ρ in the equation of rubber intercropping for farmers who perceived an increase in climate extremes. Also, the results of the Wald test of independent equations (see the bottom row in Table 5) are significantly different from zero (i.e., 2.94 and 2.75), suggesting that the unobservable factors may exist and bias the estimation referring to the rubber modification and intercropping models. The result is insignificant (i.e., 2.30) in the general case (see the bottom row in Table 4).

<Table 5>

6.3 Counterfactual analysis and interpretation of perception impacts

The estimates for the average treatment effects on the acceptance of the EFRP are presented in Table 6. The results show the impact of perception of climate extremes accounting for the sample selection bias arising from the unobservable factors that influence the estimation. The ATT and ATU effects reveal that farmers' perception significantly influences their acceptance of EFRP. Perceiving the increase in climate extremes reduces the willingness to accept the practices of EFRP. Specifically, the acceptance scores of farmers who recognized an increase in climate extremes would rise by 0.196, 0.103, and 0.421 units (i.e., by 1.51% to 6.35%) in the general case, rubber modification and rubber intercropping, respectively, if they had held a non-increase perception. Counterfactually, for farmers who did not perceive an increase in climate extremes, their acceptance scores would reduce by 0.238, 0.110, and 0.055 units (i.e., by 1.60% to 8.35%) in the corresponding three scenarios if they had believed the climate extremes had been intensified. That means farmers who claimed to perceive increasing occurrences of climate extremes are less likely to accept the practices suggested by EFRP.

<Table 6>

The results of the ESR model provide new evidence for the interpretation of the asymmetry – perceived but not accepted – using the tools of behavioural theories (e.g., Weber, 2010, 2016). Literature mainly shows a negative relation between the psychological distance of climate change and behavioural intentions when climate change and its consequences are perceived as a distant phenomenon in time and space (Weber, 2015). Cognitive bias derived from loss-aversion and reference-dependence preference inhibit farmers from accurately observing the future benefits of immediate costs and adapting to climate change. Targets (reference points) for rubber farmers to make adaptive decisions are the historical level of incomes. They compare their state quo of welfares to the pasts in the decision-making process. Declines in household income and the corresponding worse-off economic conditions may reduce the capability for adaptation. Farmers may choose evasive actions since they are not willing to take the costs of using land-use innovations and the potential risks of adaptation to climate extremes. Therefore, the empirical finding refers to an indirect mechanism: farmers' perception of climate extremes is shaped by individual information set proxied by the volatility in income performances may hinder their intentions to adapt to and cope with the climate change.

6.4 Direct impacts of experience of climate extremes and income volatility on EFRP acceptance

Next, we test the direct channel of adaptive decision-making process according to the second hypothesis [10]. This section reports the effects of farmers' experience of climate extremes and income volatility on the EFRP acceptance by using OLS and SUR regression models (see Tables 7 and 8). The results of the F-statistics or Wald test are significantly different from zero, indicating that the equations are statistically valid. Results of Breusch-Pagen test of independence indicate that the SUR model improves the efficiency of estimation accounting for the potential unobservable correlations across the error terms of system equations.

Controlling for other factors that may affect farmers' decisions, those who experienced climate extremes are more likely to accept EFRP in general, and the scenario of rubber modification. Likewise, coefficients of the number of climate extremes that farmers experienced are significantly correlated to the acceptance of EFRP in the general case as well as rubber modification. But the effect of experience and the numbers of climate extremes in the equations of rubber intercropping is not statistically significant. When we separately look at the coefficients of climate extremes with different degrees of income impact, one interesting finding is that farmers who suffered more climate extremes with no or slight effects are more likely to accept the EFRP, compared to that with high impacts. No significant effect is observed in the equation of rubber intercropping. The results imply a connection between farmers' experience of climate change and their attitudes toward the EFRP, in particular, the practices of rubber modification. Our results suggest that as a procedure of seeing-is-believing, rubber farmers who really "saw" agricultural losses may lead to acceptance and behavioural intentions in responding to future climate risks and uncertainty. It is in line with some empirical studies on farmers' adaptation

[10] We also account for the potential influences of the climate shocks on income volatility. As shown in Table A3 in the Appendix, the connection between the experience of climate extremes and the income volatility is weak.

to climate change in China (e.g., Huang et al., 2015). Additionally, the effects of income volatility on farmers' acceptance of EFRP are weak.

In the rural evidence of investigating the impact of adaptation to climate change, farmers can benefit from the adaptations which mitigate the negatives caused by the climate extremes and contribute to better food security (e.g., Di Falco et al., 2011; Huang et al., 2015; Khanal et al., 2018). The Prospect Theory predicts risk-seeking in the domain of losses, which would mean choosing the probabilistic loss over the sure loss (Tversky and Kahneman, 1991). It explains why the farmers who suffered losses from the climate shocks (i.e., as one reference-point at a status-quo of loss) are more willing to accept the changes. In this sense, a policy focusing on the mitigation of the negatives caused by climate shocks might be more favoured by farmers who suffered the losses in their agricultural productions. Motivated by these peers, other farmers might start to learn and then accept the policy. Moreover, another effective way to influence farmers' acceptance is to move their reference point away from its usual position at the status quo down to the level of the possible massive loss that could be incurred in case of different disasters or extreme weathers. This way, their irrational decision mode would be corrected.

<Tables 7 and 8>

7 Conclusion remarks

In this study, we examine the role of farmers' subjective perception of regional climate extremes as one of the main results of climate change in determining the acceptance of an environmentally-friendly rubber plantation (EFRP) programme to adapt to changing climate in Southwest China. The empirical basis is from a unique household survey of small-scale rubber farmers in Xishuangbanna Dai Autonomous Prefecture. We first hypothesize both climate risk appraisal and adaptation risk appraisal shape farmers' perception or belief of climate extremes, and then indirectly influence their intentions to adaptation. Respectively, two risk appraisals are indicated by farmers' ex-ante experience of climate extremes and income volatility. The second hypothesis describes the direct impact of farmers' experience of climate extremes and income volatility on EFRP acceptance. To test the hypotheses, we specify two empirical models: an endogenous switching approach to test the indirect channel of decision-making, and an OLS and a seemingly unrelated regression models to estimate the direct channel.

Results show that in the indirect mechanism, the income volatility can significantly affect farmers' perception of climate extremes, while the role of experience is weak. Controlling for the potential endogeneity and selection bias of perception, we find that a knowledge of the increasing occurrences of climate extreme will result in a reduction of farmers' acceptance of EFRP, i.e., an evasive reaction of "perceive dut not accepted" in adaptation to climate change. Such asymmetry attributes to farmers' limited adaptation capability and cognitive bias following their adaptation risk appraisal. Besides, the experience of climate extremes depicts a direct and strong impact on farmers' acceptance of EFRP. Our findings advance the literature to answer the question: why perception likely fail to evoke people's adaptation to climate change (e.g., Weber, 2006).

Still, the feasibility is a fundamental principle for farmers. Scholars are increasingly aware that simply providing more detailed and accurate information, though necessary, is not sufficient to generate appropriate public concern for climate risks (Leiserowitz, 2006). For smallholders with high vulnerability to the changing climate but constrained resilience and capability, to some extent, the "economic-feasible" goal should probably be emphasized at the priority over the "environmental-friendly" goal.

Tables

Table 1. Farmers' self-reported experience of climate extremes in XSBN.

Categories	Number of households reporting experience of climate extremes	The proportion of households reporting experience of climate extremes in the total sample
Heavy precipitation	50	8.2
Temperature extreme	63	10.3
Storm	81	13.3

Source: Authors' calculations.

Table 2. Relationship between experience, income volatility, and perception of climate extremes.

Categories	Perceived increase (*N*=312)	Perceived non-increase (*N*=299)	Mean diff.
Experience	0.298	0.217	0.081**
(1=w. experience; 0=w/o. experience)	(0.458)	(0.413)	(0.035)
Income volatility	-1.402	0.0606	1.462*
(1000 PPP$)	(12.04)	(10.48)	(0.915)

Notes: * indicates significance at the p<0.10 level, ** at the p<0.05 level, and *** p<0.01 level.
Source: Authors' calculations.

Table 3. Spearman's correlation between perception and experience of climate extremes, and acceptance of EFRP.

Categories	Perception (1=Increase; 0=Non-increase)	Experience (1=w. experience; 0=w/o. experience)	Income volatility (1000 PPP$)
Acceptance scores (1-10)			
General	-0.0746*	0.1164***	-0.0714*
Rubber modification	-0.0442	0.1127**	-0.0482
Rubber intercropping	-0.1104***	0.2828***	-0.0945**

Notes: * indicates significance at the p<0.10 level, ** at the p<0.05 level, and *** p<0.01 level.
Source: Authors' calculations.

Table 4. Estimation results of the endogenous switching regression model in the general case of EFRP.

	Acceptance scores (1-10)		
Variables	Selection eq. (1)	Perceived increase (2)	Perceived non-increase (3)
Perception (IV)	1.918***		
	(0.262)		
Experience	0.135	0.533**	0.481*
	(0.128)	(0.257)	(0.267)
Income volatility	-0.0385**	0.0307	-0.00530
	(0.0154)	(0.0445)	(0.0157)
Min {Income Volatility, 0}	0.0427**	-0.0225	-0.00995
	(0.0174)	(0.0471)	(0.0268)
Characteristics of Rubber Farming			
Rubber	0.00447	0.00385	-0.00463
	(0.00292)	(0.00605)	(0.00580)
Harvesting	0.00177	-0.00259	0.0107**
	(0.00247)	(0.00566)	(0.00544)
Intercropping	-0.00202	-0.00196	0.0141**
	(0.00264)	(0.00572)	(0.00638)
Tapping duration	-0.0194	0.0342	-0.00505
	(0.0248)	(0.0541)	(0.0590)
Tapping weather	-0.331*	0.0691	1.242***
	(0.195)	(0.528)	(0.359)
Services	0.0991	-0.0579	-0.169
	(0.138)	(0.263)	(0.301)
Characteristics of Respondent			
Female	0.0577	-0.0633	-0.416
	(0.124)	(0.252)	(0.275)
Age	0.00373	0.000959	-0.00327
	(0.00491)	(0.0100)	(0.0102)
High school	0.457*	0.647	0.404
	(0.264)	(0.415)	(0.579)
Off-farm	-0.337**	0.379	0.773**
	(0.162)	(0.307)	(0.346)
Spo	-0.0855	-0.495**	-0.486*
	(0.126)	(0.240)	(0.260)
Characteristics of Household			
Household size	-0.00723	0.0554	0.153*
	(0.0385)	(0.0801)	(0.0844)
Minority	0.352	-0.301	1.159**
	(0.258)	(0.549)	(0.542)
Elevation	0.000596	0.00122**	0.000758
	(0.000415)	(0.000595)	(0.000926)
Land	0.0501	0.0794	0.0131
	(0.0645)	(0.116)	(0.137)
Wealth	-0.00743	0.0237	0.0191
	(0.00740)	(0.0164)	(0.0139)
Livestock	-0.0708	0.919***	0.378
	(0.128)	(0.230)	(0.230)
Remittance	-0.215	0.636**	0.853***
	(0.134)	(0.271)	(0.318)
Insurance	-0.182	0.929**	-0.793
	(0.328)	(0.422)	(0.603)
Credit	-0.0751	0.0287	0.155

	(0.114)	(0.228)	(0.243)
Land rental	0.166	-0.0131	-0.233
	(0.127)	(0.260)	(0.257)
County			
Menghai	-0.0226	0.637*	-0.353
	(0.195)	(0.375)	(0.475)
Jinghong	-0.0274	0.380	-0.131
	(0.146)	(0.286)	(0.288)
Constant	-1.923***	4.050***	3.197**
	(0.634)	(1.228)	(1.308)
σi		1.866***	1.907***
		(0.036)	(0.073)
ρi		0.049	-0.351
		(0.218)	(0.214)
N		611	
Wald Chi-sq. (Joint significance)		67.15***	
Log pseudolikelihood		-1609.0835	
Wald Chi-sq. (Wald test of indep. Eqns.)		2.30	

Notes: * indicates significance at the p<0.10 level, ** at the p<0.05 level, and *** p<0.01 level. Robust standard errors are in parentheses.

Table 5. Estimation results of the endogenous switching regression model in cases of rubber modification and intercropping.

	Acceptance scores (1-10)					
	Rubber modification			Rubber intercropping		
Variables	Selection eq. (1)	Perceived increase (2)	Perceived non-increase (3)	Selection eq. (4)	Perceived increase (5)	Perceived non-increase (6)
Perception (IV)	1.938***			1.914***		
	(0.269)			(0.263)		
Experience	0.129	0.499	0.626*	0.138	0.592	0.149
	(0.128)	(0.305)	(0.325)	(0.128)	(0.383)	(0.373)
Income volatility	-0.0385***	0.0535	-0.00444	-0.0292***	-0.0181	-0.00990
	(0.0145)	(0.0526)	(0.0179)	(0.00990)	(0.0549)	(0.0159)
min {Income volatility, 0}	0.0427***	-0.0449	-0.0145	0.0331***	0.0250	0.00465
	(0.0165)	(0.0555)	(0.0331)	(0.0120)	(0.0590)	(0.0392)
Controls		Yes			Yes	
Constant	-1.900***	5.190**	3.313**	-1.840***	1.579	2.990
	(0.630)	(2.034)	(1.506)	(0.616)	(1.766)	(2.004)
σi		2.175***	2.291***		2.752***	2.445***
		(0.127)	(0.112)		(0.153)	(0.047)
ρi		-0.211	-0.420*		0.434	0.105
		(0.517)	(0.220)		(0.237)	(0.219)
N		611			611	
Wald Chi-sq. (Joint significance)		66.07***			55.36***	
Log pseudolikelihood		-1702.7523			-1800.521	
Wald Chi-sq. (Wald test of indep. Eqns.)		2.94*			2.75*	

Notes: Other variables are controlled but not reported. * indicates significance at the p<0.10 level, ** at the p<0.05 level, and *** p<0.01 level. Robust standard errors are in parentheses.

Table 6. Treatment effects of acceptance scores of EFRP.

Sub-samples	To hold increase perception	To hold non-increase perception	Treatment effects	% of diff.
General				
Farm households perceived increase	6.764	6.961	ATT=-0.196***	-2.91
	(0.682)	(0.858)	(0.046)	
Farm households perceived non-increase	6.808	7.046	ATU=-0.238***	-3.50
	(0.681)	(0.929)	(0.054)	
Rubber modification				
Farm households perceived increase	6.817	6.920	ATT= -0.103**	-1.51
	(0.808)	(0.903)	(0.055)	
Farm households perceived non-increase	6.869	6.979	ATU= -0.110*	-1.60
	(0.844)	(0.987)	(0.067)	
Rubber intercropping				
Farm households perceived increase	6.633	7.054	ATT=-0.421***	-6.35
	(0.965)	(0.936)	(0.057)	
Farm households perceived non-increase	6.656	7.212	ATU=-0.055***	-8.35
	(0.859)	(0.965)	(0.055)	

Notes: * indicates significance at the $p<0.10$ level, ** at the $p<0.05$ level, and *** $p<0.01$ level. Standard errors are in parentheses.
Source: Authors' calculation.

Table 7. Experience of climate extremes and general acceptance scores of EFRP, OLS model.

	Acceptance scores of EFRP: General		
Variables	(1)	(2)	(3)
Experience	0.482***		
	(0.183)		
# of experience		0.355***	
		(0.136)	
# of experience w/o. impacts			0.434*
			(0.258)
# of experience w. low impacts			0.392**
			(0.196)
# of experience w. high impacts			0.289
			(0.196)
Income volatility	-0.0116	-0.0114	-0.0113
	(0.0138)	(0.0138)	(0.0138)
min {Income volatility, 0}	0.0158	0.0156	0.0157
	(0.0164)	(0.0164)	(0.0164)
Controls	Yes	Yes	Yes
Constant	3.980***	4.042***	4.033***
	(0.858)	(0.856)	(0.858)
N	611	611	611
R-sq.	0.1484	0.1480	0.1483

Notes: Other variables are controlled but not reported. * indicates significance at the p<0.10 level, ** at the p<0.05 level, and *** p<0.01 level. Robust standard errors are in parentheses.

Table 8. Experience of climate extremes and acceptance of EFRP in rubber modification and intercropping, SUR model.

	Acceptance Scores of EFRP					
Variables	Rubber modification (1)	Rubber intercropping (2)	Rubber modification (3)	Rubber intercropping (4)	Rubber modification (5)	Rubber intercropping (6)
Experience	0.557***	0.293				
	(0.215)	(0.251)				
# of experience			0.428***	0.174		
			(0.162)	(0.189)		
# of experience w/o. impacts					0.627*	-0.0496
					(0.357)	(0.417)
# of experience w. low impacts					0.449*	0.250
					(0.230)	(0.269)
# of experience w. high impacts					0.332	0.182
					(0.230)	(0.269)
Income volatility	-0.0138	-0.00620	-0.0134	-0.00631	-0.0133	-0.00644
	(0.0154)	(0.0179)	(0.0154)	(0.0179)	(0.0153)	(0.0179)
min {Income volatility, 0}	0.0177	0.0112	0.0173	0.0113	0.0173	0.0116
	(0.0199)	(0.0232)	(0.0199)	(0.0232)	(0.0199)	(0.0232)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.434***	2.845**	4.510***	2.871**	4.499***	2.868**
	(1.028)	(1.199)	(1.029)	(1.200)	(1.029)	(1.200)
N	611	611	611	611	611	611
R-sq.	0.128	0.112	0.128	0.111	0.129	0.112
Breusch-Pagan test of independence (Chi-sq.)	34.917***		35.190***		35.389***	

Notes: Other variables are controlled but not reported. All standard errors are bootstrapped with 500 replications. * indicates significance at the p<0.10 level, ** at the p<0.05 level, and *** p<0.01 level.

Figures

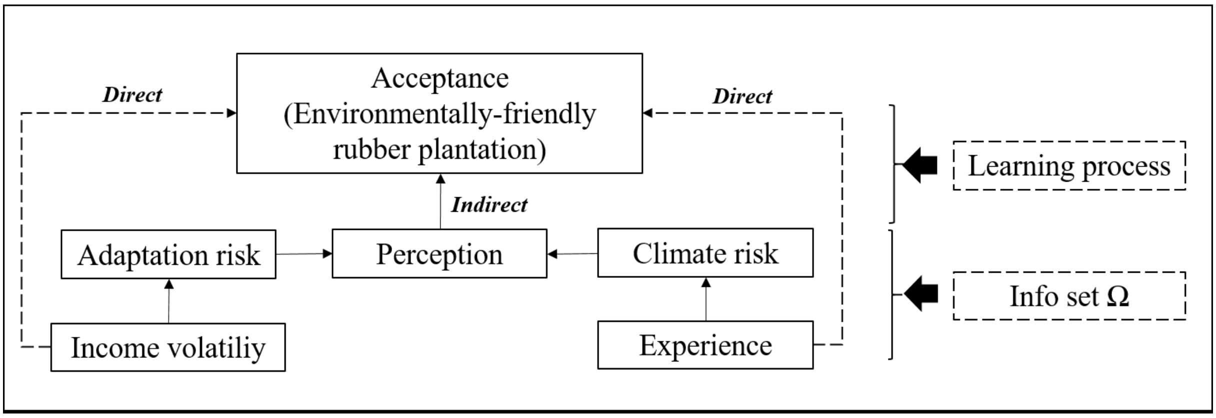

Figure 1. The theoretical framework for the adaptation decision-making process.

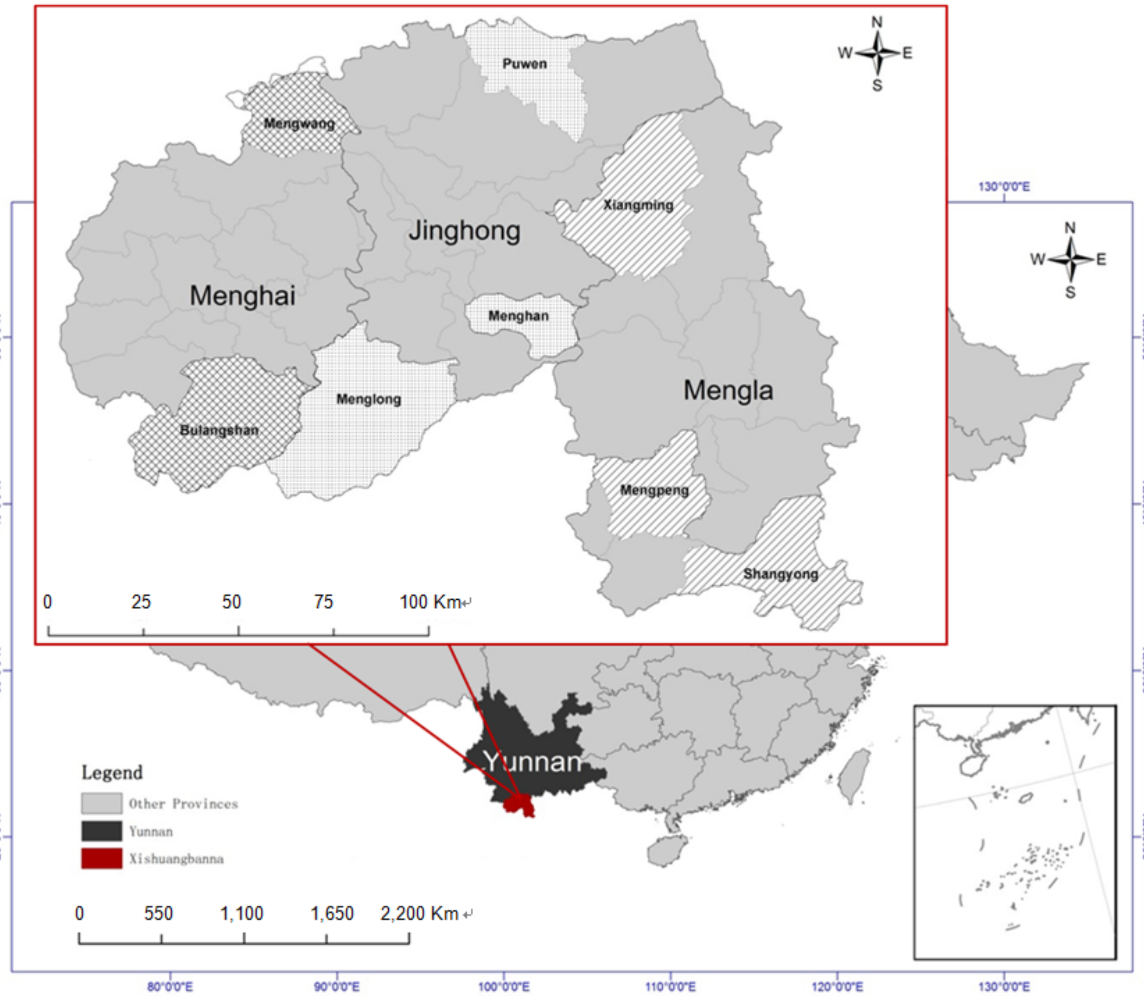

Figure 2. Location of XSBN in Southwest China.

Source: Adapted from Min et al. (2017)

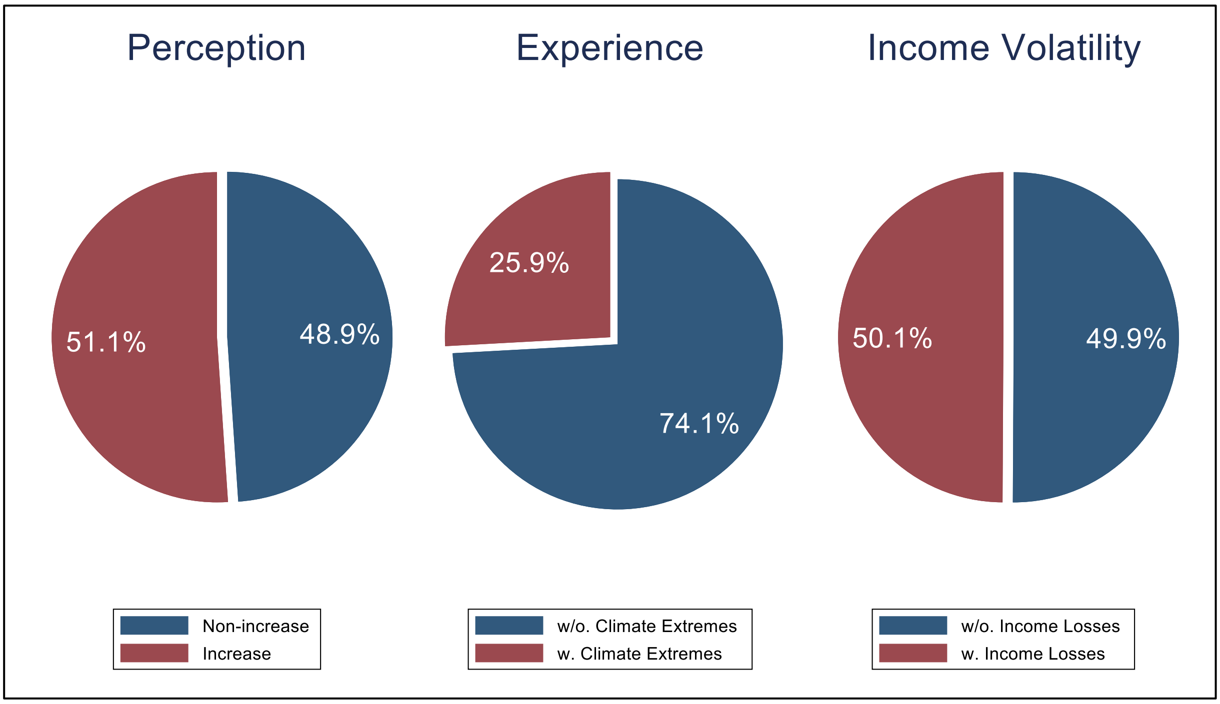

Figure 3. Farmers' perception, experience of climate extremes and income volatility.

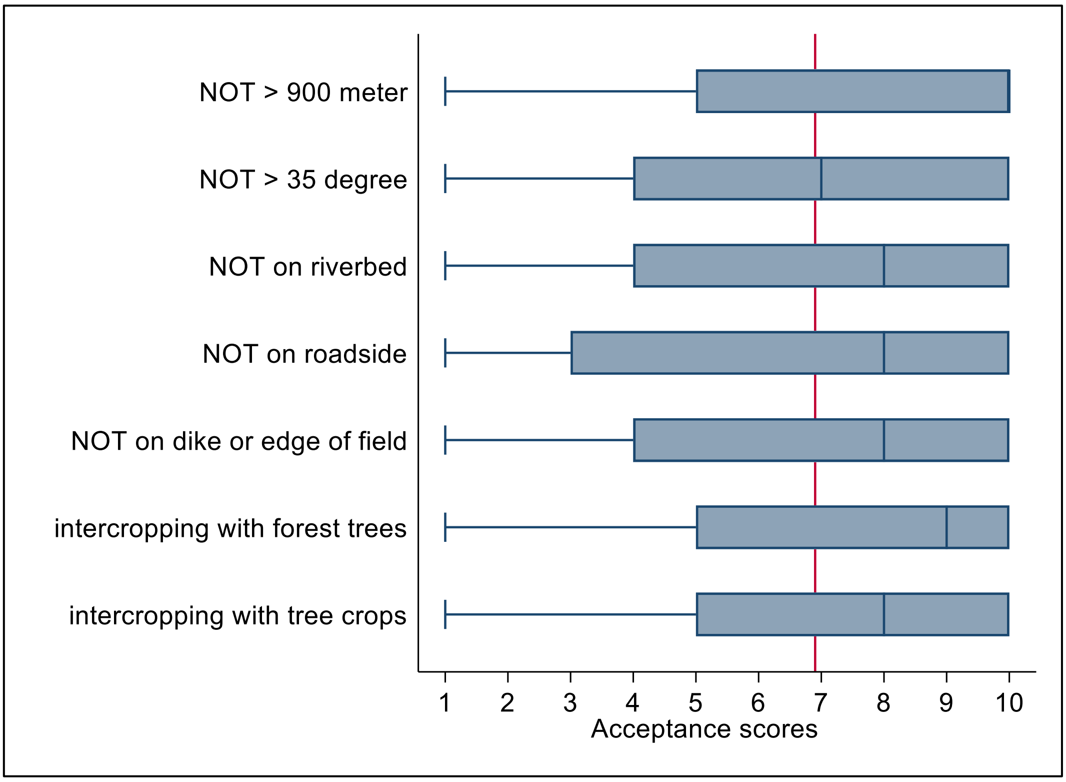

Figure 4. Farmers’ average acceptance scores of EFRP.

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Appendix

Table A1. Definition of explanatory variables

Variables	Definition	Mean	S.D.	Min	Max
Perception	dummy = 1 if the household perceived the increases in climate extremes, 0 otherwise	0.5	0.5	0.0	1.0
Experience	dummy = 1 if the household experienced any climate extremes, 0 otherwise	0.3	0.4	0.0	1.0
Income volatility	changes of household net income from 2012 to 2014 (1000 USD/person)	-0.7	11.3	-166.3	109.6
Characteristics of Rubber Farming					
Rubber	land proportion of rubber (%)	74.4	23.1	4.3	100.0
Harvesting	land proportion of rubber in harvesting (%)	39.4	33.7	0.0	100.0
Intercropping	land proportion of intercropping (%)	7.6	20.7	0.0	100.0
Tapping Duration	duration of rubber tapping (months)	4.9	3.3	0.0	9.0
Tapping Weather	dummy = 1 if the household tapping decision is based on weather, 0 otherwise	0.1	0.3	0.0	1.0
Services	dummy = 1 if the household received any technical services related to rubber plantation, 0 otherwise	0.2	0.4	0.0	1.0
Characteristics of Respondent					
Female	dummy = 1 if the respondent is female, 0 otherwise	0.3	0.5	0.0	1.0
Age	age of respondent (years)	41.1	11.6	16.0	81.0
High School	dummy = 1 if the respondent has high-school educational attainment, 0 otherwise	0.1	0.2	0.0	1.0
Off-farm	dummy = 1 if the respondent is engaged in off-farm employment, 0 otherwise	0.1	0.3	0.0	1.0
SPO	dummy = 1 if the respondent is the member of any social group, 0 otherwise	0.3	0.4	0.0	1.0
Characteristics of Household					
Household Size	household size (persons)	5.3	1.5	2.0	10.0
Minority	dummy = 1 if the household is ethic minority, 0 otherwise	1.0	0.2	0.0	1.0
Elevation	household elevation (meters above sea level)	756.8	165.0	203.0	1463.0
Land	land area per capita (ha/person)	0.9	1.0	0.0	12.2
Wealth	household assets per capita (PPP$/person)	8.9	8.1	0.0	44.0
Livestock	dummy = 1 if the household has any livestock, 0 otherwise	0.3	0.4	0.0	1.0
Remittance	dummy = 1 if the household received any remittance, 0 otherwise	0.7	0.5	0.0	1.0
Insurance	dummy = 1 if the household has any agri-insurance, 0 otherwise	0.0	0.2	0.0	1.0
Credit	dummy = 1 if the household has access to formal and informal credit, 0 otherwise	0.4	0.5	0.0	1.0
Land Rental	dummy = 1 if the household rented out any land, 0 otherwise	0.5	0.5	0.0	1.0
County					
Menghai	county dummy = 1 if the household is in Jinghong, 0 otherwise	0.1	0.3	0.0	1.0
Jinghong	county dummy = 1 if the household is in Menghai, 0 otherwise	0.5	0.5	0.0	1.0
Mengla	county dummy = 1 if the household is in Mengla 0 otherwise	0.4	0.5	0.0	1.0

Notes: * indicates significance at the p<0.10 level, ** at the p<0.05 level, and *** p<0.01 level.
Source: Authors' calculation.

Table A2. Falsification Test for Validity of Selection Instrument.

Variables	Perception of Climate Extremes	Acceptance Scores of EFRP (only for the perceived non-increase)		
		General	Rubber Modification	Rubber Intercropping
	(1)	(2)	(3)	(4)
Perception (IV)	1.912***	0.498	1.041	-0.858
	(0.262)	(0.633)	(0.744)	(0.874)
Experience	0.131	0.539**	0.692**	0.157
	(0.127)	(0.270)	(0.327)	(0.386)
Income Volatility	-0.0311***	-0.0132	-0.0158	-0.00689
	(0.0107)	(0.0161)	(0.0182)	(0.0156)
min {Income Volatility, 0}	0.0347***	-0.00162	-0.00234	0.000176
	(0.0128)	(0.0284)	(0.0346)	(0.0399)
Controls	Yes	Yes	Yes	Yes
Constant	-1.891***	3.156**	3.107**	3.278
	(0.626)	(1.325)	(1.503)	(2.127)
Wald test on selection instrument	53.38***	0.62	1.96	0.97
N	611	299	299	299
R-sq.	-	0.238	0.202	0.172
Wald Chi-sq. / F-stat.	107.90***	4.52***	3.47***	3.04***

Notes: Robust standard errors are in parenthesis. Other variables are controlled but not reported. * indicates significance at the $p<0.10$ level, ** at the $p<0.05$ level, and *** $p<0.01$ level.

Table A3. OLS estimates for the relationship between climate extremes experience and income volatility.

Variables	Income Volatility		
	Pooled (1)	Perceived Increase (2)	Perceived Non-increase (3)
Experience	-0.868	-0.553	-1.042
	(0.806)	(0.999)	(1.054)
Controls	Yes	Yes	Yes
Constant	-3.174	6.350	-20.19
	(7.594)	(4.468)	(16.12)
N	611	312	299
R-sq.	0.122	0.233	0.109
F-stat.	2.15***	4.52***	3.47***

Notes: Robust standard errors are in parenthesis. Other variables are controlled but not reported. * indicates significance at the p<0.10 level, ** at the p<0.05 level, and *** p<0.01 level.

Proofs of the conceptual model

Consider a stochastic net return per unit of rubber production at the initial period which can be specified as:

$$\tilde{\pi}_t^o = \pi^o + \varepsilon_t^o \tag{A.1}$$

with mean $E(\tilde{\pi}_t^o) = \pi^o$and variance $Var(\tilde{\pi}_t^o) = e^{\delta t}\sigma_o^2$. The mean π^o is assumed to remain constant over time. The error term ε_t^o reflects climate uncertainties that occurred in period t. We assume its variance increases with time; hence, we consider this possibility by setting $\varepsilon_t^o = e^{\delta t/2}\varepsilon_o$, where ε_o is a random variable with a zero mean and constant variance σ_o^2, and δ is a variance inflator parameter. Furthermore, the stochastic net return per unit of rubber production under sustainable land management can be represented as:

$$\tilde{\pi}_t^n = \pi^n(\Omega_t) + e^{\delta t/2}\varepsilon_t^n \tag{A.2}$$

with mean $E(\tilde{\pi}_t^n) = \pi^n(\Omega_t)$ and variance $Var(\tilde{\pi}_t^n) = e^{\delta t}\sigma_n^2(\Omega_t)$. The knowledge set Ω_t contains farmers' expectations with respect to uncertain returns of rubber under climate risks before time *t*. The expression ε_t^n is the zero-mean error term with variance $\sigma_n^2(\Omega_t)$. The correlation between ε_t^o and ε_t^n, Ω_t, is indicated by $\rho(\Omega_t)$, and the related covariance by:

$$\sigma_{on}(\Omega_t) = \rho(\Omega_t)\sigma_o\sigma_n(\Omega_t). \tag{A.3}$$

The covariance between $\tilde{\pi}_t^o$ and $\tilde{\pi}_t^n$ is thus equal to:

$$Cov(\tilde{\pi}_t^o, \tilde{\pi}_t^n) = e^{\delta t}\sigma_{on}(\Omega_t). \tag{A.4}$$

The total return, $\tilde{\Pi}_t$, is a random variable with mean, Π_t, and variance, σ_t^2, given respectively as follows:

$$\tilde{\Pi}_t = l_t\tilde{\pi}_t^n + (L - l_t)\tilde{\pi}_t^o - \Delta l_t C \tag{A.5}$$

$$\Pi_t = E(\tilde{\Pi}_t) = l_t\pi^n(\Omega_t) + (L - l_t)\pi^o - \Delta l_t C \tag{A.6}$$

$$\sigma_t^2 = Var(\tilde{\Pi}_t) = e^{\delta t}[l_t^2\sigma_n^2(\Omega_t) + (L - l_t)^2\sigma_o^2 + 2l_t(L - l_t)\sigma_{on}(\Omega_t)] \tag{A.7}$$

where L is the total rubber lands that the farmer has; l_t is the stock area of rubber lands cultivated under the sustainable land management at time *t*; Δl is defined as the area of rubber lands transferred from the existing to the new land-use systems at time *t*; C is the cost per unit of adoption of sustainable land management. Unlike the setups of TSH, we assume a constant C over time[11]. It indicates the investment loss from switching in or out of such land management, which is a critical factor for the farmers when considering the present value of net returns. Regarding the physical and economic constraints, the adoption activities Δl_t may be bounded between certain levels of land area:

$$\underline{B_t} \leq \Delta l_t \leq \overline{B}_t \tag{A.8}$$

where $\underline{B_t}$ and $\overline{B}_t$ are, respectively, the lower and upper limitations of the speed of land use transformation, Δl_t[12].

To complete the formulation, a constant absolution risk aversion utility function and a stochastic structure of the profit stream are further specified. It is thus assumed as a constant absolute risk aversion utility function:

$$U(P) = 1 - e^{-\lambda P} \tag{A.9}$$

where λ is the absolute risk aversion coefficient. P is the random present value of net returns of rubber plantation. Here, we assume an exponential structure of a discount rate γ. The formulation of P can then be specified as:

$$P = \int_0^{\infty} e^{-\gamma t}[l_t \tilde{\pi}_t^n + (L - l_t)\tilde{\pi}_t^o - \Delta l_t C]dt \tag{A.10}$$

where P is assumed to be approximated by the normal distribution with a mean $E(P) = \int_0^{\infty} e^{-\gamma t}\,\Pi_t dt$ and a variance $Var(P) = \int_0^{\infty} e^{-2\gamma t}\,\sigma_t^2 dt$. The decision process can be further described as a maximization problem that the farmer is to select the optimal adoption path Δl_t at time *t* to maximize the expected utility $E[U(P)]$ subject to the condition (2.8). Following the Euler conditions for the optimality, we obtain the optimal area of adoption l_t^* which can be given as a reduced-form function $f(\cdot)$ concerning Ω_t:

[11] Tsur et al. (1990) assume that (i) the individual adoption cannot affect $C_t$regarding the competitive market in the demand side, and (ii) C_t depends on the accumulated output of the capital goods supply industry (i.e., $C_t = C(K_t)$, where K_t represents the total adoption volumes over all users). Here, to simplify, we assume a constant value of *C*.

[12] As the lands under sustainable land management, l_t, should satisfy $0 \leq l_t \leq L$, conditions on these bounds are, $\underline{B}(l_t = 0) = \overline{B}(l_t = L) = 0$; $\underline{B_t} \geq -l_t$; $\overline{B}_t \leq L - l_t$.

Max $J = \int_0^\infty e^{-\gamma t}\{l_t \pi^n(\Omega_t) + (L - l_t)\pi^o - \Delta l_t C - 0.5\lambda e^{-(\gamma-\delta)t}[l_t^2 \sigma_n^2(\Omega_t) + (L - l_t)^2 \sigma_o^2 + 2l_t(L - l_t)\sigma_{on}(\Omega_t)]\}dt$

s.t. $\underline{B_t} \le \Delta l_t \le \overline{B}_t$ (A.11)

To solve this problem, let $M_t = e^{-\gamma t}\{l_t \pi^n(\Omega_t) + (L - l_t)\pi^o - 0.5\lambda e^{-(\gamma-\delta)t}[l_t^2 \sigma_n^2(\Omega_t) + (L - l_t)^2 \sigma_o^2 + 2l_t(L - l_t)\sigma_{on}(\Omega_t)]\}$ and $N_t = -e^{-\gamma t}C$. Then, the maximization problem (2.12) can be described as:

Max $J = \int_0^\infty e^{-\gamma t}[M_t + N_t \Delta l_t]dt$

s.t. $\underline{B_t} \le \Delta s_t \le \overline{B}_t$ (A.12)

The singular path l_t^* (i.e., the optimal land area under sustainable land management) is defined as the one that satisfies the Euler condition in the dynamic optimization, $\frac{d}{dN_t} = \frac{\partial M_t}{\partial l_t} + \frac{\partial N_t}{\partial l_t}\Delta l_t$. More specifically, each item can be further written as:

$$\begin{cases} \frac{\partial M_t}{\partial l_t} = e^{-\gamma t}\{\pi^n(\Omega_t) - \pi^o - \lambda e^{-(\gamma-\delta)t}\left[l_t V - L\left(\sigma_o^2 - \sigma_{on}(\Omega_t)\right)\right]\} \\ \frac{\partial N_t}{\partial l_t} = -e^{-\gamma t}\frac{\partial C}{\partial l_t} = 0 \\ \frac{d}{dt}N_t = \gamma e^{-\gamma t}C \end{cases} \tag{A.13}$$

where $V = Var(\tilde{\pi}_t^n - \tilde{\pi}_t^o) = \sigma_n^2(\Omega_t) + \sigma_o^2 + 2\sigma_{on}(\Omega_t)$ indicating the volatility of changes in income or profitability over time. Substituting these items into the Euler condition function, therefore, yields the optimal area of adoption l_t^* which can be given as a reduced-form function $f(\cdot)$ with respect to Ω_t:

$$l_t^* = \frac{\pi^n(\Omega_t) - \pi^o - \gamma C}{\lambda e^{-(\gamma-\delta)t}V(\Omega_t)} + L \cdot \frac{V(\Omega_t) - [\sigma_n^2(\Omega_t) - \sigma_o^2]}{2V(\Omega_t)} = f(\Omega_t). \tag{A.14}$$