Short Research Report:
Farmers' Adaptation to Extreme Weather Events in the Chao Phraya River Basin
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ABSTRACT

The major problems of climate change in Thailand are droughts and floods. Given these discouraging prospects, the identification of adaptation strategies is vital to support the crop yields as these adaptation strategies can help the farm households buffering against climate change and extreme weather events and play a crucial role in enhancing resilience and livelihood of farm households. This study examines the factors that influence farm households' decisions to adapt to floods and droughts in the Chao Phraya River Basin of Thailand. Access to agricultural credit, the average rainfall during the rainy season, land tenure, number of members in the households and the socio-economic characteristics of household head are found to be the main drivers behind adaptation to severe flood. Results from our analysis indicate that access to credit, land ownership, vehicle ownership, household size and gender of household head influence farm households' adaptation to severe drought. We also analyze the benefit of adaptation on crop productivity.. Our results show that adaptation to floods that took place in Chao Phraya River Basin over the past 25 years increases wet-season rice productivity. In the case of dry-season rice, it is not clear whether adaptation to drought increases dry-season rice productivity.

Key words: adaptation, flood, drought, determinants, productivity, Chao Phraya River Basin of Thailand, endogenous switching

JEL classification: Q12, Q18, Q54

1. Introduction

Agriculture has an important driver of Thailand's economy in the past. During 1960s and the early 1980s, there was a rapid agricultural growth based on utilization of underused land and labor as new lands were opened up for farming, facilitated by the existence of a forest frontier where squatting was tolerated. Later on, agriculture began to transform, as Thailand experienced rapid economic growth led by manufacturing; labor began to leave this sector and it became harder to open up new land. Agricultural sector thus becomes more mechanized and more capital intensive (Leturque and Wiggins, 2010). Despite undergoing a transformation, at present, Thailand is still among the major exporters of several agricultural commodities, such as rice, and the agricultural sector still employ quite a large proportion of the Thai labor force.

The agricultural sector is challenged by many factors, of which the major ones are the climate-related disasters (Attavanich, 2012). The major problems of climate change in Thailand are droughts and floods due to fluctuated rainfalls. Basing on the data from Department of Disaster Prevention and Mitigation and Ministry of Agriculture and Cooperative during 1989-2010, Tadkaew and Kasem (2012) reported that a large amount of agricultural areas were damaged by flood and drought. Supnithadnaporn et al. (2011) argued that during 1989-2010, on average, 8.6 and 2.9 million rai of agricultural areas were damaged by flood and drought. The potential physical impact of climate change on major crops include the impact of uncertain rainfall at the beginning of rainy season on wet season rice; the impact of uncertain rainfall at the end of rainy season on second rice; the cassava's root damage due to heavy rain and the impact of water shortage on sugarcane. In general, extreme weather events such as flood and drought could affect crop productivity and give rise to crop yield losses.

Given these discouraging prospects, the identification of adaptation strategies is vital to support the crop yields. These adaptation strategies can help the farm households buffering against climate change and extreme weather events and play a crucial role in enhancing security and livelihood of farm households. There is, indeed, a large a growing literature that investigate the farmers' adaptation decision to climate change. By using econometric analysis of cross-sectional data, Di Falco et al. (2011) found that factors that influence Ethiopian farmers' adaptation to climate change include information on farming practices and on climate change and adaptation increases crop productivity. Deressa et al. (2008) used the multinomial logit model to study the determinants of farmers' choice of adaptation methods. Their results show that wealth attributes of households, availability of information, agroecological features, social capital and temperature influence adaptation to climate change in the Nile Basin of Ethiopia. Piya et al. (2012) used the multivariate probit model to analyze the factors that influence the adoption of various adaptation practices of highly marginalized indigenous community in Nepal. The results from their analysis show that perception of rainfall change, size of landholding, status of land tenure, distance to motor road, access to productive credit, information, extension services and skill development training all influence households to adopt adaptation practices to climate change.

The key objective of this study is to provide a micro perspective on the issue of farmers' adaptation to climate change. To achieve this objective, we examine the driving forces behind farm households' decisions to adapt to extreme weather events, i.e. severe flood and drought, and analyze the impacts of adaptation on the productivity of wet-season and dry-season rice. Though there exist a number of papers that identified the adaptation actions implemented in the Thai agricultural sector, some of these studies look at adaptation from the macro perspective (Supnithadnaporn et al., 2011), while others look at the

adaptation implemented at the community level (Chinvanno and Kerdsuk, 2013). The objective of this study is to guide policymakers on ways to promote adaptation.

The research questions asked here are as follows. First, *why some farmers choose to adapt to extreme weather events, while others do not*? *Whether farmers' adaptations to floods and droughts worth to do so*? To find answers to these questions, this study consists of two main parts. The first part of the analysis is devoted to use the probit model to analyze the determinants of farmers' adaptation to specific severe flood and drought events. In the second part of our analysis, we consider farmers' adaptation to floods and droughts that took place over the past 25 years. By using the endogenous switching model, we examine the driving forces behind farm households' adaptation decisions to floods and droughts and investigate the impact of adaptation on crop productivity and costs of production in the Chao Phraya River Basin in Thailand

This part of the technical report is organized as follows. Section 2 contains description of the study sites and the survey instruments. Section 3 is devoted to discuss the empirical methodology used to model determinants of farmers' adaptation and to estimate benefits of adaptation. Section 4 presents the results from our empirical analysis. Section 5 is devoted to present and discussion other results, and section 6 contains some concluding remarks.

2. Description of Study Sites and Data

The data used in this study came from our farm household survey in six Central provinces in the Chao Phraya basin, namely Pitsanulok, Nakornsawan, U-taithani, Lopburi, Suphanburi and Ayutthaya. In overall, 815 households from 80 sub-districts ("tambols") took part in the survey, comprising of 484 households from the 52 tambols in the flood-prone areas and 331 farm households from the 28 tambols in drought-zone areas. Figure 1 shows the survey villages in the Chao Phraya Basin of Thailand. The cross-sectional household survey was conducted during October-November 2013. The sample districts were purposely selected according to the drought and flood severity indices constructed by the Department of Disaster Prevention and Mitigation (DDPM). Moreover, additional districts were purposely selected as these districts contain areas to be designated as flood retention under the flood management master plan of the Thai Government. Then, in each of the selected district, two sub-districts or tambols were randomly selected. To ensure that there is greater degree of variety in the survey data, we impose a condition that two sub-districts to be selected must not be adjacent to each other. (Table 1)

Figure 1: Survey Villages in the Chao Phraya Basin of Thailand

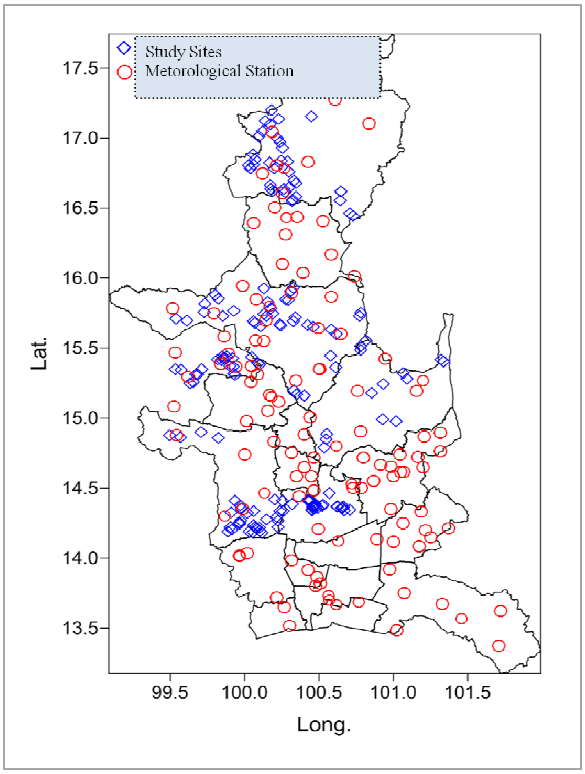


Table 1: Description of study sites and survey instrument

Region/Province	Number of tambols			Number of villages			Number of farm households		
	Floods	Droughts	Total	Floods	Droughts	Total	Floods	Droughts	Total
Lower North									
-Phitsanulok	14	4	18	30	7	37	154	42	196
-Nakhon Sawan	12	7	19	23	14	37	123	89	212
-Uthai Thani	2	9	11	3	18	21	14	98	112
Central Plains									
-Lop Buri	2	5	7	3	11	14	21	68	89
-Suphan Buri	11	3	14	25	7	32	90	34	124
-Ayutthaya	11	0	11	27	0	27	82	0	82
Total	52	28	80	111	57	168	484	331	815

The data collected comprises of seven main parts, namely household characteristics, agricultural land utilization and land tenure, agriculture and livestock production, perceptions

of climate change, incidence of severe flood, incidence of severe drought and perception of Government's flood management projects.

3. Research Methodology

3.1 Determinants of Adaptation to Specific Extreme Weather Events

In the literature, the decision of the farm household whether or not to adapt to climate change is considered under the utility maximization framework (Norris and Batie 1987; Deressa et al. 2008). Under such framework, it is assumed that the farm household will adopt a new farm technology (i.e. adaptation strategy) only if the perceived utility or profit from using the new technology is greater than the old method. The utility of farm household is specified as:

$$U_{ij} = \boldsymbol{\beta}_j \boldsymbol{x}_i + \varepsilon_j \text{ and } U_{ik} = \boldsymbol{\beta}_k \boldsymbol{x}_i + \varepsilon_k, \quad (1)$$

where U_{ij} and U_{ik} are the perceived utility of farm household i from adopting strategy j and k, respectively; $\boldsymbol{x}$ is the vector of explanatory variables that influence the perceived desirability of the strategy; $\boldsymbol{\beta}$ is the vector of coefficients to be estimated; ε_j and ε_k are identically and independently distributed error terms. If farm household i chooses strategy j instead of k, it implies that the perceived utility derived from j is greater than k or can be expressed as:

$$U_{ij} > U_{ik}, k \neq j \quad (2)$$

According to Deressa et al. (2008), the utility derived from adaptation strategy cannot be observed, but the actions of farm households are observed through the choices they make. In what follows, we use the latent variable to transform equation (2) and use the probit model in the analysis.

Provided that what we are examining is the probability of adaptation in response to extreme flood and drought, then y could be 1 if the farm household adapts and 0 otherwise. Given the binary response, one could consider the binary response model, with the following response probability:

$$P(y - 1|\boldsymbol{x}) - P(y - 1|x_1, x_2, \ldots, x_n), \quad (3)$$

where $\boldsymbol{x}$ denotes the full set of explanatory variables, including farm household characteristics (age, education, gender and marital status of household head), and other factors that affect adaptation decision, including climate variables, access to credit, and land tenure.

To avoid the limitation of the linear probability model, we consider a class of binary response model of the form:

$$P(y = 1|\boldsymbol{x}) = H(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k) = H(\beta_0 + \boldsymbol{x}\boldsymbol{\beta}), \quad (4)$$

where $H(.)$ is a function such that $H: x \mapsto [0,1], \forall x \in \mathbb{R}$. Though various nonlinear functions have been suggested for the function H to make sure that the probabilities are between zero and one, in this paper, we consider the probit model. Under the probit model, it is assumed that the function $H(.)$ follows a normal (cumulative) distribution,

$$H(x) = \Phi(x) = \int_{-\infty}^{x} \phi(z)dz,$$

where $\phi(z)$ is the normal density function:

$$\phi(z) = \frac{1}{\sqrt{2\pi}} exp(-z^2/2)$$

The probit model can be derived from the latent variable model. Let y^* be the latent variable, determined by:

$$y^* = \beta_0 + x\beta + e, y = \mathbb{I}[y^* > 0], \quad (5)$$

where $\mathbb{I}[\cdot]$ is an indicator function which takes on the value one if the event in brackets is true and zero otherwise. Thus, y is one if $y^* > 0$ and y is zero if $y^* \leq 0$. It is assumed that e is independent of x and that e has the standard normal distribution. The response probability for y can be derived as follows:

$$P(y = 1|x) = P(y^* > 0|x) = P(e > -(\beta_0 + x\beta)|x)$$
$$= 1 - H[-(\beta_0 + x\beta)] = H\big(-(\beta_0 + x\beta)\big)$$

To estimate the limited dependent variable model, maximum likelihood method is indispensable.

3.2 Impacts of Adaptation to Extreme Weather Events over 25 Years on Crop Productivity

To model adaptation decision and its impact on crop productivity[1], a two-stage framework is used (Di Falco et al., 2011). In the first stage, a selection model for adaptation is used: a farm household chooses to adapt if the adaptation strategy generates net benefits. Let I^*be the latent variable that captures the expected benefits from adaptation with respect to not adapting. This variable is specified as follows:

$$I_i^* = Z_i\gamma + \eta_i \quad with \ I_i = \begin{cases} 1 \ if I_i^* > 0 \\ 0 \ otherwise \end{cases} \quad (6)$$

The model considered here describes the behavior of a farm household with two regression equations. The criterion function, I_i in equation (6) determines which regime the farm household will face. The farm household i will choose to adapt if $I^* > 0$ and will choose not to adapt otherwise. The vector, Z, comprises of variables that affect the expected benefits of adaptation.

The second stage models the impact of adaptation on crop productivity via a representation of the production technology. The functional form considered here is a linear specification. Given that the OLS estimation of impact of adaptation on productivity yields biased estimates because of the assumption that adaptation is exogenously determined, in this paper, we address this endogeneity of the adaptation decision by *estimating model of adaptation and crop productivity with endogenous switching regression model by using maximum likelihood method* (Lokshin and Sajaia, 2004). The farm households face 2 regimes (Regime 1) to adapt and (Regime 2) not to adapt:

[1] In this paper, two crops are considered: wet-season rice and dry-season rice.

Regime 1: $y_{1i} = \boldsymbol{M}_{1i}\boldsymbol{\alpha}_1 + \varepsilon_{1i}$ if $I_i = 1$ (7a)

Regime 2: $y_{2i} = \boldsymbol{M}_{2i}\boldsymbol{\alpha}_2 + \varepsilon_{2i}$ if $I_i = 0$ (7b)

where y_i denotes the quantity of rice produced per rai in regimes 1 and 2; $\boldsymbol{M}_i$ is a vector of inputs and of the farmer head's and the farm household's characteristics, assets and the climatic factors. Assume that the error terms in equation (6), (7a) and (7b) have a trivariate normal distribution with mean vector zero and covariance matrix:

$$\Omega = \begin{bmatrix} \sigma_\eta^2 & \sigma_{1\eta} & \sigma_{2\eta} \\ \sigma_{1\eta} & \sigma_1^2 & \cdot \\ \sigma_{2\eta} & \cdot & \sigma_2^2 \end{bmatrix},$$

where σ_η^2 is the variance of the error term in the selection equation (6); σ_1^2 and σ_2^2 are variances of the error terms in the productivity functions (7a; 7b); $\sigma_{1\eta}$ is the covariance of η_i and ε_{1i} ; and $\sigma_{2\eta}$ is the covariance of η_i and ε_{2i}. Given that y_{1i} and y_{2i} are never observed simultaneously, the covariance between ε_{1i} and ε_{2i} is not defined. Since γ is estimable only up to a scalar factor, we can assume that $\sigma_\eta^2 = 1$ (Maddala, 1983; Lokshin and Sajaia, 2004). Given the assumptions regarding distribution of the disturbance terms, the logarithmic likelihood function for the system of (7a and 7b) is:

$$lnL_i = \sum_{i=1}^{N} I_i \left[ln\phi\left(\frac{\varepsilon_{1i}}{\sigma_1}\right) - ln\sigma_1 + ln\Phi(\lambda_{1i}) \right] + (1 - I_i) \left[ln\phi\left(\frac{\varepsilon_{2i}}{\sigma_2}\right) - ln\sigma_2 + ln\left(1 - \Phi(\lambda_{2i})\right) \right],$$

where $\phi(\cdot)$ is the standard normal probability density function; $\Phi(\cdot)$ is the standard normal cumulative density function and $\lambda_{ji} = \frac{(z_i\gamma + \rho_j \varepsilon_{ji}/\sigma_j)}{\sqrt{1-\rho_j^2}}$ with ρ_j denoting the correlation coefficient between the error term η_i and the error term ε_{ji} of equations (7a) and (7b), respectively.

After estimating the parameters of the model, one can calculate the unconditional and conditional expectations of crop productivity of the farm households that adapted with respect to the farm households that did not adapt. The unconditional expectations are given by:

$$E(y_{1i}|\boldsymbol{X}_{1i}) = \boldsymbol{X}_{1i}\boldsymbol{\alpha}_1 \quad (8a)$$

$$E(y_{2i}|\boldsymbol{X}_{2i}) = \boldsymbol{X}_{2i}\boldsymbol{\alpha}_2 \quad (8b)$$

and the conditional expectations for crop productivity are given by:

$$E(y_{1i}|I_i = 1) = \boldsymbol{X}_{1i}\boldsymbol{\alpha}_1 + \sigma_{1\eta}\varphi_{1i} \quad (9a)$$

$$E(y_{2i}|I_i = 0) = \boldsymbol{X}_{2i}\boldsymbol{\alpha}_2 + \sigma_{2\eta}\varphi_{2i} \quad (9b)$$

$$E(y_{2i}|I_i = 1) = \boldsymbol{X}_{1i}\boldsymbol{\alpha}_2 + \sigma_{2\eta}\varphi_{1i} \quad (9c)$$

$$E(y_{1i}|I_i = 0) = \boldsymbol{X}_{2i}\boldsymbol{\alpha}_1 + \sigma_{1\eta}\varphi_{2i} \quad (9d)$$

where $\varphi_{1i} = \frac{\phi(Z_i\gamma)}{\Phi(Z_i\gamma)}$ and $\varphi_{2i} = -\frac{\phi(Z_i\gamma)}{1-\Phi(Z_i\gamma)}$. Table 2 summarizes different cases of conditional expectations for crop productivity, both the actual expectations and the counterfactual expected outcomes.

Table 2: Conditional Expectations, Treatment Effects and Heterogeneity Effects

Subsamples	Decision Stage		Treatment Effects
	To Adapt	Not to Adapt	
Farm households that adapted	(9a) $E(y_{1i}\|I_i = 1)$	(9c) $E(y_{2i}\|I_i = 1)$	TT
Farm households that did not adapt	(9d) $E(y_{1i}\|I_i = 0)$	(9b) $E(y_{2i}\|I_i = 0)$	TU
Heterogeneity effects	BH_1	BH_2	TH

From Table 2, the following treatment effects are calculated: first, the effect of treatment on the treated (TT) and, second the effect of the treatment on the untreated (TU):

$$TT = E(y_{1i}|I_i = 1) - E(y_{2i}|I_i = 1)$$

and

$$TU = E(y_{1i}|I_i = 0) - E(y_{2i}|I_i = 0).$$

Note that TT represents the effect of adaptation on crop productivity of the farm households that actually adapted to climate change, and TU represents the effect of adaptation on crop productivity of the farm households that did not adapt. Besides the treatment effects, the heterogeneity effects will also be calculated. As shown in Table 2, the effect of base heterogeneity for the group of farm households that decided to adapt, BH_1, and the effect of base heterogeneity for the farm households that decided not to adapt, BH_2, can be calculated as follows:

$$BH_1 = E(y_{1i}|I_i = 1) - E(y_{1i}|I_i = 0)$$

And

$$BH_2 = E(y_{2i}|I_i = 1) - E(y_{2i}|I_i = 0).$$

Last but not least, the transitional heterogeneity (TH=TT-TU), which captures whether the effect of adapting on crop productivity is larger or smaller for farm households that actually adapted relative to farm households that actually did not adapt.

4. Research findings

4.1 Estimation Results: Determinants of Adaptation to Specific Extreme Weather Events

4.1.1 Adaptation to the 2011 Flood

The results from the estimation of probit model of determinants of adaptation decision in response to the 2011 flood and the 2012 drought are presented in Tables 3 and 4 respectively. In each case, different model specifications are considered.

The results of the probit model estimation (column (2)) presented in Table 3 suggest that farm households with access to agricultural credits are found to be more likely to adopt adaptation strategies in response to 2011 flood. This result highlights that farm households may need financial resources to adapt. Access to affordable credit increases the farm households' financial resources and their ability to meet transaction costs associated with the adaptation strategies they might want to adopt. According to Nhemachena and Hassan (2007), with higher financial resources through the agricultural credit, farm households are able to purchase new crop varieties, new technology or important inputs that would be more suitable for the climatic conditions.

The results of our analysis also show that land ownership matters. Farm households who do not own their farm land have less propensity to invest in adaptation strategies

compared to with ownership. The key implication of this result is that secure tenure arrangement is an important factor that influence or facilitate investment in long-term adaptation by farmers. Land ownership provides a positive incentive for farmers to invest in their farms, including investment in adaptation and changes the agricultural practices.

Increasing average annual night temperature increases the probability of farm households adopting adaptation strategies in response to the 2011 flood (column (3)). This is along the line of Nhemachena and Hassan (2007), which found that increasing warming could result in higher evapotranspiration rates and water shortage that require farmer responses; for instance, changes in crop varieties and variation in planting dates. Increasing the mean precipitation or rainfall during the rainy season increases the probability of adaptation by farm households as more extreme rainfall could raise the possibility of flooding.

Table 3: Results of probit analysis of determinants of adaptation to the 2011 flood

Dependent Variable **Adaptation 1/0**	(1)	(2)	(3)	(4)
Farm household and head characteristics				
household size	-0.0575**	-0.0520**	-0.0832*	-0.0646*
	(0.0257)	(0.0242)	(0.0484)	(0.0373)
d_male	-0.1844	-0.0460	0.1791	0.1239
	(0.2209)	(0.2219)	(0.2651)	(0.2320)
age	0.0227	0.0213	0.0098	0.0194
	(0.0182)	(0.0169)	(0.0171)	(0.0205)
age-squared	-0.0002	-0.0002*	0.0002	-0.0003*
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
d_single		0.4542*	0.9562*	0.9805**
		(0.2615)	(0.5071)	(0.5011)
d_at least secondary education	0.2185***	0.1911***	0.2752*	0.2746*
	(0.0792)	(0.0618)	(0.1629)	(0.1472)
d_access to agricultural credit		0.1869*	0.0592	0.1203
		(0.1064)	(0.1444)	(0.1009)
d_total agricultural credit	-0.0000019***			
	(0.0000009)			
d_public land			-0.7426***	-0.5541***
			(0.0833)	(0.0914)
Assets				
possession of agricultural tools	1.0174***			
	(0.2670)			
d_household non-farm income				-0.0383
				(0.2799)
2011 Flood				
crop damage			0.5913**	0.4766*
			(0.2402)	(0.2714)
debt suspension			-0.0173	
			(0.2726)	
Climatic factors				
average wet season rainfall				0.0005*
				(0.0002)
average night temperature			0.4202*	
			(0.2169)	
perception that average rainfall increase			0.0797	0.1214
			(0.1620)	(0.1265)

constant	-1.2299***	-0.9813**	-11.3511**	-1.1858**
	(0.4689)	(0.3981)	(5.6501)	(0.5487)
number of observation	446	454	267	283
Log Pseudolikelihood	-250.1545	-258.2076	-150.4620	-160.8436
Pseudo R-squared	0.0293	0.0190	0.0770	0.0607

*, **, *** statistically significant at 10%, 5% and 1% respectively; data are clustered by province and the robust standard errors are shown in the parentheses

Farm households who were adversely affected by the 2011 flood in term of high crop damages are more likely to take up adaptation strategies. We also found that some socio-economic characteristics of the household and household's head matter. The households with well-educated and single head are more likely to adopt adaptation strategies. According to Norris and Batie (1987), higher level of education is found to be associated with access to information on improved technology and higher productivity. As argued in Deressa et al. (2008), evidence from various sources indicates that there is a positive relationship between the education level of the household head and the adoption of improved technologies (Igoden, et al. 1990; Lin 1991) and adaptation to climate change (Maddison 2006).

Last but not least, farm households with access to agricultural tools and machinery (such as harvester, large tractor) have higher possibility of taking up adaptation strategies. With access to farming technology, farmers are able to vary their crop calendar, change crop varieties, switch to new crop, etc. Moreover, ownership agricultural tools represent wealth. According to Knowler and Bradshaw (2007), the adoption of agricultural technologies requires sufficient financial wellbeing.

4.1.2 Adaptation to the 2012 Drought

The estimation results presented in Table 4 show that possession of assets is associated with adaptation to extreme drought event. Having access to vehicles reflects the financial status of the households, and we found that vehicle ownership facilitates investment in long-term adaptation to drought. Unlike flood, lack of land ownership does not deter the households from taking up adaptation strategies. As shown in Table 4 (columns (1) and (3)), farm households that grow rice in the public land have higher propensity to invest in drought adaptation strategies compared to other types of land ownership.

When it comes to adaptation to drought, we find that households with higher proportion of members engaging in farm activities are more likely to respond to drought by adopting adaptation strategies. According to Deressa et al. (2008), households with more members assisting in the farming activities are associated with higher labor endowment, which would enable a household to accomplish various agricultural tasks. Croppenstedt et al. (2003) argue that households with a larger pool of labor are more likely to adopt agricultural technology and use it more intensively because they have fewer labor shortages at peak times; thus, it is hypothesized that households with large families are more likely to adapt to drought.

Our results show that gender of the household head also matters. According to Table 4, households with male head have lower probability of uptaking the drought adaptation strategies. The effect of gender of household head on the adaptation decision in the previous studies is mixed. While Asfaw and Admassie (2004) and Tenge De Graffe and Heller (2004) found that male-headed households are more likely to get information about new technologies and undertake risky businesses than female-headed households, Nhemachena and Hassan (2007) finds contrary results, arguing that female-headed households are more likely to take up climate change adaptation methods. Thus, the adoptions of new technologies or adaptation methods appear to be rather context specific.

Table 4: Results of probit analysis of determinants of adaptation to the 2012 drought

Dependent Variable **Adaptation 1/0**	(1)	(2)	(3)
Farm household and head characteristics			
Proportion of member engaging in farm	0.4147**	0.3629***	0.4251**
	(0.1659)	(0.1230)	(0.1971)
d_male	-0.5145***	-0.4558***	-0.5383***
	(0.1541)	(0.1677)	(0.1595)
age	0.1131*	0.1097*	0.1002
	(0.0670)	(0.0631)	(0.0722)
age-squared	-0.0011*	-0.0011*	-0.0010
	(0.0006)	(0.0006)	(0.0006)
d_single	-0.1388	-0.1168	-0.1448
	(0.1892)	(0.1882)	(0.1745)
d_at least secondary education	0.2881	0.2593	0.2409
	(0.2750)	(0.2558)	(0.2765)
d_access to agricultural credit	-0.3966**	-0.3167*	-0.4346**
	(0.1747)	(0.1838)	(0.1733)
d_public land	0.7104***		0.6085***
	(0.1597)		(0.1716)
Assets			
possession of vehicle	0.3373***	0.4364***	0.3605**
	(0.1316)	(0.1602)	(0.1605)
Climatic factors			
average rainfall			-0.0015
			(0.0011)
average temperature			-0.3826*
			(0.1982)
perception that average rainfall increase		-0.0252	
		(0.2386)	
constant	-2.9246	-2.8924	10.9641
	(1.8569)	(1.8008)	(7.6622)
number of observation	128	127	128
Log Pseudolikelihood	-73.6772	-73.3219	-73.2420
Pseudo R-squared	0.0536	0.0431	0.0592

*, **, *** statistically significant at 10%, 5% and 1% respectively; data are clustered by province and the robust standard errors are shown in the parentheses

Though some previous studies found that the availability of credit eases the cash constraints of the farm households and facilitates the purchases of inputs such as fertilizer, improved crop varieties, and irrigation facilities (Yirga, 2007; Pattanayak et al., 2003), the results in Table 4 show that there is a negative relationship between the adaptation decision and the access to credit. This is consistent with the findings of Ndambiri et al. (2012) which also found that access to credit is inversely related to farmers' adaptation to climate change. The reason they gave for this result is that the adoption of an agricultural technology may demand the use of owned or borrowed funds. Since such an investment in technology adoption may be hampered by lack of borrowing capacity (El Osta and Morehart, 1999), this may negatively end up affecting any perception of the farmers or even the taking up of adaptation measures.

Next, we consider the impact of current climatic variables on the probability of adaptation in response to the 2012 drought. Our results show that the average rainfall plays

no role in determining the probability of adaptation. The estimated coefficient of the average rainfall variable is negative indicating that lower amount of precipitation is associated with higher probability of uptaking of drought adaptation strategies but it is not statistically significant. Ndambiri et al. (2012) found a negative relationship between change in precipitation and farmers' adaptation. The possible reason for this negative relationship is that increased precipitation in a water scarce area is unlikely to constrain farm production and, therefore, unlikely to promote the need to adapt to the changing climate. Unlike rainfall, higher temperature over the survey period appears to work in the opposite direction with regard to the likelihood of adoption of adaptation techniques. Our results show that higher average temperature reduces the probability of adaptation.

4.2 Estimation Results: Impacts of Adaptation to Extreme Weather Events over 25 Years on Crop Productivity

4.2.1 Adaptation to Flood Events over 25 Years

Table 5 shows the estimation results for the case of adaptation to extreme flood events and wet-season rice productivity. Column 1 shows the OLS estimation of wet-season rice productivity function with no switching but with the dummy variable for adaptation. Columns 2, 3 and 4 show the estimation results of the selection equation (6) and of the wet-season rice productivity functions (7a) and (7b) for farm households that adapted and did not adapt to severe floods that struck over the past 25 years.

The unconditional expectation of quantity of wet-season rice produced per rai for farm households that adapted is 683.87 kilograms per rai and the unconditional expectation of quantity of wet-season rice produced per rai for farm households that did not adapt is 617.75 kilograms per rai. The difference in the amount of quantity produced per rai between the two groups of farm households is 66.12 kilograms per rai. Nevertheless, this difference does not represent the benefit of adaptation on wet-season rice productivity. It is important that we proceed to calculate the conditional expectation of quantity of wet-season rice produced per rai under actual and counterfactual conditions.

Table 6 shows these results. Cells (a) and (b) represent the expected quantity of wet-season rice produced per rai observed in the sample. According to Table 6, the expected quantity of wet-season rice produced per rai among the adapted farm households is about 696 kilograms, while the expected quantity of wet-season rice produced per rai by the non-adapted farm households is about 576 kilograms. Yet, one should not conclude that, on average, the farm households that adapted produced 120 kilograms more than the farm households that did not adapt, as the treatment effects need to be calculated. The last column of Table 6 shows the treatment effects of adaptation on wet-season rice productivity. Cell (c) shows one of the counterfactual cases, whereby the farm households who actually adapted choose not to adapt at the decision stage. As shown in the table, *farm households who actually adapted would have produced about 31 kilograms less if they did not adapt. Given the average wet-season rice productivity among adapted households of 697 kilograms, if the adapters instead choose not to adapt, their average yield would be reduced by around 4 percent*. In the second counterfactual case (d), results presented in Table 6 show that *farm households that actually did not adapt would have produced about 94 kilograms more if they had adapted. This implies that, if the non-adapters instead choose to adapt, their average wet-season rice productivity would be increased by approximately 14 percent*. The implication drawn from these results is that adaptation increases productivity of wet-season rice. However, given that the transitional heterogeneity (TH) is negative, the effect of adaptation on wet-season rice productivity is smaller for the farm households that adapted relative to the farm households that did not adapt.

Table 5: Parameters Estimates of Adaptation to Floods and Wet-Season Rice Productivity Equations

	[1]	[2]	[3]	[4]
		Endogenous Switching Regression		
Model	OLS		Regime 1 Adaptation =1 (Farm HH that adapted)	Regime 2 Adaptation =0 (Farm HH that not adapted)
Dependent Variable	Quantity of Wet-Season Rice per Rai	Adaptation to Flood 1/0	Quantity of Wet-Season Rice per Rai	Quantity of Wet-Season Rice per Rai
Adaptation 1/0	-4.2598 (33.0957)			
Climatic factor: Rainfall during rainy season	0.5113** (0.2367)	0.0026 (0.0017)	0.3852 (0.2879)	1.3967*** (0.3993)
Inputs: Seed quantity per rai	-0.073 (1.8829)		-9.6174*** (3.3708)	4.4544** (2.1344)
Manure quantity per rai	1.7446*** (0.6543)		1.5765* (0.8170)	0.8209 (0.8245)
Plot Size	-2.0842* (1.2192)		-0.5870 (1.9418)	-2.9380* (1.6026)
Farm HH characteristics: Number of members on farm	25.3956 (18.8248)	0.1953 (0.1323)	15.9732 (25.7653)	-48.6293* (26.9470)
Married HH Head	-61.4768 (81.3436)	0.8257 (0.6695)	-91.8556 (174.3721)	-22.6188 (87.9050)
Debt: agricultural credit	1.6220 (50.1590)	-0.6004* (0.3470)	-61.8170 (59.9071)	465.5958*** (95.9533)
Perception: Perception about rainfall		0.4376* (0.2539)		
Constant	427.72** (186.77)	-2.3719* (1.4253)	850.3315*** (297.7367)	-467.9752* (249.8715)
σ_i			164.7331*** (13.1062)	160.3512*** (23.8089)
ρ_i			-0.0031 (0.4562)	-0.3057 (0.6523)

Remark: Estimation by maximum likelihood at the plot level (153 plots)

* Significant at 10% level; ** significant at 5% level, *** significant at 1% level

Next, we examine the potential heterogeneity in the sample by considering the bottom row of Table 6. Since both BH_1 and BH_2 are positive, these results imply that there are some sources of heterogeneity (i.e. unobservable characteristics such as skills) that makes the adapters better producers than the non-adapters irrespective of the issue of climate change.[2]

[2] See Di Falco et al. (2011) for similar findings.

Table 6: Average Expected Wet-Season Rice Production per Rai

Subsamples	Decision Stage		Treatment Effects
	To Adapt	Not to Adapt	
Farm households that adapted	(a) 695.81 (13.3797)	(c) 664.46 (14.8840)	TT = 31.35*** (2.2934)
Farm households that did not adapt	(d) 669.79 (13.8864)	(b) 575.69 (22.6851)	TU = 94.10*** (3.0151)
Heterogeneity effects	BH_1 = 26.02*** (2.2072)	BH_2 = 88.77*** (3.0788)	TH = -62.75

Note: Standard errors in parentheses

4.2.1 Adaptation to Drought Events over 25 Years

In what follows, we examine the impact of adaptation to drought and dry-season rice productivity. The first column of Table 7 shows the OLS estimation of dry-season rice productivity function with no switching but with the dummy variable for adaptation, while columns 2, 3 and 4 show the estimation results of the selection equation (6) and of the dry-season rice productivity functions (7a) and (7b) for farm households that adapted and did not adapt to extreme drought that struck the areas over the past 25 years.

The unconditional expectation of quantity of dry-season rice produced per rai for farm households that adapted, is 905 kilograms per rai and the unconditional expectation of quantity of dry-season rice produced per rai for farm households that did not adapt is 727.11 kilograms per rai. The difference in the amount of quantity produced per rai between the two groups of farm households is 177.90 kilograms per rai. Next, we calculate the conditional expectation of quantity of dry-season rice produced per rai under actual and counterfactual conditions. Table 8 presents the results.

Table 7: Parameters Estimates of Adaptation to Droughts and Dry-Season Rice Productivity Equations

	[1]	[2]	[3]	[4]
Model	OLS	Endogenous Switching Regression		
			Regime 1 Adaptation =1 (Farm HH that adapted)	Regime 2 Adaptation =0 (Farm HH that not adapted)
Dependent Variable	Quantity of Dry-Season Rice per Rai	Adaptation to Drought 1/0	Quantity of Dry-Season Rice per Rai	Quantity of Dry-Season Rice per Rai
Adaptation to drought 1/0	-66.7382 (47.5827)			
Climatic factor:				
Annual rainfall	0.2724* (0.1643)	0.0005 (0.0014)	-0.2209 (1.1532)	0.2687* (0.1655)
Night temperature	69.3754* (41.2718)	0.5257 (0.3473)	-2857.033 (1825.323)	69.1188* (42.7908)
Inputs:				
Manure quantity per rai	1.2088** (0.5423)		0.8485 (1.1838)	1.1484* (0.6888)
Assets:				
Agricultural tools index	107.3349 (92.0770)	1.9580** (0.7984)	730.5529* (424.2428)	78.02655 (110.7071)
Farm HH characteristics:				
Number of members on farm	-39.1231* (21.1359)	-0.3880** (0.1773)	-147.8869* (87.87016)	-31.2640 (24.0845)
At least secondary education	27.04636 (42.94704)	-0.7611** (0.4063)	126.8271 (168.5219)	29.6167 (48.2940)
Debt: agricultural credit	-67.8387 (45.8886)	-0.4014 (0.3434)	234.2928 (150.3982)	-78.4917 (53.2702)
Perception:				
Perception about rainfall		-0.3958 (0.3337)		
Constant	-1368.025 (1122.066)	-14.9777 (9.4992)	73864.01 (47317.43)	-1353.987 (1149.06)
σ_i			182.7427*** (27.5855)	207.1728*** (12.4635)
ρ_i			-0.0856 (0.8970)	-0.0855 (0.4512)

Remark: Estimation by maximum likelihood at the plot level (170 plots)

* Significant at 10% level; ** significant at 5% level, *** significant at 1% level

Table 8: Average Expected Dry-Season Rice Production per Rai

Subsamples	Decision Stage		Treatment Effects
	To Adapt	Not to Adapt	
Farm households that adapted	(a) 700.63 (22.5415)	(c) 725.83 (6.5547)	TT = -25.21*** (4.4544)
Farm households that did not adapt	(d) 941.90 (108.6289)	(b) 734.16 (13.0725)	TU = 207.74*** (9.4084)
Heterogeneity effects	BH_1 = -241.27*** (10.0742)	BH_2 = -8.33*** (2.6213)	TH = -232.95

Note: Standard errors in parentheses

Table 8 shows the average expected dry-season rice production per rai under actual and counterfactual cases. Cells (a) and (b) represent the expected quantity of dry-season rice produced per rai observed in the sample. The table shows that the expected quantity of dry-season rice produced per rai among the farm households that adapted to drought is about 701 kilograms, while the expected quantity of dry-season rice produced per rai by the non-adapted farm households is about 734 kilograms. Yet, one cannot rush to the conclusion that on average the farm households that adapted produced less than the farm households that did not adapt. One should calculate the treatment effects. The last column of Table 8 shows the treatment effects of adaptation on dry-season rice productivity. In this case, the impact of adaptation on dry-season rice productivity is unclear. Cell (c) shows that *farm households who actually adapted would have produced about 25 kilograms more if they did not adapt. This implies that, by instead choosing not to adapt, the adapters' average dry-season rice productivity would have increased around 4 percent*. In the second counterfactual case (d), *farm households that actually did not adapt would have produced about 208 kilograms more if they had adapted. Basing on this result, if the non-adapted households instead choose to adapt, their average yield per rai would have increased by 28 percent*. With these conflicting results, one cannot conclude at this point that adaptation to drought would unambiguously increase productivity of dry-season rice. Moreover, with the negative transitional heterogeneity (TH), the effect of adaptation on dry-season rice productivity is smaller for the farm households that adapted relative to the farm households that did not adapt.

5. Other Findings Related to Adaptation

5.1 Types of Adaptation Strategies for Flood and Drought Adopted by Farm Households

Among the households that adapted to floods over the past 25 years, the top three adaptation strategies commonly embraced by the adapters include changing crop varieties to flood-resistant varieties (32 percent); land elevation and dyke construction (21 percent) and changing crop calendar (19 percent). The rest of the adaptation strategies include changing crop type, changing cropping pattern, changing crop calendar and crop varieties, and pumping water out of farmland. However, we receive information from farmers that participated in our deliberative forum that these flood adaptation strategies are not mutually exclusive. In fact, we learn from these deliberative forum participants that, in fact, farm households might need a combination of adaptation strategies to reduce long-term risk of future flood. For instance, to change crop calendar to avoid the wet-season rice from being affected by flood, farm households also need short-duration rice varieties. Besides, no universally optimal strategy exists. Though one adaptation strategy works well with one location, it is not necessarily optimal for other location. Diversity of adaptation strategies also resulted from individual farmers' specific characteristics, such as farmers' knowledge about technical issues and whether markets exist.

In the case of adaptation to drought, the most commonly adopted adaptation strategies among the households in our sample include finding alternative water sources (43 percent), changing crop calendar (14 percent) and changing crop types (14 percent). It is interesting to remark that, in the case of adaptation to drought, some farm households decided to quit farming, especially the households that cannot find alternative water supplies for growing dry-season rice and domestic consumption during the dry season.

5.2 Adaptation and Cost of Production

In this analysis, we also investigate the impact of adaptation on the cost of production for both wet- and dry-season rice. The results from our study are summarized in Table 9.

Table 9: Adaptation and Cost of Production for Wet-Season and Dry-Season Rice (unit: Percentage)

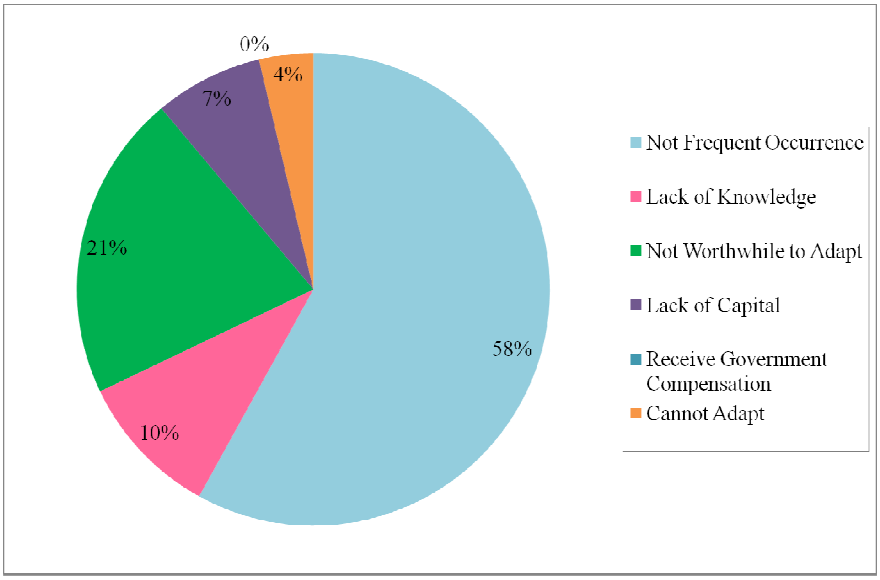
	Wet-Season Rice	Dry-Season Rice
Change in cost of production among farm households that adapted	17.28	22.63

Source: Farm Household Survey by TDRI

5.3 Barriers to Adaptation

Even though floods and droughts that took place over 25 years have imposed adverse impacts on livelihood, agricultural production and properties of the farm households in the Chao Phraya River Basin, it is important to highlight that not all farm households decided to adapt to make themselves more resilient to these extreme weather events. What factors explain why some farm households choose not to adapt? The analysis of barriers to adaptation to flood and drought in the Chao Phraya River Basin of Thailand indicates that there are six major constraints or barriers to adaptation (Figures 2 and 3)[3].

Figure 2: Barriers to Adaptation to Flood

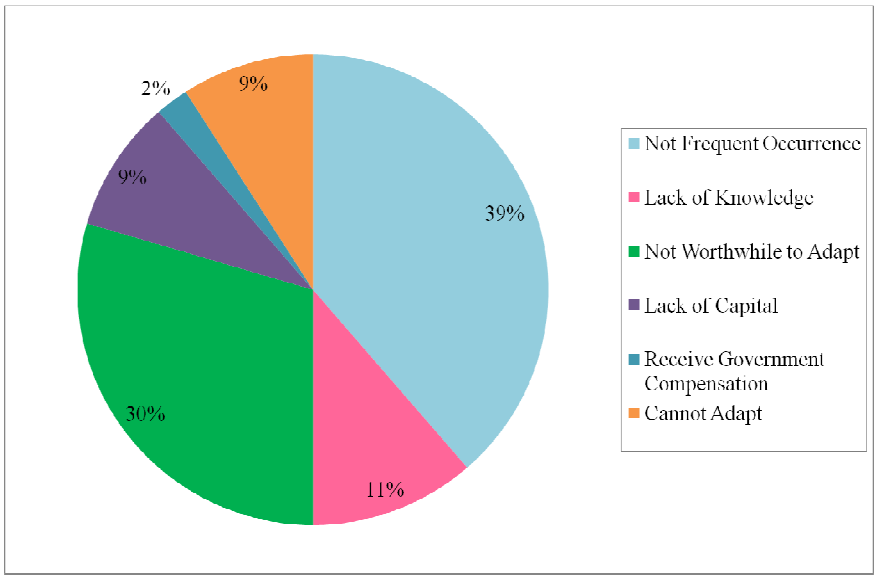


As shown in Figure 2, the three most commonly cited reasons for not adapting to flood include the perception that floods that took place were rare events; the perception that it is not worthwhile to implement adaptation strategies; and the lack of knowledge, information

[3] Some of these barriers to adaptation are consistent with the findings of Deressa et al. (2008).

and knowhow about adaptation strategies. The most commonly reported barriers to adaptation to drought are similar to those in the case of adaptation to flood. Perception that droughts that took place are rare events and lack of capital are main factors that hinder adaptation to drought among the farm households in our sample.

Figure 3: Barriers to Adaptation to Drought



For factors that explain why some farm households did not adapt to drought (Figure 3), the most commonly cited factor is the farmers' perception towards drought events, i.e. whether they perceive that severe droughts are rare events. If farmers perceive that very severe droughts do not occur on a frequent basis, they do not pursue long-term adaptation. Instead, they rely on the short-term strategies to cope with droughts such as finding temporary jobs. A large number of farmers reported that it is not worthwhile to adapt and they lack capital to implement adaptation strategies. Besides, lack of knowledge about adaptation options and markets also reported by our respondents as important barriers to adaptation to severe droughts. To promote wider adoption of adaptation strategies among farm households in the Chao Phraya River Basin, it is vital that the responsible government agencies step in to help these farm households overcome these barriers to adaptation. The policy implications that arise from this analysis are contained in the next section.

6. Concluding Remarks and Policy Implications

Given that extreme weather events, particularly flood and drought, are known to affect crop productivity, identification and implementation of "climate-proofing" adaptation strategies are vital to support crop productivity of farm households, reduce food insecurity and buffer against climate change. In this part of the study, we study the determinants of adaptation to specific extreme events. We also analyze the benefit of adaptation on crop productivity by estimating the endogenous switching regression model. Our results show that there are differences in productivity of wet-season rice between the farm households that adapted to flood and those that did not adapt to flood. Adaptation to flood that took place in Chao Phraya River Basin over the past 25 years increases wet-season rice productivity.

However, the impact of adaptation on wet-season rice productivity is smaller for the farm households that actually adapted than for the farm households that did not adapt. In the case of dry-season rice, our results show that it is not clear whether adaptation to drought increases dry-season rice productivity. On one hand, farm households who actually adapted would have produced more if they did not adapt. On the other hand, farm households that actually did not adapt would have produced more if they had adapted. Thus, one cannot conclude that adaptation to drought would unambiguously increase productivity of dry-season rice.

This study also analyzes the drivers behind adaptation. Our estimation results show that awareness about climate change and information on climate variables; asset possession and lack of financial burdens are crucial in affecting the probability of adaptation. Together with the analysis on barriers to adaptation, the following policy implications can be drawn. First, concerning the lack of knowledge, technical knowhow and information on appropriate adaptation options, the relevant government agencies, such as the Department of Agricultural Extension and District Agricultural Extension Offices, can play important roles in disseminating information, sharing knowledge on crop types, crop calendar, cropping pattern or crop varieties. In addition, given that market access is a factor that influences adoption of agricultural technologies since markets provide an important platform for farmers to gather and share information according to previous studies (Maddison, 2006), some steps should be taken by the Thai Government agencies to improve farmers' access to market. Second, given that adapting to flood and drought is costly, Bank for Agriculture and Agricultural Cooperatives can help farm households by providing financial assistance, perhaps in the form of soft loans. Availability of credit eases the cash constraints and allows farm households to acquire inputs (such as improved crop varieties) and new farming technology

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