ESSAYS ON RISK ATTITUDES, KNOWLEDGE, EXTREME WEATHER, AND FARMERS' BEHAVIORS IN RURAL SOUTHEAST ASIA

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ZUSAMMENFASSUNG

Der Nordosten Thailands und Zentralvietnam sind zwei Regionen, in denen Armut trotz allgemeiner Erfolge bei der Armutsbekämpfung auf nationaler Ebene fortbesteht. Zwar gibt es tiefgreifende strukturelle Unterschiede zwischen Thailand und Vietnam, aber ein gemeinsames Merkmal beider Länder ist, dass die Regierungspolitik die Abwanderung von Arbeitskräften aus ländlichen Gebieten fördert, um das Wachstum im Industrie- und Dienstleistungssektor zu erleichtern. Darüber hinaus haben die politischen Entscheidungsträger in beiden Ländern die Vision, ihre Landwirtschaft nach westlichem Vorbild auf Großbetriebe umzustellen. Während Abwanderung aus ländlichen Gebieten stattgefunden hat und der Anteil des außer- und nichtlandwirtschaftlichen Einkommens am Gesamteinkommen der Haushalte gestiegen ist, liegt der Anteil des landwirtschaftlichen Einkommens in vielen Fällen jetzt unter 50 %. Heutzutage ist die Arbeit und nicht, wie in der Vergangenheit, der Boden, der wichtigste einkommensschaffende Faktor. Dennoch spielt die Landwirtschaft in den ländlichen Gebieten dieser beiden Länder nach wie vor eine wichtige Rolle. Die Betriebe sind, wie in der Vergangenheit, klein, und in den letzten Jahrzehnten fast unverändert geblieben. Der von den politischen Entscheidungsträgern angestrebte Strukturwandel in den ländlichen Gebieten findet nicht im gewünschten Ausmaß statt. Die Haushalte behalten ihre Landwirtschaft als Absicherung, die kleinbäuerliche Landwirtschaft dominiert weiterhin. In beiden Regionen sind die Landwirte zunehmend durch Klimawandel verursachten schweren Wetterereignissen ausgesetzt, was sie anfällig für Armut und Ernährungsunsicherheit macht (ADB, 2009; IPCC, 2014a; Blanc & Reilly, 2017). Ziel dieser Studie ist es daher, das Verständnis für die Entscheidungsfindung von Landwirten zu verbessern. Insbesondere wird untersucht, wie das Wissen und die Fähigkeiten der Landwirte sowie ihre Risikoeinstellung einerseits und die zunehmend auftretenden extremen Wetterereignisse andererseits, ihre Entscheidungen in Bezug auf die Bewirtschaftung des Betriebs beeinflussen. Dabei untersucht diese Arbeit die folgenden drei Forschungsfragen: 1. Wie beeinflusst die Risikoeinstellungen die Entscheidungen der Landwirte? 2. Wie wirkt sich landwirtschaftliches Wissen auf die Agrarproduktion und Produktivität aus? 3. Wie verändern Landwirte den Einsatz landwirtschaftlicher Betriebsmittel als Reaktion auf extreme Wetterereignisse?

Um diese Fragen zu beantworten, verwendet diese Arbeit zwei primäre Datenquellen. Die erste Quelle ist die Datenbank des Thailand-Vietnam Socio-economic Panel (TVSEP). Diese Daten wurden im Zeitraum von 2007 bis 2017 erhoben wurde. Für dieses Panel wurde ingesamt sechs Befragungswellen durchgeführt, in denen Daten von zirka 4.400 ländlichen Haushalten in den

nordostthailändischen Provinzen Nakhon Phanom, Ubon Ratchathani und Buri Ram sowie in den vietnamesischen Provinzen Ha Tinh, Thua Thien Hue, beide an der Küste von Zentral-Vietnam gelegen und Dak Lak im zentralen Hochland, erhoben wurden. Die zweite Datenquelle sind historische Wetterdaten. Es werden hierbei monatlichen Temperatur- und Niederschlagsdaten von 1948 bis 2016 benutzt (Schneider et al., 2018; Fan & Dool, 2008).

Die Ergebnisse der Arbeit werden in drei Aufsätzen vorgestellt.

Der erste Aufsatz lautet "*Risikoeinstellungen und ihre Auswirkungen auf die Strategie zur Sicherung des Lebensunterhalts - Erkenntnisse aus zwei Provinzen in Thailand und Vietnam*." Unter Verwendung einer Ordinary Least Square (OLS) und einer Probit-Regression mit unterschiedlichen Spezifikationen werden die Determinanten der Risikopräferenz für die Entscheidungsfindung der Haushalte analysiert. Die Ergebnisse zeigen, dass die Risikobereitschaft signifikant mit individuellen Merkmalen wie Alter, Geschlecht, Größe und Haushaltsvermögen zusammenhängt. Es bestehen Korrelationen zwischen der Risikobereitschaft und den realen Entscheidungen der landwirtschaftlichen Haushalte. Die Ergebnisse zeigen zudem, dass risikofreudige Kleinbauern eher dazu bereit sind, ihre einkommensschaffenden Aktivitäten zu diversifizieren, um ihr Risiko abzufedern. Diese Kleinbauern investieren in die Selbstständigkeit und in andere nicht landwirtschaftliche Einkommensquellen, während sie gleichzeitig weiterhin Landwirtschaft betreiben.

Der zweite Aufsatz mit dem Titel "*Wissen der Landwirte und landwirtschaftliche Produktivität im ländlichen Thailand und Vietnam*" untersucht die Beziehung zwischen dem Wissen und Fähigkeiten der Landwirte, und der landwirtschaftlichen Produktivität. In dieser Arbeit werden Primärdaten zu landwirtschaftlichen Kenntnissen und Fertigkeitstests basierend auf einem gesonderten Datensatz aus den Provinzen Ubon Ratchathani, Thailand und Hue, Vietnam verwendet. Um die Auswirkungen von landwirtschaftlichen Kenntnissen und Fertigkeiten auf die landwirtschaftliche Produktivität zu ermitteln, wurde ein zweistufiger Ansatz der kleinsten Quadrate (2SLS) entwickelt, der die Ergebnisse der Wissens- und Fertigkeitstests mit Produktivitätsdaten aus späteren Befragungswellen kombiniert. Die Ergebnisse zeigen, dass technisches Wissen in der Landwirtschaft signifikant positiv mit dem Gewinn, aber signifikant negativ mit den Reiserträgen und den Ausgaben für Betriebsmittel verbunden ist. Dies deutet darauf hin, dass sachkundige Landwirte eher nach optimalen als nach maximalen Erträgen streben und die Betriebsmittel umsichtiger einsetzen, was sich grundsätzlich positiv auf Ökonomie und Umwelt auswirkt.

Der dritte Aufsatz trägt den Titel "*Extreme Wetterereignisse und landwirtschaftliches Input-Management im ländlichen Thailand und Vietnam: Intensify or de-intensify*?". In diesem Artikel wird untersucht, wie sich extreme Wetterereignissen, insbesondere Dürren, auf die Entscheidungen der Haushalte im Nordosten Thailands und in Zentralvietnam bezüglich des Inputmanagements auswirken. Es werden acht unterschiedliche Inputs erfasst: Anbaufläche bzw. Anbauintensität, Arbeit (Familien- und Fremdarbeitskräfte), Mineraldünger, Pestizide, Bewässerung, und landwirtschaftliche Maschinen. Es werden zwei binäre Dürreindikatoren, nämlich schwere Dürre und extreme Dürre, unter Verwendung des Standardized Precipitation Evapotranspiration Index (SPEI) als Kriterium, definiert. Darauf aufbauend wird ein Modell mit fixen Effekten (FE) verwendet. Die Ergebnisse zeigen, dass die Landwirte auf schwere Dürreperioden reagieren, indem sie den Einsatz von Arbeitskräften, Pestiziden, die Anzahl der angebauten Kulturpflanzen und landwirtschaftliche Maschinen reduzieren. Zweitens setzen von schweren Dürreperioden betroffene Landwirte zunehmend gemietete Maschinen als Ersatz für eigene Geräte und für Familienarbeitskräfte ein. Drittens nimmt das Ausmaß der Anpassungen mit dem Schweregrad der Dürre zu. Eine Differenzierung der Analyse nach Ländern sowie Berg- und Tieflandreisanbau zeigt, dass der Grad der De-Intensivierung variiert. So setzen thailändische Landwirte beispielsweise mehr Familien- und Leiharbeitskräfte für die landwirtschaftliche Produktion ein; vietnamesische Landwirte investieren in landwirtschaftliche Anlagen. Reisbauern im Hochland konzentrieren sich auf verschiedene Betriebsmittel wie Pestizide, Maschinen und landwirtschaftliche Vermögenswerte, während Landwirte im Tiefland sich auf die verfügbaren Bewässerungssysteme konzentrieren.

Aus allen drei Aufsätzen ergeben sich wichtige Erkenntnisse für die Regierungen beider Länder. Es wird empfohlen Maßnahmen zu implementieren, welche die ländlichen Haushalte dabei unterstützen, extreme Wetterereignisse und den Klimawandel zu bewältigen.

Stichworte: Risikobereitschaft, Wissen, Dürre, SPEI, Landwirtschaft, Einsatz von Betriebsmitteln, Südostasien.

ABSTRACT

Northeastern Thailand and Central Vietnam are two regions where pockets of poverty persist despite overall success in poverty reduction on the national level. While there are profound structural differences between Thailand and Vietnam, a common feature for both countries is that government policies promote the migration of rural labor to facilitate growth in the industrial and service sectors. Furthermore, policymakers in both countries have the vision to transform their agriculture towards large-scale farming, following the model of western agriculture. While out-migration from rural areas has taken place and the share in off- and non-farm income in total household income has been growing, the share of agriculture income in many cases is now less than 50 %. To date, labor rather than land (as in the past) is the main income-generating factor. However, agriculture still plays an essential role in the rural areas of these two countries. Farms are still small, and farm sizes almost remained the same over the past decades. Structural transformation of the rural areas as envisaged by policymakers does not take place. Households keep their agriculture as a backup and safety net and hence small-scale farming continues to dominate. At the same time, farmers in the two regions are increasingly exposed to severe weather events caused by climate change which makes them vulnerable to poverty and food insecurity (ADB, 2009; IPCC, 2014a; Blanc & Reilly, 2017). In this study, it is therefore aimed to obtain a better understanding of farmers' decision-making in agriculture. In particular, the thesis aims to investigate how farmer knowledge and skills and their risk attitudes, on the one hand, and the increasingly occurring extreme weather events, on the other hand, influence their decision-making with regard to farm management decisions. There are three specific research questions to be answered in this research: (1) how do risk attitudes affect household decision-making; (2) what is the impact of agricultural knowledge on agricultural production; (3) how do farmers manage their agricultural inputs in response to extreme weather events.

To answer these questions, the thesis draws on two primary data sources. The first is the database of the Thailand Vietnam Socio Economic Panel (TVSEP) project during the period of 2007 to 2017, i.e., six-year panel dataset was collected from some 4,400 rural households in the Northeastern Thailand provinces of Nakhon Phanom, Ubon Ratchathani, and Buri Ram; and in Vietnam’s Central Coastal and Central Highlands provinces of Ha Tinh, Thua Thien Hue (Hue), and Dak Lak. The second data source is historical weather data. We use the monthly high-resolution (0.5) temperature and precipitation data observed from 1948 until 2016 from the Global Precipitation Climatology Centre (GPCC; Schneider et al., 2018), and the Global

Historical Climatology Network Monthly - Version 2 and the Climate Anomaly Monitoring System (GHCN + CAMS; Fan & Dool, 2008), respectively.

The results of the thesis are presented in three essays.

The first essay is *"Risk attitudes and implication for livelihoods strategy – evidence from two provinces in Thailand and Vietnam."* Utilizing an Ordinary Least Square (OLS) and a Probit regression with different alternative specifications, the determinants of risk preference for household decision-making are analyzed. Results show that risk attitudes are significantly related to individual characteristics such as age, gender, height, and household wealth. There are correlations between the willingness to take risk and real-life decisions of farm households. The findings show that risk-seeking individuals likely diversify income-generating activities as a cushion against the risk of small-scale farmers in these areas. They invest in self-employment and other non-farm enterprises while still capitalizing in agriculture.

The second essay**,** named *"Farmers' knowledge and farm productivity in rural Thailand and Vietnam"*, investigates the relationship between farmers' knowledge, skills, and agricultural productivity. This paper uses primary data on agricultural knowledge and skill tests among "TVSEP households" in the provinces of Ubon Ratchathani in Thailand and Hue in Vietnam. A Two-Stage Least Squares (2SLS) approach combining knowledge and skills test results with productivity data of later waves was developed to identify the effects of agricultural knowledge and skills on agricultural productivity. The major finding is that technical knowledge in agriculture is significantly and positively associated with profit but significantly negative with rice yields and cost of input costs. This suggests that knowledgeable farmers may strive for optimal rather than maximum yield and are more judicious in the use of inputs which is good for the economy and the environment.

In the third essay, named *"Extreme weather and agricultural input management in rural Thailand and Vietnam: Intensify or de-intensify?"* we investigate the impact of extreme weather events, namely drought, on household input management decisions in Northeastern Thailand and Central Vietnam. Eight inputs are captured: land, labor (household labor and hired labor), chemicals (i.e., fertilizer and pesticides), irrigation, machinery, and other agricultural investments. We define two binary drought indicators, namely severe drought and extreme drought, using the Standardized Precipitation Evapotranspiration Index (SPEI) as the

criterion. We then use Fixed Effects (FE) model for this paper's purpose. Results indicate that farmers tend to de-intensify agricultural production in terms of hired labor, pesticides, number of crops grown, and agricultural investments in response to severe droughts. Second, farmers increasingly hire machinery as a substitute for owned equipment and for household labor. Third, the magnitude of the effects increases with the severity of drought. Differentiating the analysis between countries, and upland versus lowland rice production, shows that the level of de-intensification varies. For example, Thai farmers allocate more family and hired labor to agricultural production; Vietnamese farmers invest in agricultural assets. Upland rice farmers focus on several inputs such as pesticides, machinery, and agricultural assets, while lowland farmers focus on available irrigation systems.

All three essays have generated important policy messages for Governments in both countries to consider public support measures to strengthen rural households coping strategies toward extreme weather events and climate change.

Key words: Risk attitudes, knowledge, drought, SPEI, agriculture, input use, Southeast Asia

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LIST OF ABBREVIATIONS

2SLS	Two-Stage Least Squares
ArcGIS	Geographic Information System Software
Asl	Above Sea Level
CAMS	Climate Anomaly Monitoring System
DEM	Digital Elevation Model
e.g.	Exampli gratia
FE	Fixed Effect
GPS	Global Positioning System
ha	Hectare
i.e.	id est
IV	Instrumental Variable
IPM	Integrated Pest Management
Kg	Kilogram
ln	Logarithm
N	Number of Observations
OLS	Ordinary Least Square
PPP	Purchasing Power Parity
SPEI	The Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
TVSEP	The Thailand and Vietnam Socio-Economic Panel
THB	Thai Baht
UK	United Kingdom
USD	United States dollar
VND	Vietnamese Dong
WTR	Willingness To Take Risk

CHAPTER 1: INTRODUCTION

1.1 Motivation

Human capital is a source of economic growth (Lucas, 1988; Mankiw et al., 1992; Barro & Lee, 1994; Behrman, 2010). Human capital encompasses either innate or acquired features through formal or informal channels containing education, knowledge, skills, and experience (Welch, 1970; Hayami & Ruttan, 1970; Foster & Rosenzweig, 1995; Becker, 2009; Behrman, 2010; Holden & Biddle, 2017). The set of these encompasses characteristics make a variety of decision-making that contribute to the production process, both in the industry and agriculture sectors. Decision-making is considered to be the bottom line of microeconomics. Knowledge and education belong to the most critical factors of decision-making. Advancement in knowledge and education seems to be a significant factor causing the long-term rise in labor and business productivity through individual decision-making. Higher education has improved decision-making leading to higher-income jobs and higher outputs (Welch, 1970; Barro & Lee, 1994; Schultz, 1988; Huffman, 2001; Gregorio & Lee, 2002). In the industrial sector, decision-making impacts the outputs directly. That is not necessarily the case in the agricultural sector. Agricultural outputs are affected not only by human capital and technology but also, significantly, by weather variation. Management decisions in agriculture may not straightforwardly impact agriculture's output as it is affected considerably by extreme weather events such as droughts, floods, and typhoons. Thus, the efficiency of human decision-making in agriculture is based on both in internal factors (e.g., education, knowledge) and external factors (e.g., weather variation).

By the increasing and spreading of extreme weather events in recent years, agriculture is considered a vulnerable-risk activity. How farmers make decisions under uncertain scenarios is also influenced by their individual attitudes toward risk. Risk attitudes influence the decision-making in farmers' choice of livelihood strategies and affect household welfare (Hardaker, 2004; Verschoor et al., 2016).

Thailand and Vietnam are two emerging economies in Southeast Asia. In the last decade, their respective agricultural sectors have been undergoing profound changes. The share of agriculture income, in many cases, reduces beneath 50 percent of total household income (OECD-FAO, 2017). While, in general, world population growth is slowing down, Asia will still see considerable population growth, especially in less developed areas (FAO, 2017). Hence, promoting productivity in agriculture is vital, as the sector is a key source of employment for the poor and vulnerable population groups, especially in rural areas (FAO, 2017; Faostat, F.A.O., 2019). Furthermore, promoting agricultural productivity is critical to meet the needs of a global, ongoing expansion population and being a safety net in crisis situations (e.g., COVID19).

In addition, Thailand and Vietnam, are highly vulnerable to extreme weather events. Extreme weather events are predicted to become more frequent, severe, and longer-lasting (ADB, 2009) (IPCC, 2014a; Miyan, 2015). In rural areas of Thailand and Vietnam, most households cultivate small-scale farms and mainly use household labor. Thus, human capital plays a vital role in making the decisions that ultimately determine agricultural productivity. In some way, farmers can said to be caught between a "rock and hard place", i.e., whatever the decisions they take, nature may turn against them. Therefore, a better understanding the decision-making processes of small-scale farmers, subject to their knowledge, skills and education, as well as the presence of extreme weather events is needed and can provide the basis for better policies.

Overall, the aim of this thesis is to investigate the role of human capital (internal factors), in the context of increasing vulnerability to weather extremes (external factors), in influencing agricultural management behaviors of small-scale farm holders in rural areas of Thailand and Vietnam. More specifically, the thesis examines the determinants of farmers' risk attitudes and its impact on household livelihoods decision-making. Furthermore, the thesis studies the impact of education and knowledge on agricultural productivity. Investigating how farmers manage their input sources in the presence of extreme weather events takes center stage in this thesis. The thesis consists of three essays:

Essay 1: Risk attitudes and implication for livelihoods strategy – evidence from two provinces in Thailand and Vietnam.

Essay 2: Farmers' knowledge and farm productivity in rural Thailand and Vietnam.

Essay 3: Extreme weather and agricultural input management in rural Thailand and Vietnam: Intensify or de-intensify?

In the next section, the objective of each essay is introduced in more detail. The methodologies and data are presented in sections three and four. Sections five and six briefly present the results and conclusions. Finally, section seven illustrates the outline of the overall thesis.

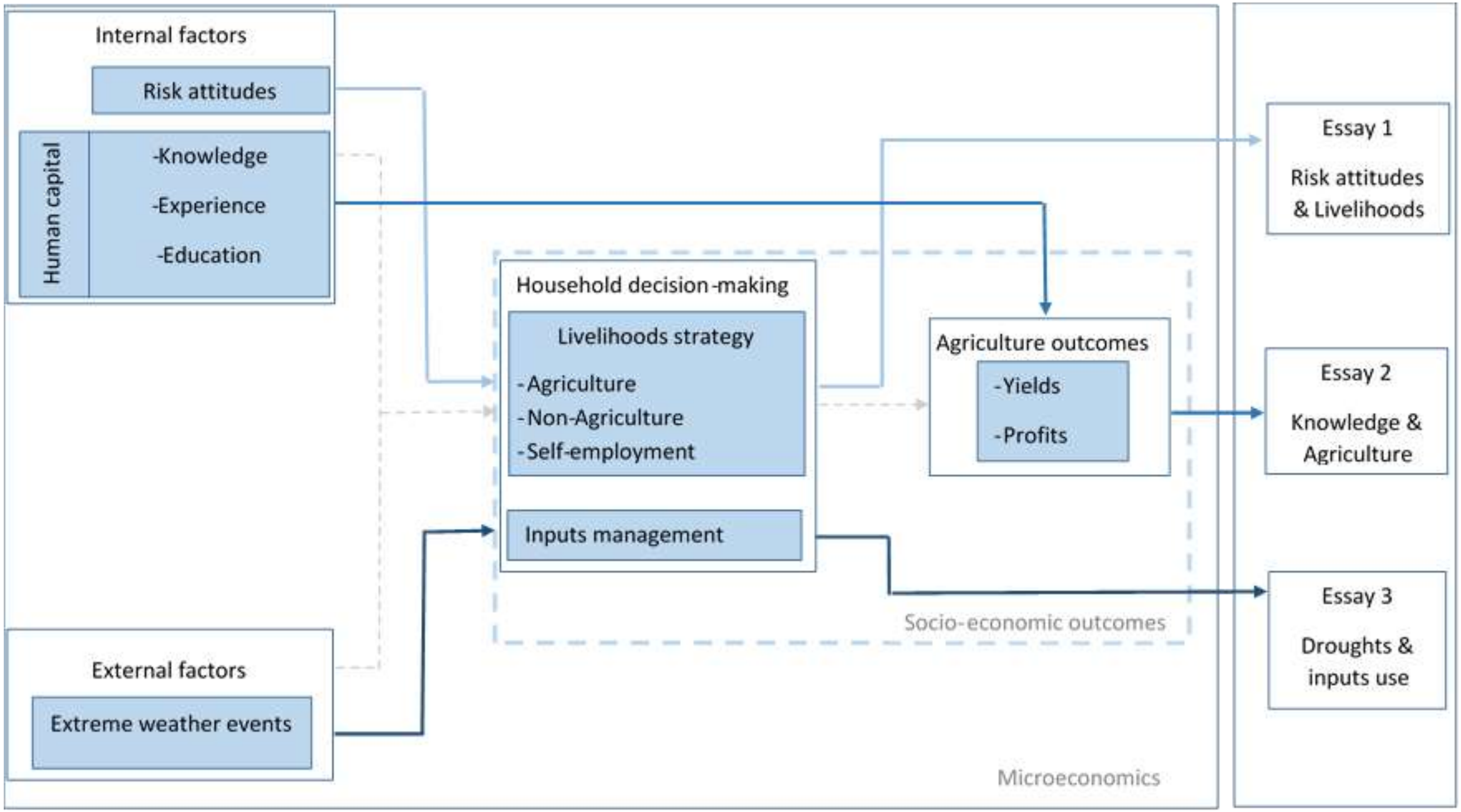

Figure 1. 1 Overall framework

Source: Own depiction

1.2 Objective

The overall objective of the thesis is to contribute a comprehensive understanding of farmers' decision-making on their livelihood strategies and agricultural production on the ground of either the external factors (i.e., extreme weather events) or the internal factors (i.e., knowledge and risk attitudes). The main goal is achieved in three essays contained in this thesis as follows:

The **first essay** addresses the issue of the correlation between the risk attitudes of farmers and livelihood decision-making in Ubon Ratchathani and Hue provinces of Thailand and Vietnam. Agricultural households are exposed to different types of risk and uncertainty ranging from weather variability, pest and diseases, the policy environment, and personal risks. All of these variables affect productivity gains, thereby influencing the overall welfare of these households (Hardaker, 2004; Verschoor et al., 2016). Following the literature, farmers who are living in a risky environment tend to be risk-averse (Yesuf & Bluffstone, 2009; Laajaj, 2011). Fearing risks and uncertainty not only prevents farmers from taking up opportunities, it can even keep farmers locked into non-action. Accurately measuring risk attitudes and preferences is challenging because these are unobservable on an independent, objective basis (Bruhin, A., Fehr-Duda, H., & Epper, 2010; Liu & Huang, 2013; Trujillo-Barrera et al., 2016). In such studies, respondents are asked to state their risk preference directly on a given Likert scale to measure risk attitude. Another methodology is an incentive-compatible experiment in which risk attitudes are elicited through observed behavior such as lottery, derived from economic theory and based on an utility function. Such experiments, however, are costly. The aim of the first essay is to understand the determinants of individual risk attitudes, especially the innate characteristics of small-scale farmers; validate the consistency of risk preference measures by using different methods, and, investigate how risk attitudes drive household livelihood decisions and agricultural production management behaviors. In particular, the essay aims to answer the following research questions:

(i) What are the determinants of individual risk attitudes?

(ii) How closely do different measures of a survey-based measure and an experimental measure correlate?

(iii) To what extent do the two measures predict respondents' real-life decisions?

In the **second essay,** the focus is to examine the impact of human capital on agricultural production in two provinces of Thailand and Vietnam. Human capital plays an essential role in decision-making which then drive the productivity of outcomes. Investigating the impact of human capital has long been mentioned in the economic development literature, mostly capturing formal education channels, i.e., schooling years. Based on a more thorough review of literature, however, it appears that the number of years in school might not be a precise parameter for capturing the role of human capital in agricultural activities (Card, 1999; Huffman, 2001; Pritchett, 2001; Ingram & Neumann, 2006; Behrman, 2010). In this essay, we examine the impact of farmers' knowledge and experience on agricultural productivity by applying tests for technical knowledge in agriculture and management skills. Thereby, the essay contributes to the literature in three ways. First, the study considers more adequate parameters beyond schooling years to measure knowledge and skills in agricultural productivity. Second, it examines these alternative indicators of human capital as they affect agricultural production. Third, the study investigates the correlation between the reason for decision-making and its outcomes. In detail, the second essay raises the following three research questions:

(i) What is the impact of technical knowledge in agriculture on agricultural production?

(ii) What is the explanatory power of alternative indicators of human capital on aspects of production?

(iii) What is the correlation between farmers' rationale of decision-making and the performance of agricultural activities?

The **third essay** investigates farmers' behaviors in the presence of extreme weather events in three provinces in Thailand and three provinces in Vietnam. As the first and the second essays focus on the impact of internal factors, this third essay focuses on the impact of external factors on agriculture management behaviors. In recent years, extreme weather events have increased, spread transboundary, and have seriously harmed human life in all sectors of the economy, especially the agricultural sector both in developed and developing countries (Hagman, 1984; Mendelsohn et al., 1994; Fisher et al., 2012; IPCC, 2014a; Miyan, 2015; Carter et al., 2018; Kunze, 2021). Investigating the adverse effects of extreme weather events on agricultural outcomes as well as farmers' adaptation strategies has become an important research topic (Wang et al., 2009; Schlenker & Lobell, 2010; Deschênes & Greenstone, 2012; Lesk, Rowhani, & Ramankutty, 2016; Gammans, Mérel, & Ortiz-Bobea, 2017). However, how farmers, especially small-farm holders in vulnerable regions, manage their agricultural inputs in response to these shocks is still unclear. In order to shed light on this aspect, the third essay investigates the effect of severe drought events on management of different farm inputs. More specifically, the third essay addresses the following research questions:

(i) Do farmers intensify or de-intensify agricultural inputs in response to extreme weather events in order to minimize economic losses?

(ii) What is the heterogeneity in this decision-making between (i) Thailand and Vietnam and (ii) agro-ecological zones?

1.3 Methodologies

To achieve the detailed objectives in the three mentioned-above essays, the thesis applies a number of theoretical and empirical methodologies that are briefly described in what follows.

In the **first essay**, the intent is to explore the determinants of risk preferences of small farm holders. An incentivized experiment – a paid lottery game is used to measure risk tolerance and test its predictive power. For this purpose, the implementation process of individual risk interpretation then followed the methodology of Dohmen et al. (2011) and Hardeweg et al. (2013). Two models are examined, and the empirical estimation proceeds in three steps. In the first step, the essay implements the Ordinary Least Square (OLS) strategy to empirically estimate the factors that influence the personal willingness to take risk and the effects of willingness to take risks on household decision-making; those decisions are binary variables. The personal willingness to take risks is measured by the monetary value of the safe option at the switched row in the lottery game. In the second step, the Ordinary Least Square (OLS) is also used to test how consistent risk attitude is in both risk measurement methodologies, i.e., traditional risk survey questions and paid lottery experiments. The experimentally elicited risk measure is the dependent variable, while the willingness to take risk variable, measured in the survey questionnaires, is the independent variable. In the absence of a valid instrument variable, we proceed with this empirical model with different specifications. Furthermore, the essay explores the correlation of risk attitudes across contexts by conducting Spearman's rank correlation coefficients. In the final step of this essay, a Probit regression is used as the dependent variables are the binary variables of alternative household livelihood decisions. In both models, the variables signifying respondents' risk attitudes are standardized by subtracting the sample mean and dividing by its standard deviation.

In the **second essay**, we identify the powers of the significant explanation of alternative indicators of human capital and the correlation of the decision-making's reason on agricultural activities. Based on the availability of variables in different survey waves, the essay uses an Ordinary Least Square (OLS) model for a pooled regression. The explained outcomes of the regression observed at a later point in time by regressors observed at an earlier point for the same identical households reduce the concern of endogeneity to some extent. We then also apply a Two-Stage Least Squares (2SLS) approach to test the implications of possible endogeneity.

In the **third essay**, we examine the impact of drought events on small-scale farmers' input management decisions. The analysis is based on monthly high-resolution (0.5) precipitation and temperature data from 1948 to 2016 from the Global Precipitation Climatology Centre (GPCC; Schneider et al., 2018), and the Global Historical Climatology Network Monthly - Version 2 and the Climate Anomaly Monitoring System (GHCN + CAMS; Fan & Dool, 2008) to calculate the Standardized Precipitation Evapotranspiration Index (SPEI) at sub-district level following Vicente-Serrano, Beguería, & López-Moreno (2010). We then relate the gridded precipitation and temperature data to the TVSEP household data using third-level administrative shape files representing all sub-district in our research locations. The main explanatory variable of interest – droughts are defined at two levels of severity: (i) a severe drought indicator that is equal to one if the SPEI is smaller than or equal to negative 1.5 standard deviations, zero otherwise, and (ii) an extreme drought indicator if the SPEI is smaller than or equal to negative two standard deviations, zero otherwise (Dai, 2011; Labudová, Labuda, and Takáč, 2017). The fixed effects model is then applied to investigate the correlation between drought severities and alternative indicators of input management decisions. In the empirical strategy, we control for household fixed effect, village fixed effect, and time fixed effect. Further, this essay also used a geographic information system (ArcGIS) to conduct topography variables (i.e., lowland and upland) and drought severity maps. All the econometrics analyses in each essay are written in Stata 15.

1.4 Data

This thesis mainly uses a primary dataset from the Thailand Vietnam Socio-economic Panel (TVSEP)[1] research project capturing individual household and village characteristics and two add-on lab-in-the-field experiments capturing responders' risk attitudes, knowledge, and skill management. Additionally, the essay uses satellite weather data to capture extreme weather events.

The long-term, comprehensive, and unique TVSEP project started in 2007 and spanned over a decade period in three provinces: Buri Ram, Nakhon Phanom, and Ubon Ratchathani, located in the Northeastern region of Thailand and in three provinces located in Central Vietnam, including Ha Tinh and Hue in the North Central Coast and Dak Lak in the Central Highlands. The TVSEP dataset includes comprehensive socio-economic information of these study areas, collecting identical households in multiple components over a long period. Households were selected from a stratified random sampling approach, which involves a three-stage clustering process that accounts for country-specific differences and captures the heterogeneity of agroecological characteristics (Hardeweg, Klasen & Waibel, 2013). The original sample of 4,400 households from 440 villages in 220 sub-districts represents the rural and vulnerable population in the purposely selected provinces with similar conditions. Two sets of questionnaires were used to collect information at the household and village level. The household questionnaire addresses the respective head of the household and infers information related to the socio-economic characteristics of each household member, e.g., occupation, health, and education. Furthermore, the survey contains a rich agricultural module, including detailed questions related to agricultural inputs and productivity. The village questionnaire captures information about the local economy within a village and its social structure by interviewing the village head. The detailed combined data used in each essay is elaborated as follows.

[1] https://www.tvsep.de/

Figure 1. 2 Study areas

Source: https://www.tvsep.de/en/project/survey-sites

The **first essay** uses a combined dataset of two standard survey waves of the TVSEP in 2013 and 2016 and an add-on risk survey in 2015. The latter involved 1200 households previously interviewed in Ubon Ratchathani province in Thailand and Hue province in Vietnam as part of the TVSEP project. In this risk survey, we used two measurements to capture individual risk attitudes: survey-based questions and lab-in-the-field risk game experiments. The survey-based risk question typically asks the respondent to rank their risk preferences subjectively using an eleven-point Likert scale of 0 – 10. The incentivized experiment is designed as a paid lottery game. The risk game questionnaires keep the same basic sections created in the TVSEP survey waves, and the risk game section is added at the end. After completing the questionnaires, respondents are asked if they are willing to participate fully in the incentivized experiment by the enumerator. The interview ends if the respondents do not want to participate in the experiment. The enumerators were specifically trained to ensure that the game's presentation to the respondents was as homogenous as possible. This process ensures that non-sampling errors resulting from enumeration interpretation and comprehension bias that arise from ambiguity in the wording of the game are minimized. After finishing the lottery game, the win option is noted and paid in cash at the end of the interview when the respondent finished all other incentivized games.

We then combined the risk game data to TVSEP survey waves from 2013 and 2016, which includes the base information of the respondents, households, and village's characteristics in 2013 and household decision-making regarding agricultural production in 2016 to have the full dataset of this essay's purpose.

In the **second essay**, a combination of data sets is used. The main explanatory variables of interest are extracted from a sub-sample of TVSEP households in the provinces of Ubon Ratchathani (Thailand) and Thua Thien Hue (Vietnam) in 2014. The particular survey focused on specific technical knowledge questions in agriculture as well as management choice tests. The sample was limited to rice farmers in the two provinces, which resulted from a total sample of 1,290 households. These data were combined with regular TVSEP survey waves in 2013 and 2017, i.e., before and after the knowledge tests. As in the first essay, data on respondents' characteristics, farm and household information as well as village characteristics from the 2013 survey, were used. Rice production performance data such as yield, revenue, and profit were derived from the 2017 survey.

The data used in the **third essay** come from two primary data sources. First, the individual-level panel data come from six waves over the last decade of the TVSEP project. In this essay, we use balanced household panel data collected in 2007, 2008, 2010, 2013, 2016, and 2017 from the same small-scale farmers located in the study's six sample provinces in Thailand and Vietnam. The overall attrition rate of the TVSEP survey over the decade is 13.88%. The basic information on household and village characteristics and input management decisions related to land and labor allocation, fertilizer use, pesticides, machinery, irrigation, and agricultural investment are obtained from household and village questionnaires, respectively. The second data source is monthly historical precipitation and temperature data from 1948 until 2016 to obtain the main explanatory variables of interest: drought severities. Further, using the Global Positioning System (GPS) information from the TVSEP, we then extract the elevation information from Digital Elevation Model (DEM) to define our lowland and upland rice farms.

1.5 Results

The **first essay** examines the individual risk preference of small-scale farmers using survey-based questions and incentivized experiments. The descriptive statistics from both measurements of risk attitudes (i.e., the based-survey questions and the incentivized experiment) show the heterogeneity of the willingness to take risks of farmers between Thailand and Vietnam. The results using the survey-based questions illustrate that the respondents in Vietnam are slightly risk-seeking with an overall sample mean of 6.050, greater than the median on the Likert scale. By comparison, Thailand does not show any particular trend of skewness to suggest risk-averse or risk-seeking behavior. Rather, the respondent seems to be clustered around the extreme two sides of the Likert scale, i.e., 0 and 10, with a sample mean value of 5.283. Our sample's descriptive statistics from Thailand is consistent with the previous study by Hardeweg et al. (2013). The descriptive statistics from the incentivized experiment closely mirrors the results of the willingness to take risk using the general survey question. The Spearman's rank correlation test shows the consistent correlation of self-assessed risk attitudes in different situations (i.e., general and financial decisions) and measurements (i.e., survey questions and lottery games). The overall message drawn from the descriptive statistics is that risk preference is context- and personality-specific.

We examine the determinants of respondents' innate characteristics (e.g., age, gender, and height) on the willingness to take risks. The results show gender impacts in the same direction on the respondents' willingness to take risk (WTR) in both countries. However, the impact of age is significantly associated with WTR in Thailand but is insignificant in Vietnam. Regarding respondents' height, the results show significance in Vietnam and are insignificant in Thailand. This essay's results align with the findings of Dohmen et al. (2011); Liu, (2012), and Gloede et al. (2015).

Further, the empirical econometrics investigating the correlation between WTR with actual decision-making of rural households indicate that the WTR is significantly associated with the behavior of the respondents in Thailand and Vietnam. The direction of these impacts has commonalities and differences between the two countries. For example, Thais were likelier to be decisive, and that could motivate their participation in self-employment, but no such effect was found for the Vietnamese. However, in terms of agriculture investment decisions, one standard deviation of the respondent's WTR increases the likelihood of investing in agricultural production by approximately 4% across both countries. These results are robust across alternative specifications of the model.

The **second essay**, conducting technical knowledge and skills, financial literacy and decision-making tests, aimed to examine the correlation between better human capital indicators on the performance of agricultural activities. The results show that knowledge and experience as a proxy of human capital have an impact on the performance of rice production. More specifically, farmers with higher technical knowledge in agriculture and more farm experience obtain higher profits with, at the same time, fewer input costs albeit lower rice yields. It is remarkable that farmers with higher formal education and higher financial literacy scores are less successful in rice farming. They experience lower profits, higher input costs but higher yields which obviously do not pay off.

In the **third essay**, the results show that extreme weather events significantly impact small-scale farmers' agricultural management behaviors. This essay aims to answer the question: do farmers intensify the use of agricultural inputs according to drought severity events in order to minimize yield losses? Or do they reduce the use of inputs to save on production costs? Overall, the results indicate that farmers, on the one hand, tend to de-intensify agricultural production in terms of hired labor, pesticides, the number of crops grown, and agricultural durable good investments in response to severe droughts. On the other hand, farmers increasingly hire machinery as a substitute for their own investment and own household labor. The magnitude of these effects increases as the severity of drought increases. By capturing all alternative inputs of agricultural activities, our findings are both different and similar to other studies around the world by Koundouri et al., (2006), Alem et al., (2010), Reidsma et al., (2010), Praneetvatakul, Phung, and Waibel (2013), Aragón, Oteiza, and Rud's (2018), Auffhammer and Kahn, (2018). Taken together, these variabilities in findings demonstrate that agricultural management behaviors of farmers under the stress of extreme weather events are local.

Further, investigating the heterogeneity between two countries and the different altitudes (i.e., lowland and upland rice) shows the variety of de-intensification levels. For example, while responses in terms of own household labor, irrigation, fertilizer, and machinery use remain robust, the responses tied specifically to extreme droughts are different in terms of land intensity, pesticide use, and investments in durable agricultural goods.

1.6 Conclusion and policy implications

The thesis has studied the behaviors of small-scale farmers in Southeast Asia taking into account both internal (i.e., risk attitudes, knowledge) and external factors (i.e., extreme weather events). Based on the empirical results of the three essays, some general conclusions and policy recommendations are drawn.

The conclusion from the **first essay** is that a general survey-based question is an acceptable method for investigating a farmer's risk preference and its impact on the decision-making. Moreover, risk attitudes are personal- and context-specific. Risk attitudes are significant predictors of decision-making in terms of income generation and agricultural management choices. Since individual participation in higher return activities is found to be positively associated with risk attitudes, one policy implications is that improving insurance against risk can provide financial cushions, and may reduce the fear of loss. This can stimulate farmers' participation in riskier but potentially higher returns from income-generating activities. A second recommendations is that in general agricultural policy should aim to reduce the risks inherent in small-scale agriculture. For example, providing reliable irrigation and better extension services can help farmers to take more rational and judicious management decisions for the benefit of long-term food security.

The most important conclusions of the **second essay** are that human capital plays an essential role for small-scale rice farmers. Therefore, given the rising challenges for agriculture due to climate change, rising energy prices, and other uncertainties, it is important that governments strengthen human capital in rural areas. More qualified and motivated extension workers who can offer good training, the provision of adult education programs in rural villages, combined with improving information-communication technologies are key contributions that governments in the two countries can make for a better future of agriculture and the rural areas in general.

In the **third essay**, the empirical results show that farmers de-intensify their agricultural input under the stress of extreme weather events in order to reduce production costs. Farmers, in most cases, reduce the number of crops grown, expenditure for irrigation, and investment in agricultural assets. However, our results raise concern that the uncertainty of agricultural production and income will increase in the future, with detrimental effects for food security. Therefore, policy makers expand the scope of social protections by including, for example, community-level emergency funds and affordable crop insurance schemes based on weather indices. Furthermore, rehabilitation investments of existing irrigation schemes or establishing new irrigation systems wherever possible and ecologically justifiable. Since most farms in our research areas, especially in Thailand, are rain-fed farms. Most importantly, water in agriculture must be used much more efficiently than in the past. Policymakers should also improve drought information by supporting drought mapping, forecasting, and establishing early warning systems at the district or communal level.

1.7 Outline

The thesis used the Thailand and Vietnam Socio-Economic Panel (TVSEP) dataset between 2007 and 2017. The author was part of the TVSEP team, participating in the development of most of the project's processes: formulation of questionnaires, data collection, data cleaning, data processing, data visualization, project coordination, administrative management, and personnel recruitment. In particular, the author was entirely responsible for conducting the lab-in-the-field experiment in 2015, coordinating the 2016 survey in Vietnam, and technical support for the survey in Thailand. In 2017, the author supported data cleaning and managed a data-checking team and personal recruitment for the national research data collection center in

Vietnam. In addition, the author was a member of the data cleaning of the TVSEP surveys from 2014 to 2017. These efforts contributed significantly to the TVSEP database, a valued resource for researchers and scholars all over the world, and the scope of which goes well beyond this thesis.

The three essays are arranged in three chapters according to the topic from chapters two to four. The overview of these essays is demonstrated in Table 1.1. The author contributed to the chapters as follows:

Chapter 2 contains the **first essay:** “Risk attitudes and implication for livelihoods strategy – evidence from Southeast Asia.” In this essay, Huong Jaretzky processed the data, cleaned data, estimated the empirical model, and wrote the manuscript. Alirah Emmanuel Weyori and Sabine Liebenehm gave advice and provided comments on the essay content.

The **second essay**, titled: “Farmers’ knowledge and farm productivity in rural Thailand and Vietnam” is organized in Chapter 3. Huong Jaretzky cleaned and processed the data, estimated the empirical, and finished the manuscript. Sabine Liebenehm gave advice on the methodology and provided suggestions for the paper. Prof. Dr. Hermann Waibel provided suggestions and comments on the paper.

The **third essay** is included in Chapter 4 with the title: “Extreme weather and agricultural input management in rural Thailand and Vietnam: Intensify or de-intensify?”. Huong Jaretzky participated in the household surveys in 2016, prepared and processes the dataset of other survey waves included in the analysis, estimated the empirical, and wrote the manuscript. Sabine Liebenehm advised on the model setup and provided suggestions and comments on different aspects. Prof. Dr. Hermann Waibel gave comments and suggestions.

Table 1.1 Overview of the essays

Essay	Title	Authors	Status
1	Risk attitudes and implication for agricultural investment evidence from Southeast Asia	Huong Jaretzky, Alirah Emmanuel Weyori, Sabine Liebenehm,	Earlier version presented at: Tropentag Conference: Global food security and food safety: the role of University, 17 – 19 September, 2018, Ghent, Belgium.
2	Farmers' knowledge and farm productivity in rural Thailand and Vietnam	Huong Jaretzky, Sabine Liebenehm, Hermann Waibel,	Presented at: Seminar International Doctoral Studies, November 11, 2019, Hannover, Germany Published working paper at: Hannover Economic Paper (HEP). Number 702, Nov 2022, pp.32
3	Extreme weather and agricultural input management in rural Thailand and Vietnam: Intensify or de-intensify?	Huong Jaretzky, Sabine Liebenehm, Hermann Waibel,	Paper under review at: Agricultural Economics (2022) Presented at: The 10th Asian Society of Agricultural Economists (ASAE), international conference, 6– 8 December, 2022 Beijing, China The international TVSEP conference on Shocks and Resilience in rural southeast Asia, 23- 24 May, 2022 Göttingen, Germany The IFAD Conference 2022 "Jobs, innovation and rural value chains in the context of climate transition: Bridging the gap between research and policy, 21 – 24. June 2022, Rome, Italy The Asian Economic Development Conference (AEDC),international conference, 14 – 15 July, 2022 Tokyo, Japan

Source: Own illustration

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CHAPTER 2: RISK ATTITUDES AND IMPLICATION FOR LIVELIHOOD STRATEGIES- EVIDENCE FROM TWO PROVINCES IN THAILAND AND VIETNAM

Earlier version of paper presented at:

Tropentag Conference: Global food security and food safety: the role of University September 2018, Ghent, Belgium.

Abstract

Risk and uncertainty play an essential role in almost every economic decision in a rural household's life. Understanding risk attitudes and how they relate to livelihood decisions is thus essential for the structural transformation of rural economies, especially in South East Asia. Combining representative rural household survey data with incentivized risk experiments involving some 1,200 respondents, we investigate risk attitudes and how such attitudes explain real-life decisions of rural households in the Ubon and Hue Provinces of Thailand and Vietnam. The results show that risk attitudes are significantly determined by individual characteristics such as age, gender, height, and wealth. We further find results that show a correlation between real-life decisions and risk attitudes. Our results show that risk-seeking individuals spread their investment across sectors that could be a form of informal hedging system against risk. They invest more in agricultural production while at the same time diversifying into self-employment and other non-farm enterprises.

Keywords: Agriculture, risk attitudes, experiments, Thailand and Vietnam

JEL codes: C9, D9, 015

2.1 Introduction

Risk and uncertainty are critical factors impacting household economic decisions, especially for agricultural households in developing countries characterized by uninsured risks, imperfect or even missing markets. Agricultural households are exposed to different types of risks ranging from weather variability, pests and diseases, market prices (both output and input), the policy environment, and personal risks, sometimes inhibiting productivity gains and affecting the welfare of these households (Hardaker, 2004; Verschoor et al., 2016). For example, risk and uncertainty not only limit participation in high return opportunities but in the long-term, it can also keep households perpetually in deprivation because of the level of investment and inputs used by these households. In this regard, understanding risk preference and attitudes and factors that drive these critical determinants of livelihood outcomes is important for improving the resilience and welfare of poor and vulnerable households. This is against the background that developing countries, especially rural areas, are exposed to greater adverse risk events yet often lack resourced and functioning rural infrastructure (Haushofer and Fehr, 2014). To sustain their livelihoods, it is compelling to understand how agricultural production decisions related to input use and income diversification are linked to risk attitudes.

Although the study of risk and farm decisions is not new, studies that investigate and explicitly link risk attitudes to resource allocation or farm investment largely remain inconclusive (Binswanger, 1980; Tanaka et al., 2010; Charness et al., 2013). Empirical studies broadly rely on one of two methods, i.e., (i) survey-based method and (ii) incentivized experiments. While the measurement of risk attitudes remains topical to behavioral researchers, how much risk attitudes predict real-life decisions is of even greater interest for understanding behavioral patterns as it concerns rural household development. Yet, only a few studies go beyond validating different elicitation methods and link risk measures to real-life decisions (Dohmen et al. 2011, Hardeweg et al. 2013, Gloede et al. 2015). This is notwithstanding the fact that a number of studies show that small-scale farming households are rational economic agents whose occupations and investment decisions can partly be explained by their perception of risk or attitudes to risk (Feder et al., 1985; Isik and Khana, 2003; Duflo et al., 2011; Dercon and Christiaensen, 2011; Menapace et al., 2012; Liu, 2012; Liebenehm and Waibel, 2014; Barham et al., 2014). Thus, a number of important and lingering questions remain to be answered relating to risk and real-life decisions. For example, does it matter how risk attitudes are elicited and does an individual's risk attitude explain farm investment decisions, choice of employment, or resource allocation? The objective of this study is to contribute to answering these pertinent empirical questions in a three-dimensional way. First, we determine the drivers of risk attitudes of rural households in UBon (Thailand) and Hue (Vietnam) using Dohmen's et al. (2011) survey-based measure. We particularly emphasize innate variables' role in determining an individual's risk attitude. Second, we validate the outcome of the survey-based question adjusted to different situations using the incentivized lottery experiment. In line with earlier studies, Bonin et al. (2007), Caliendo et al. (2009), Jaeger et al. (2010), and Dohmen et al. (2011), we contribute to a growing literature that aims to validate the use of survey-based measures to elicit risk. Finally, using our respondents' typical farm investment and employment data, we link elicited risks attitudes to real-life decisions to explain such behavioral patterns.

Our results show that rural Ubon and Hue are generally heterogeneous regarding risk preference, suggesting that risk attitudes are context and person-specific. Also, our results show that risk attitudes elicited using survey-based questions compare favorably with the incentivized risk experiment outcomes. Finally, our results show that individual risk attitudes can predict real-life farm decisions to a greater extent. Specifically, the results show that risk attitudes are positive and significant in explaining farm investment, purchasing and using chemical inputs (fertilizer and pesticide), and off-farm income-generating activities, including self-employed and non-farm enterprises.

The rest of the paper proceeds as follows. Section 2 briefly looks at the literature on risk elicitation. Section 3 presents the data and methodology—the study design of the experiment and the data collection process. Also, the data description is presented in this section. Next, section 4 describes the empirical estimation strategy. Section 5 presents the results and discussion. Finally, section 6 summarizes and concludes the paper with policy implications.

2.2 Elicitation of risk attitudes

Measurement of risk attitudes has been studied a lot in the empirical literature, however, because of the critical role of risk in agriculture in developing countries, the topic remains relevant to policymakers and development economists (Just and Just, 2016; Iyer et al., 2020). This is especially important given the divergent conclusions that are often reported in the literature (Bruhin, A., Fehr-Duda, H., and Epper, 2010; Liu and Huang, 2013; Trujillo-Barrera et al., 2016). Measurements of individual risk attitudes can be categorized into one of two categories, i.e., (i) survey elicitation, where respondents are asked to state their willingness to take risk on a Likert-scale, and (ii) experimental elicitation through incentivized lotteries

(Moscardi and de Janvry, 1977; Binswanger, 1980; Pennings and Garcia, 2001; Dohmen et al., 2011). These methods, like any social research method, have their strengths and weaknesses. For example, whereas the survey methods may be relatively easy and inexpensive to implement, concerns related to context-dependent nature likely confound these measures making them a less desirable stand-alone risk attitude measure. Experimental methods, on the other hand, although an incentive-compatible measure less likely to be driven by contextualization issues, costs related to implementing experiments on a large scale reduce their desirability. This drawback discounts their ability to pass the external validity test (Binswange, 1980; Camerer and Hogarth, 1999; Eckel and Grossman, 2008). These shortcomings have given rise to a school of thought arguing for the combination of methods to increase the acceptability, robustness, and efficiency of risk attitude measures. The proponents of such a combination continue to argue that a proper measurement of individual risk attitudes would improve the understanding of how and why many resource-poor farmers in rural areas behave the way they do. This can explain the reasoning behind the use or non-use of certain farm technologies or risk mitigating tools in an environment that is increasingly exposed to uninsured risk events. In recent times, several studies have combined survey-based measures and incentivized experiments, for example, Dohmen et al. (2011) in Germany and Hardeweg et al. (2013) in Thailand. Two important conclusions can be drawn from these studies. First, the results of the survey-based instrument are validated by incentivized experiment results. Second, some real-life decisions are explained by risk attitudes. Together these results serve as a motivation to extend and investigate risk elicitation methods in developing country contexts such as Thailand and Vietnam. In the next section, we present the data and experimental setup in the field.

2.3 Data and method

2.3.1 Data setting and description

The study is based the Thailand Vietnam Socioeconomic Panel (TVSEP) data (https://www.tvsep.de). The TVSEP data set is a long-term panel of a nationally representative sample of 4,400 households selected following a multistage random procedure across 440 villages in six provinces in rural Thailand and Vietnam that started in 2007[2]. The data set

[2] For a detailed description of the sampling procedure and how the questionnaire has been administered, see Hardeweg et al. (2013).

includes comprehensive socio-economic and behavioral information of households that have been collected through a standardized household survey instrument and is repeated every two to three years. However, for the purposes of this current study, we rely primarily on TVSEP data from 2013 and 2016 and an add-on risk attitude survey conducted in 2015.

The add-on risk attitude survey involved a sub-sample of 1,200 households that were previously interviewed as part of the TVSEP project, i.e., 649 from Ubon Ratchathani (Thailand) and 551 from Hue (Vietnam). The risk survey elicited risk attitudes of respondents using two different methods, namely Dohmen et al. (2011) survey question and an incentivized experiment. The 2015 risk attitude data were then merged with the TVSEP panel data from 2013 and 2016 that involves information on respondents' socio-demographic characteristics and further important information at household and village level. Our data set is hence structured in a way that respondents' risk attitudes and their socioeconomic characteristics are not observed in the same period. More specifically, we use respondents' sociodemographic characteristics from 2013, whereas respondents' decision-making has been observed in 2016. In this way, our data presents some unique advantages for our empirical analysis particularly in addressing concerns of endogeneity between risk attitudes and real-life behaviors. This issue will be dealt with in more detail in the empirical sections. Next, we present the two risk attitude measures.

2.3.2 Survey-based and experimental measure of individual risk attitudes

Dohmen et al.'s (2011) survey-based risk question typically asks the respondents to rank their willingness to take risk using an eleven-point Likert scale between zero and ten, where a value of zero corresponds to "unwilling to take risk", and ten is "fully prepared to take risk." The risk preference question is formulated as follows: "Are you generally a person who is willing to take risk, or do you try to avoid risks?". The given response is then captured as the respondents' general Willingness to Take Risks (WTR). In addition to this general formulation, another survey-based measure was formulated to capture the behavior of respondents with respect to the specific scenario of taking financial decisions. More specifically, the survey question regarding financial decisions was formulated as "When thinking about financial decisions, are you a person who is fully prepared to take risk or do you try to avoid taking risk?"[3].

[3] See Table 2.A1 in the Appendix for the detail.

The incentivized experiment was designed as a paid lottery game[4]. After completing the survey questionnaire, all respondents were introduced to the experiment with an option to participate or not. In total, only four households in Ubon Ratchathani chose not to participate and were excluded from the analysis. The experiment was set up as a table with 20 rows, whereby each row corresponded to a choice between a lottery (Option A) and a sure amount (Option B). Row by row, the sure amount increased, whereas the lottery remained the same (Table 2.A2 in the Appendix shows the incentivized lottery game as presented to the respondents). As such, row by row, the enumerator then asked the respondent what option she prefers, an unknown outcome in rows of option A or a known outcome in rows of Option B. As a means of inducing the interest of the respondent, the monetary amounts are set such that they are greater than the official daily minimum wage in each country. For example, in the first row, the participant had to decide whether they prefer to play the "lottery" (Option A) that involves a 50:50 chance to win either THB 0 (VND 0) or THB 300 in Thailand (VND 200,000 in Vietnam) or the safe amount (Option B) with 0 gains[5]. In total, the respondent had to make 20 choices. The row number at which the respondent prefers the sure amount, i.e., where she switches from Option A to Option B, represents her individual measure of certainty equivalent, where the respondent is indifferent between the lottery and the sure amount. For interpretation, if someone switched to the sure amount before row 11 in Ubon (16 in Hue), she would be considered risk averse as her certainty equivalent is smaller than the lottery's expected value, risk-seeking otherwise. After all 20 choices were made, the respondents' payoff from the experiment was randomly determined.

A number of steps are adopted throughout the experiment to reduce possible confounding and ambiguity bias. A rigorous enumerator training was organized to ensure homogeneity in interpretation and presentation of the experiment to respondents in the field. The training was implemented over six days, it involved role games and pre-tests in the respective study areas not involved in the analytical sample. In this way, non-sampling errors caused by enumerator interpretation and comprehension are minimized. The experiment only started if the respondent fully understood the rules and gave her consent.

[4] For the purposes of this study, respondents who did not agree to participate in the lottery game have been excluded in the analysis to ensure consistency from using data of the same respondents across the survey and the incentivized experiment.

[5] Using 2015 as the base year, this corresponds to PPP$14.79 and PPP$17.44 for Ubon and Hue, respectively.

2.3.3 Summary statistics of individual and household characteristics

Table 2.1 below shows the summary statistics for some selected key variables. As explained earlier, village, household, and respondent characteristics are based on the 2013 TVSEP survey data.

The demographic characteristics of the sample show significant differences: age, gender, education, religion, health conditions, self-employment and total assets value. A significant number of respondents (more than 90%) in both provinces, have access to paved roads and live on average 13km away from the district capital.

Table 2.1 Descriptive statistics of control variables

	Ubon	**Hue**	**Difference**
Respondent characteristics (2015)			
Age (years)	60.39(12.00)	54.81(13.28)	-7.82***[b]
Female (1=yes)	0.32(0.46)	0.20(0.40)	17.97***[c]
Height (cm)	159.53(8.167)	160.06(7.39)	1.31[b]
Other characteristics (2013)			
Education (schooling years)	5.01(2.81)	5.35(3.79)	2.28**[b]
Religion (Buddhist=1)	0.99(0.070)	0.20(0.40)	812.44***[c]
Marital status	2.14(0.48)	2.14(0.44)	0.67[b]
Health conditions	0.84(0.36)	0.67(0.47)	14.27***[a]
Self-employment (1=yes)	0.06(0.23)	0.11(0.32)	12.82***[c]
Dependency ratio	0.67(0.73)	0.66(0.67)	0.49[b]
Total assets value ($PPP)	6303.50(10989.8)	935.59(2339.38)	-12.95***[b]
Weather condition (SPEI)	-1.59(0.24)	-1.33(0.10)	-2.82**[b]
Paved road (1=yes)	0.97(0.18)	0.90(0.30)	24.78***[c]
Distance from villages to district towns(km)	15.53(9.55)	11.16(8.74)	-8.79***[b]
N	**649**	**551**	

Note: Standard deviation in parenthesis. [a]T-test, [b]non-parametric two-sample tets: Wilcoxon-Mann-Whitney test, [c]Chi square test, and triple asterisks (*, **, ***) denote p < 0.10, 0.05, and 0.01 significance respectively
Source: Authors' calculations

Next, Figure 2.1 presents a histogram of the willingness to take risk survey question, whereas the left side of Figure 2.1 represents the responses of Vietnamese respondents, while the right-hand side represents Thai respondents. Casually looking at the bars for Hue show as left-skewed distribution, where the most frequent willingness to take risk response is larger than the overall mean of 6.050. This result suggests slight risk-seeking behavior of respondents in Hue. Ubon Ratchathani, on the other hand, does not show any particular trend of skewness to suggest risk-averse or risk-seeking behavior. Rather, the responses seem to be clustered around the extreme ends of the Likert scale, i.e., 0 and 10, with a sample mean value of 5.283. Our sample's descriptive statistic is consistent with studies by Hardeweg et al. (2013), who describe Thai farmers as decisive.

Figure 2.1 Respondent's self-assessment of willingness to take risk based on the survey based Question, "On a scale of 0-10, are you generally willing to take risk or do you try to avoid risk?". 0 (unwilling to take risk) to 10 (fully prepared to take risk)

Source: Authors' calculations

The results of the incentivized lottery game are shown in Table 2.2. The distribution of risk attitudes from the incentivized experiment mirrors to some extent the results of the general willingness to take risk survey question. For example, 63% of respondents in Hue opt for the safe amount before row 16 – the risk neutrality point[6]. In Ubon, approximately 75% of the respondents prefer a safe option before the risk-neutral value corresponding to row 11. This

[6] The risk-neutral row in this game setup is given as the row in which the safe payout amount is equal to the value of the expected lottery outcome (50% of the lottery game value). Row 11 in Ubon and 16 in Hue.

suggests that Vietnamese respondents are, on average, slightly more risk-seeking than Thais, similar to what we concluded from the survey-based measure. Second, there is the tendency for extreme choices (i.e., the first row and the last row) among Thai respondents, as there are around 5% of participants declined the lottery (Option A) even though they gained nothing with the safe amount (Option B). The respondents explained that they had never played any lottery, so they did not want to play. In contrast with respondents who never play any lottery, a relatively large group of 124 participants (i.e., around 20%) insist on playing the lottery, neglecting how much they may receive in the safe option.

Table 2.2 Outcome of the lottery game experiment

		Lottery Payoffs		**Ubon**		**Hue**	
Row switched	**Safe amount**	**ρ= 0.5**	**ρ=0.5**	**Frequency**	**Cumulative frequency**	**Frequency**	**Cumulative frequency**
1	0	0	300/200[a]	34	5.24	4	0.73
2	10	0	300/200[a]	104	21.26	50	9.80
3	20	0	300/200[a]	40	27.43	55	19.78
4	30	0	300/200[a]	29	31.90	38	26.68
5	40	0	300/200[a]	14	34.05	35	33.03
6	50	0	300/200[a]	35	39.45	55	43.01
7	60	0	300/200[a]	20	42.53	36	49.55
8	70	0	300/200[a]	10	44.07	26	54.26
9	80	0	300/200[a]	19	47.00	26	58.98
10	90	0	300/200[a]	19	49.92	26	63.70
11	100	0	300/200[a]	77	61.79	79	78.04
12	110	0	300/200[a]	18	64.56	17	81.13
13	120	0	300/200[a]	22	67.95	16	84.03
14	130	0	300/200[a]	13	69.95	12	86.21
15	140	0	300/200[a]	7	71.03	7	87.48
16	150	0	300/200[a]	25	74.88	21	91.29
17	160	0	300/200[a]	7	75.96	8	92.74
18	170	0	300/200[a]	11	77.66	4	93.47
19	180	0	300/200[a]	7	78.74	6	94.56
20	190	0	300/200[a]	14	80.89	11	96.55
21[b]	200			124	100.00	19	100.00
N				**649**		**551**	

Note: Monetary value in local currency is BATH in Thailand and VND in Vietnam. 300/200[a]: The number of this option is 300 BATH in Thailand and is 200 VND in Vietnam. 21[b]: Respondents insist on staying in the lottery game at any given level of the same amount of value
Source: Authors' calculations

Since we investigate how real-life decisions are linked to risk attitudes, we summarize some critical outcome variables that reflect real-life decisions of respondents in the study area. The real-life decisions include occupation choices such as self-employment, non-agricultural enterprises, investment in agriculture, or land rental for agricultural production. The outcome variables, together with their summary statistics, are shown in Table 2.3. All variables in Table 2.3 were constructed using the 2016 TVSEP survey data set. Table 2.3 shows that self-employment is relatively low among respondents across the study area. Approximately 8% of respondents were self-employed in 2016. Furthermore, about 28% of respondents in Ubon and 29% in Hue invested in agricultural production, such as fertilizer, machinery, and hired labor. In terms of purchasing chemical inputs (i.e., fertilizer and pesticides), the data showed that respondents spent on average PPP$221 and PPP$525 per ha in Ubon and Hue to enhance agricultural production. On the other hand, 17% and 13% of respondents in Ubon and Hue respectively had indicated that they made any form of investment in non-agricultural enterprises. These statistics clearly show how respondents perceive the role of agriculture compared to non-farm enterprises, as explained by the resource allocation by way of investments in the two sectors of the rural economy. The main inference from Table 2.3 is that rural Ubon and Hue are structurally agrarian with less diversification outside agriculture. A significantly higher proportion of respondents in Ubon rent-out land and invest in non-agricultural enterprises compared to Hue. However, respondents in Hue spend more on agricultural inputs than compared to respondents in Ubon.

Table 2.3 Descriptive statistics of alternative dependent variables

	Ubon	**Hue**	**Difference**
Decision making (2016)			
Self-employment (1=yes)	0.08(0.27)	0.08(0.27)	0.02[c]
Agricultural investment (1=yes)	0.28(0.45)	0.29(0.45)	0.36[c]
Agricultural land rent out (1=yes)	0.12(0.32)	0.09(0.28)	6.12**[c]
Non-agricultural investment (1=yes)	0.17(0.38)	0.13(0.33)	4.21**[c]
Costs of fertilizer and pesticides per hectare (PPP$)	221.17(177.65)	525.00(739.83)	8.15***[b]
N	**649**	**551**	

Note: Standard deviation in parenthesis. [b]non-parametric two-sample tets: Wilcoxon-Mann-Whitney test, [c]Chi square test, and triple asterisks (*, **, ***) denote p < 0.10, 0.05, and 0.01 significance respectively
Source: Authors' calculations

Since our sampled respondents are small-scale farmers facing depleting soil fertility, the use of fertilizers may be considered a risk mitigating strategy to boost crop productivity, a key livelihood strategy of these rural households. As argued by Verschoor et al. (2016), investing in agriculture should both raise the expected value and reduce the variability of farm outcomes.

Investing in inputs such as fertilizer is expected to increase productivity on one hand while serving to reduce income volatility arising from poor harvests. In the next section, we present the empirical estimation strategy followed by an investigation of the determinants of observed heterogeneity in risk attitudes and how this can explains real-life decisions.

2.4 Empirical estimation strategy

Our empirical estimation proceeds in three steps. In the first step, we investigate the correlation between our survey-based measure of willingness to take risk and respondents' socio-economic characteristics. We employ a simple Ordinary Least Square (OLS) strategy for practicability and ease of implementation as follows:

$$WTR_i = \alpha + \beta X_i + \gamma Z_i + \delta V_v + \varepsilon_i \qquad (1)$$

where WTR_i is the standardized[7] response of respondent i's WTR at the time of 2015. As described earlier, our cross-sectional data set contains information observed at different points in time. As such, X_i represents a set of time-invariant characteristics observed at the same time as the WTR response in 2015 including age, gender, and height. Z_i is a vector of time-variant characteristics at respondent level, (including education, Buddhist religion, marital status, health conditions and occupation), and at household level (including dependency ratio and the depreciated value of total household assets), V_v is a vector of time-variant village characteristics such as access to paved road, the distance to district capital and weather conditions (SPEI). Z_i and V_v were observed in 2013. ε_i is the error term. Standard errors are clustered at the household level.

We implement different specifications of the equation, (i) a baseline specification that includes only the respondent's age, gender, and height; (ii) a specification that includes the baseline variables plus two variables that controls the respondent's wealth and religion. A number of studies have shown that a household's wealth can determine the risk perception and attitudes towards risk (Dohmen et al., 2011; Hardeweg et al., 2013). Theoretically, the relationship between wealth and WTR can occur in one of two possible ways; greater wealth increases the willingness to take risks, and on the other hand, increased willingness to take risk may also increase the respondent's wealth. Therefore, including the wealth in the estimation raises concerns of a confounding bias as a result of the reverse causality between risk and wealth. A

[7] Willingness to take risk is standardized by subtracting the sample mean and dividing by its standard deviation.

two-stage estimation of this specification should have been followed to address the potential endogeneity issue. However, in the absence of a strong and verifiable instrument, in our case, we rely on the novel nature of our data to address this possible endogeneity issue. Instead of regressing risk attitudes on current wealth, we rather use lagged wealth variable, which was measured two years before the risk survey. In this case, we assume there is no correlation between present WTR and retrospective wealth outcome. The wealth indicator is a log-transformed value of total depreciated assets of the household, while religion is a binary variable equal to one if the respondent is Buddhist and zero otherwise[8]. We assume that the religion variables control for possible cultural heterogeneities, its conclusion enhances the understanding of risk attitudes across the cultural cast, and (iii) a final specification to include all possible control variables based on the risk literature (Binswanger, 1980; Persico et al., 2004; Harrison et al., 2010; Tanaka et al., 2010; Dohmen et al., 2011; Hardeweg et al. 2013). This specification is done as a robustness check for our main variables of interest in the first and second specifications.

In the second step of our empirical strategy, we test whether the survey-based risk question can predict the outcome of the incentivized risk experiment. To do so, we estimate the following equation:

$$SR_i = \sigma + \alpha WTR_i + \beta X_i + \lambda Z_i + \delta V_v + \mu_i \qquad (2)$$

where, SR_i is the standardized value of the row at which the respondent switched from the lottery to the sure amount. WTR_i is the standardized willingness to take risk response of the i^{th} respondent with mean 0 and standard deviation 1. X_i, Z_i, and V_v are defined as in equation 1. The error term μ_i is clustered at the household level. Although equation 2 may likely suffer simultaneity bias between SR_i and WTR_i, we are interested in the correlation of the two variables. We proceed to estimate equation 2 as an OLS sequentially in different specification: (i) a baseline specification using only the WTR_i variable as the main predictor variable, (ii) a second specification adding time invariant controls such as age, gender, and height of the respondent, (iii) a third specification with all other control variables.

In the third and final step of the empirical analysis, we aim to answer whether risk attitudes, either measured through the survey-based measure or through the incentivized experiment can explain respondents' real-life decision-making. We estimate the following model:

[8] We capture the most popular religion in both countries. Vietnamese are mostly non-religious, but Buddhism is prevalent, especially in Hue.

$$Y_i = \alpha + \beta RA_i + \lambda HV_{iv} + \varepsilon_i, \qquad \varepsilon_i \sim N(0,1) \tag{3}$$

Where, Y_i is an index of observed behavioral outcomes such as self-employment, investment in agriculture or non-agriculture enterprises, agricultural land rent-out, and amount spent on fertilizer and pesticide purchases of the i^{th} respondent in 2016. These variables are all estimated at binary levels, i.e., equals to 1 if the respondent answers yes to any of the outcome variables above respectively, and zero otherwise, except for the monetary variable of purchasing chemical inputs. RA_i is respondents' risk attitude measured as the standardized willingness to take risk measure from the survey-based measure or as the switching row from the experiment. HV_{iv} are other control variables at household and village level. The control variables at the household level are education, marital status, health conditions, and dependency ratio, while village level controls include the distance to district capital and weather conditions (SPEI). The error term ε_i is clustered at village level. To address endogeneity concerns such as reversed causality between risk attitudes and real-life decision variables, we rely on the lagged nature of the risk attitude measures from 2015 to explain observed decision outcomes in 2016. In the next section, we present the results and discussion of the empirical results.

2.5 Econometric results and discussions

2.5.1 Correlates of survey-based measure

Table 2.4 shows the estimated correlation coefficients between our survey-based measure of WTR and two different sets of socio-economic characteristics usually used in the literature. Column (1) presents the results of the baseline specification using time-invariant characteristics such as respondents' age, gender, and height, whereas Column (2) adds religion and assets, while Column (3) includes other household-level variables such as marriage status, self-assessed health status, educational level, occupation of the respondent, and dependency ratio. We further control for village level heterogeneities such as access to quality of road (paved road), the distance from villages to district towns, and weather conditions (SPEI).

Across the different specifications, there are hardly any changes in estimated coefficients and their level of significance. For example, Table 2.4 shows that Thai women were less likely to take risk than Thai men in Ubon. However, although the coefficient for Hue follows a similar direction, the effect is insignificant. In terms of respondent's age, the results show that WTR decreases significantly with age in Hue but show no statistical significance for respondents in Ubon. This result is found to be in line with the literature on risk and its determinants (Dohmen et al., 2011; Liu, 2012; Gloede et al., 2015). Respondent's height is inversely correlated with WTR in Hue. This means WTR decreases with the respondent's height, contrary to what Dohmen et al. (2011) found and reported in Germany. Furthermore, wealth and religion variables show a mixed relationship with WTR. For example, while they show no association between respondents' wealth and WTR in Ubon, it is positive and significant for Hue. This means that increased wealth is significantly correlated with the WTR in Vietnam, in line with the findings of Dohmen et al. (2011), Liebenehm and Waibel (2014), and Gloede et al. (2015). Regarding religion, the results in column (2) show that the respondent's religion does not correlate with WTR in both countries.

Table 2.4 Primary determinants of general risk attitudes in Ubon and Hue

	Dependent variable: Willingness to take risk in general (standardized)					
	Ubon			**Hue**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Age (years)	-0.005	-0.005	-0.002	-0.010***	-0.010***	-0.008***
	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
Female	-0.287**	-0.275**	-0.235*	-0.130	-0.088	-0.029
	(0.122)	(0.123)	(0.129)	(0.089)	(0.089)	(0.104)
Height (cm)	-0.006	-0.006	-0.005	-0.012***	-0.014***	-0.013***
	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)
Buddhist religion	No	-0.475	-0.493	No	-0.046	-0.024
		(0.491)	(0.500)		(0.080)	(0.080)
Log of total assets value ($PPP)	No	0.024	0.020	No	0.113***	0.098***
		(0.024)	(0.024)		(0.027)	(0.028)
Controls	No	No	Yes	No	No	Yes
Constant	1.302	1.628	0.964	2.822***	2.402***	3.054***
	(1.238)	(1.361)	(1.450)	(0.774)	(0.772)	(0.907)
R^2	0.013	0.016	0.028	0.044	0.073	0.095
N	649	649	649	551	551	551

Note: Additional controls include education, marital status, self-reported health conditions, self-employed occupation of respondents, dependency ratio at household level, SPEI and the distance to district town, the quality of the road at village level. Single, double, and triple asterisks (*, **, ***) denote p < 0.10, 0.05, and 0.01, respectively. Standard errors in the parentheses, are clustered at the household level
Source: Authors' calculations

2.5.2 Correlation between survey-based measure and incentivized experiment

This section explores the consistency of two different measures of risk attitudes. To do so, first, we present a simplified Spearman correlation between the WTR and the incentivized lottery outcome (SR) measure in Table 2.5. Second, we regress SR on WTR in Table 2.6.

The upper panel of Table 2.5 shows the correlation between the general WTR and WTR in financial situations, while the lower panel shows the correlation between the two WTR measures and the incentivized experiment. The correlation matrix shows that WTR is strongly correlated across the two different contexts. Furthermore, both WTR measures are positively correlated with the switching row in the experiment. However, the general WTR yields a higher correlation among Vietnamese respondents, while the financial WTR seems to perform better in Thailand. However, since the correlations reported in Table 2.5 are only suggestive in nature with no predictive power and the fact that earlier results show that risk attitudes are individual and context-driven, we proceed to run a full econometric estimation of the relationship between WTR and the incentivized lottery outcome.

Table 2.5 Correlation of risk attitudes across contexts

	Pooled	**Ubon**	**Hue**
	Willingness to take risk in financial decisions (standardized)[9]		
Willingness to take risk in general (standardized)	0.554 (0.000)	0.566 (0.000)	0.532 (0.000)
	Value of the safe option of paid lottery choice (standardized)		
Willingness to take risk in general (standardized)	0.129 (0.000)	0.077 (0.047)	0.144 (0.000)
Willingness to take risk in financial decisions (standardized)	0.111 (0.000)	0.113 (0.003)	0.085 (0.045)
N	**1200**	**649**	**551**

Note: Coefficients refer to Spearman's ρ, p-value in parentheses
Source: Authors' calculations

The econometric results of the estimation are presented in Table 2.6. The upper panel shows the results using the general WTR, whereas the lower panel uses the financial WTR. We first run a baseline regression without further controls in Columns (1). The results show a positive and significant coefficient of the standardized general WTR value and the incentivized lottery outcome in both countries at the 99% confidence interval. Adding controls in Columns (2) and (3) only marginally changes the coefficient of the standardized general WTR. We obtain the

[9] The survey extended the question about willingness to take risk in a financial context-specific, that uses the same Likert scale measurement. See Table 2.A1 in the Appendix.

same pattern of results for the financial WTR. In contrast to the Spearman's rank correlation results in Table 2.5, both the general WTR and the financial WTR show a stronger correlation with the experimental outcome in Hue than in Ubon.

Table 2.6 Validation of survey risk measure with incentivized experiment[10]

	Dependent variable: The switching point value (standardized)					
	Ubon			**Hue**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Willingness to take risk in general (standardized)	0 .059**	0.054*	0.054*	0.254***	0.249***	0.248***
	(0 .029)	(0.029)	(0.029)	(0.058)	(0.060)	(0.062)
Controls for age, gender, height	No	Yes	Yes	No	Yes	Yes
Other controls	No	No	Yes	No	No	Yes
Constant	-0.212***	-0.254	-0.325	0.218	-2.085*	-1.873
	(0.033)	(0.859)	(1.023)	(0.044)	(1.171)	(1.299)
R^2	0.006	0.016	0.021	0.030	0.044	0.063
Willingness to take risk in finance decisions (standardized)	0.087***	0.080***	0.078**	0.162***	0.155**	0.136**
	(0.030)	(0.030)	(0.030)	(0.060)	(0.062)	(0.065)
Controls for age, gender, height	No	Yes	Yes	No	Yes	Yes
Other controls	No	No	Yes	No	No	Yes
Constant	-0.216***	-0.234	-0.306	0.249***	-1.749	-1.433
	(0.033)	(0.854)	(1.026)	(0.045)	(1.166)	(1.284)
R^2	0.013	0.022	0.027	0.014	0.029	0.047
N	**649**	**649**	**649**	**551**	**551**	**551**

Note: Additional controls include education, marital status, self-reported health conditions, self-employed occupation of respondents; dependency ratio and total assets value at household level, SPEI and the distance from village to district town, the quality of the road at village level. Single, double, and triple asterisks (*, **, ***) denote p < 0.10, 0.05, and 0.01, respectively. Standard errors in the parentheses, are clustered at the household level

Source: Authors' calculations

Overall, these results are in line with what has been found elsewhere by Dohmen et al. (2011). In summary, the results of the predictability of incentivized experiments using survey-based risk questions have implications both methodologically and practically for empirical risk studies in developing countries. Methodologically, the results show that when properly implemented, general risk questions, regardless of context, can accurately predict risk attitudes,

[10] For the sake of brevity, we do not report coefficient estimates for all of the additional controls. See Table 2.A4 in the Appendix for full results.

just like incentivized experiments. In terms of practicality, these findings present a less costly and efficient risk attitude estimate.

2.5.3 Correlation between risk attitudes and real-life decisions

In this sub-section, we investigate whether and to what extent the two risk attitude measures are correlated with respondents' and their households' real-life decisions such as self-employment, renting-out of agricultural land, and investment decisions (agriculture and non-agriculture). The alternative dependent variables are mostly binary. With regards to agricultural investment, however, we also go beyond a simple binary measure to look at the actual aggregated input purchases expenditure (particularly fertilizer and pesticides) per hectare converted to PPP$. This way, we examine if risk attitudes are correlated with agricultural expenditure.

Table 2.7 presents marginal effects, results for Ubon are represented in the top panel of the table, while Hue is presented in the lower panel.

Column (1) shows the results for being self-employed. The results show a positive correlation between general WTR and being self-employed in Ubon, with no significant association found for Hue. Specifically, an increase in one standard deviation of the general WTR measure significantly increased the probability of being self-employed by about 2% in Ubon. On the other hand, although the coefficient of the incentivized risk measure follows a similar direction, the effect is statistically not significant. We do not find any significant correlation between risk attitudes and self-employment decisions in Hue.

Table 2.7 The measurement of marginal effects of risk attitudes to explain risky behaviors[11]

Ubon	Self-employed (1)	Land rent out (2)	Agricultural investment (3)	Non-farm investment (4)	Fertilizer & Pesticides costs(ln) (5)
WTR (standardized)	0.017(.009)*	-0.010(0.011)	0.031(0.015)**	0.011(0.013)	0.048(0.023)**
Other controls	Yes	Yes	Yes	Yes	Yes
Log pseudo-likelihood	-173.075	-235.606	-383.989	-291.524	
Pseudo R^2	0.044	0.050	0.030	0.013	
R^2					0.028
Value of safe option (standardized)	0.007(0.012)	0.010(0.016)	-0.014(0.021)	-0.001(0.017)	-0.002(0.030)
Other controls	Yes	Yes	Yes	Yes	Yes
Log pseudo-likelihood	-174.761	-235.836	-385.810	-291.933	
Pseudo R^2	0.035	0.049	0.025	0.011	
R^2					0.021
N	**649**	**649**	**649**	**649**	**649**
Hue					
WTR (standardized)	-0.010(0.017)	-0.035(0.014)**	0.042(0.026)*	0.054(0.022)***	-0.122(0.095)
Other controls	Yes	Yes	Yes	Yes	Yes
Log pseudo-likelihood	-139.828	-146.236	-316.290	-202.739	
Pseudo R^2	0.073	0.075	0.036	0.033	
R^2					0.201
Value of safe option (standardized)	-0.011(0.010)	-0.020(0.010)*	0.024(0.015)	0.011(0.013)	0.028(0.073)
Other controls	Yes	Yes	Yes	Yes	Yes
Log pseudo-likelihood	-139.508	-147.396	-316.593	-205.808	
Pseudo R^2	0.075	0.068	0.035	0.018	
R^2					0.198
N	**551**	**551**	**551**	**551**	**551**

Note: Additional controls include age, gender, height, education, marital status, health conditions, dependency ratio, SPEI and the distance from villages to district towns at village level. The standard errors in parentheses. Single, double, and triple asterisks (*, **, ***) denote p < 0.10, 0.05, and 0.01, respectively. Standard errors in the parentheses, are cluster at the village level: Source: Authors' calculations

The country-specific difference in the correlation between risk attitudes and employment may be explained by the structural difference in risk attitudes between the two countries. In Figure 2.1 presented earlier, we found that Thais were likely to be decisive, which could motivate their participation in self-employment.

Column (2) shows the result for the agricultural land rental decision. The results show that both the general WTR and the experimental measure are negatively correlated with the decision to

[11] For the sake of brevity, we do not report coefficient estimates for all of the additional controls. See Table 2.A5 in the Appendix for full results.

rent out land in Hue, with no significant effect found for Ubon. A one standard deviation increase in the general WTR is associated with a 3.5% decrease in the respondent's probability of renting-out land in Hue. The effect of the incentivized lottery measure shows a similar effect on land rent-out decisions, although the magnitude of the coefficient is smaller. This result can be interpreted to mean that risk-seeking respondents are more likely to continue investing in agricultural production than they are less likely to rent out agricultural land in Hue.

The dependent variable in Column (3) is agricultural investments, which is a binary indicator of whether the respondent has made any investment in agricultural production, mainly crop input purchases in the past 12 months. In both countries, we obtain a positive and significant correlation between the WTR measure and agricultural investments. However, no correlation is found for the incentivized measure. This result means that, those with higher willingness to take risk are more likely to invest in agricultural production.

Next, we consider investment patterns in non-farm investments in Column (4). Here, we obtain only a positive and significant correlation with the general WTR among Vietnamese respondents.

Finally, in Column (5), we investigate the correlation between the two risk measures and fertilizer and pesticide expenditures. The results show a positive and significant correlation coefficient on the general WTR measure among Thai respondents, but no significant association found for Vietnamese. Two critical inferences can be made by interpreting columns (3) and (5) together. First, Thai respondents with a higher willingness to take risks are more likely to invest in agricultural production by purchasing fertilizer and pesticides. Second, although risk-seeking respondents invest in agricultural production in Hue, this investment is less likely to go into fertilizer and pesticide purchases. An indication that risk-seeking farmers may be investing in other agricultural intensification inputs such as seeds, machinery, and land rather than fertilizer and pesticides.

Overall, a number of observations can be drawn from Table 2.7. First, although agricultural production remains a risky enterprise because of climate change and its attendant shocks to crop production, risk-seeking small-scale farmers in these countries are willing to invest in agricultural production. Second, aside from investing in agricultural production, risk-seeking individuals in Ubon pursue self-employment, while such individuals in Hue invest in non-farm enterprise as a livelihood strategy. This reason, we argue, is the explanation for the structural transition from agricultural production to an entrepreneur-driven economy in Thailand. In Vietnam, the rural economy is largely agrarian, with few non-agricultural activities. Third, real-life decisions of individuals, although they can be predicted by their affinity towards risk (willingness to take risk), remain heterogeneous across different outcomes. This heterogeneity may be driven by localized infrastructure and economic opportunities to which each respondent is exposed in each country. For example, while Thailand is an upper-middle-income country, Vietnam, on the other hand, is a lower-income country (WB, 2018). Such structural differences could therefore be driving the context specificity of the relationship between a respondent's willingness to take risk and real-life decisions. Fourth, general WTR measure based on the survey questions seems to perform better in explaining risky real-life decisions than the risk attitudes elicited through an incentivized experiment both in Ubon (Thailand) and Hue (Vietnam).

2.6 Conclusions

Understanding the risk behavior of rural populations remains important to help them build resilience and improve their livelihoods. This is particularly so because of the increased frequency of occurrence of uninsured risk invents in rural areas. While economists continue to explore the topic of risk broadly, such studies are scant in the developing country context. This is notwithstanding the fact that literature shows that risk attitudes play an important role in explaining poverty traps (Mosley and Verschoor, 2005; Liu and Huang, 2013; Brick & Visser, 2015). Understanding risk attitudes and how they can contribute to our understanding of rural household decisions remain empirically important.

In this study, we studied risk attitudes of small-scale farmers in two provinces in rural Thailand and Vietnam using a combined-data set of risk attitudes measured by an incentivized experiment and based on a survey question. The data set allowed us to investigate three objectives. First, we investigated the correlates of the survey-based measure; second, we examined the correlation between the survey-based measure and the incentivized experiment; and third, we explored the correlation of both risk attitude measures with respondents' real-life decisions.

We find a number of interesting results in this study. First, the results show that risk attitudes are person and context-specific. For example, respondents in Vietnam are relatively risk-seeking, while Thais are rather risk-averse. Second, some factors, including respondent age, gender, and height, are significant variables that explain the heterogeneity of risk attitudes. Third, in terms of behavioral outcomes, the results show that individual risk attitudes are significant predictors of income-generating choices. However, the type and intensity of the respondent's activity are context specific. Specifically, we find that individuals with a higher affinity towards risk engage in agricultural activities. Fourth, we find that the survey-based risk measure is relatively stable, less noisy, and able to more predict real-life risky decisions compared to the incentivized experiment. Finally, the results of the survey-based risk measure have been validated by the incentivized risk experiment and are in line with Hardeweg et al. (2013).

The results of this current study have a number of implications. Asking questions on risk behavior would shed light on understanding the vertical integration into higher income-generating activities by these households. First, since individual participation in high returns activities is found to be positively associated with respondents' willingness to take risk, policies targeted at improving informal risk insurance should be deliberately pursued. In this way, it can provide a form of cushioning, alleviating the fear of loss, thereby stimulating the participation of the rural population in risky but high return income-generating activities. For example, specific policy instruments like access to properly functioning input and output markets, provision of gender-based credit opportunities, and crop insurance schemes should be pursued and strengthened as ways of inducing risk affinity among the rural population. Second, risk-loving individuals, who are diversifying away from agriculture could have long-term consequences for food production and food security. Therefore, policy instruments that aim at reducing the risk associated with small-scale agriculture, for example, the provision of irrigation and extension services, should be systematically and pursued in rural Thailand and Vietnam to reduce agricultural-associated risk. This will encourage investment, leading to both expansion and intensification of agricultural production on one hand while at the same time building the resilience of the rural population.

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Appendix

Table 2.A1 Willing to take risk questions in Ubon and Hue

Willing take risk in general

"Are you generally a person who is willing to take risk or do you try to avoid taking risk?"

0	1	2	3	4	5	6	7	8	9	10

0 =

unwilling to take risks

10 =
fully prepared to take risk

Please circle the number given by the respondent

Willing to take risk in financial decision

"When thinking about financial decisions are you a person who is fully prepared to take risk or do you try to avoid taking risk?"

0	1	2	3	4	5	6	7	8	9	10

0 =

unwilling to take risks

10 =
fully prepared to take risk

Please circle the number given by the respondent

Source: TVSEP Survey 2015

Table 2.A2 Lottery game

Thailand

1. Do you prefer to play the 50:50-lottery (Option A) or to obtain a safe amount (Option B)? (Please show the show card to the respondent and ask him row by row which option he prefer. Tick the appropriate cell that corresponds to respondent's choice and stop to ask when the respondent switches from A to B)

Row	Option A: Lottery	Option B: Safe amount	Choice	
	THB	THB	A	B
1	300 : 0	0		
2	300 : 0	10		
3	300 : 0	20		
4	300 : 0	30		
5	300 : 0	40		
6	300 : 0	50		
7	300 : 0	60		
8	300 : 0	70		
9	300 : 0	80		
10	300 : 0	90		
11	300 : 0	100		
12	300 : 0	110		
13	300 : 0	120		
14	300 : 0	130		
15	300 : 0	140		
16	300 : 0	150		
17	300 : 0	160		
18	300 : 0	170		
19	300 : 0	180		
20	300 : 0	190		

2. What is the number of the card randomly drawn? Card drawn ☐

3. Please tick how you continue:

Pay safe amount (If number of the card drawn ≥ number of row ticked) ☐

Play lottery (If number of the card drawn < number of row ticked) ☐

4. If lottery, please flip the coin and note down if "King" or "Palace" show up ☐

Source: TVSEP Survey 2015

Vietnam

1. Do you prefer to play the 50:50-lottery (Option A) or to obtain a safe amount (Option B)? (Please show the show card to the respondent and ask him row by row which option he prefer. Tick the appropriate cell that corresponds to respondent's choice and stop to ask when the respondent switches from A to B)

Row	Option A: Lottery	Option B: Safe amount	Choice	
	VND	VND	A	B
1	200 : 0	0		
2	200 : 0	10		
3	200 : 0	20		
4	200 : 0	30		
5	200 : 0	40		
6	200 : 0	50		
7	200 : 0	60		
8	200 : 0	70		
9	200 : 0	80		
10	200 : 0	90		
11	200 : 0	100		
12	200 : 0	110		
13	200 : 0	120		
14	200 : 0	130		
15	200 : 0	140		
16	200 : 0	150		
17	200 : 0	160		
18	200 : 0	170		
19	200 : 0	180		
20	200 : 0	190		

2. What is the number of the card randomly drawn? Card drawn ☐

3. Please tick how you continue:

Pay safe amount (If number of the card drawn ≥ number of row ticked) ☐

Play lottery (If number of the card drawn < number of row ticked) ☐

4. If lottery, please flip the coin and note down if "Star" or "Number" show up ☐

Source: TVSEP Survey 2015

Table 2.A3 Definition of variables used in regression analysis

Variable Name	Description
Data in 2013	
Age	Age of household head in year
Female	Household head is female= 1, male=0.
Height	Household head's height (cm)
Buddhist religion	Household head is Buddhist= 1, otherwise=0.
Total assets value	The depreciated value of total household assets in $PPP
Education	Years of schooling of household head
Married status	Household head's married status (1= Not married, 2= Married, 3= Window, 4= Divorced or separated)
Health conditions	Household head's health conditions (1= Healthy, 2= Can manage, 3= Sick)
Self-employment	Main occupation of household head is self-employment = 1, otherwise=0.
Dependency ratio	The number of dependent household member (above 15 and below 64) divided by the number of independent household member (below 15 and above 64)
SPEI	Standardized precipitation evapotranspiration index
Distance	Distance from village to district town in km
Paved road	Main road is paved road=1, otherwise=0.
Data in 2015	
Willingness to take risk in general	Risk preference in general of household head (0-10)
Willingness to take risk in financial decision	Risk preference in financial decision of household head (0 -10)
Incentivized lottery game	The value of safe option at the switching row of the lottery game
Data in 2016	
Self-employment	Second occupation of household head is self-employment = 1, otherwise=0.
Agricultural land rent out	Renting out agricultural land=1, otherwise=0.
Agricultural investment	Increasing or Investment in agriculture=1, otherwise=0.
Non-agricultural investment	Increasing or Investment in non-farm enterprise=1, otherwise=0.
Costs of fertilizer and pesticides per hectare	Total costs of fertilizer and pesticides per hectare ($PPP)

Source: Authors' calculations.

Table 2.A4 Primary determinants of general risk attitudes in Ubon and Hue (continued)

	Dependent variable: willingness to take risk in general (standardized)					
	Ubon			Hue		
	(1)	(2)	(3)	(1)	(2)	(3)
Education			-0.005			0.007
			(0.017)			(0.008)
Marital status			-0.077			-0.079
			(0.098)			(0.083)
Health conditions			0.060			-0.027
			(0.127)			(0.068)
Self-employment			0.173			0.002
			(0.179)			(0.103)
Dependency ratio			-0.115*			-0.132***
			(0.070)			(0.047)
SPEI			-0.173			0.448
			(0.191)			(0.320)
Paved road			0.206			0.002
			(0.206)			(0.099)
Distance to district towns			0.005			-0.000
			(0.004)			(0.003)

Note: Single, double, and triple asterisks (*, **, ***) denote $p < 0.10$, 0.05, and 0.01, respectively. Standard errors in the parentheses, are clustered at the household level.

Source: Authors' calculations.

Table 2.A5 The measurement of marginal effects of risk attitudes to explain risky behaviors (continued)

Ubon	**Self-employed (1)**	**Land rent out (2)**	**Agricultural investment (3)**	**Non-farm investment (4)**	**Fertilizer costs(ln) (5)**
WTR (standardized)					
Age	-0.002(0.001)**	0.002(0.001)**	-0.005(0.001)***	-0.002(0.001)	-0.004(0.002)*
Female	-0.000(0.028)	-0.014(0.033)	-0.067(0.047)	-0.028(0.040)	-0.148(0.070)**
Height	0.000(0.001)	-0.004(0.001)**	-0.002(0.002)	-0.000(0.002)	-0.001(0.003)
Education	0.002(0.003)	0.009(0.004)**	0.007(0.006)	0.000(0.005)	-0.019(0.010)*
Marital status	-0.010(0.028)	-0.025(0.028)	-0.011(0.038)	0.053(0.032)*	0.044(0.057)
Health conditions	0.011(0.031)	-0.024(0.031)	-0.047(0.048)	-0.032(0.039)	0.002(0.069)
Dependency ratio	0.002(0.018)	0.020(0.019)	0.043(0.026)	-0.006(0.023)	-0.005(0.039)
SPEI	0.031(0.044)	-0.059(0.053)	-0.021(0.073)	0.017(0.060)	-0.021(0.115)
Distance	0.000(0.001)	-0.001(0.001)	-0.001(0.001)	-0.000(0.001)	-0.002(0.002)
Value of safe option (standardized)					
Age	-0.002(0.001)**	0.002(0.001)**	-0.005(0.001)***	-0.002(0.001)	-0.004(0.002)*
Female	-0.006(0.029)	-0.011(0.033)	-0.077(0.047)	-0.032(0.041)	-0.160(0.070)**
Height	0.000(0.001)	-0.004(0.001)**	-0.002(0.002)	-0.006(0.002)	-0.001(0.004)
Education	0.002(0.003)	0.009(0.004)**	0.007(0.006)	-0.000(0.005)	-0.019(0.010)*
Marital status	-0.010(0.027)	-0.025(0.028)	-0.015(0.038)	0.052(0.032)*	0.040(0.057)
Health conditions	0.013(0.031)	-0.024(0.031)	-0.046(0.049)	-0.031(0.039)	0.005(0.068)
Dependency ratio	0.001(0.018)	0.022(0.019)	0.040(0.027)	-0.007(0.023)	-0.011(0.038)
SPEI	0.030(0.044)	-0.059(0.053)	-0.023(0.073)	0.017(0.060)	-0.030(0.115)
Distance	0.000(0.001)	-0.001(0.001)	-0.000(0.001)	-0.000(0.001)	-0.002(0.002)
N	**649**	**649**	**649**	**649**	**649**
Hue					
WTR (standardized)					
Age	-0.001(0.000)	0.001(0.000)	-0.004(0.001)***	-0.001(0.001)	0.027(0.006)***
Female	0.100(0.038)***	0.033(0.038)	0.009(0.063)	0.054(0.044)	0.107(0.287)
Height	0.002(0.001)	0.000(0.001)	-0.007(0.002)***	0.001(0.002)	0.031(0.011)***
Education	0.008(0.002)***	0.001(0.003)	0.001(0.005)	0.004(0.003)	-0.022(0.020)
Marital status	-0.001(0.030)	0.014(0.031)	-0.061(0.052)	0.019(0.035)	0.101(0.269)
Health conditions	0.026(0.026)	0.006(0.024)	0.031(0.041)	0.020(0.030)	0.332(0.157)**
Dependency ratio	0.031(0.013)**	0.020(0.015)	-0.003(0.030)	0.024(0.021)	-0.019(0.127)
SPEI	-0.010(0.110)	-0.107(0.101)	-0.059(0.183)	0.122(0.136)	-4.394(0.613)***
Distance	-0.001(0.001)	-0.002(0.001)**	0.002(0.002)	-0.000(0.001)	-0.019(0.007)**
Value of safe option (standardized)					
Age	-0.001(0.000)	0.001(0.000)*	-0.004(0.001)***	-0.001(0.001)	0.028(0.006)***
Female	0.101(0.037)***	0.039(0.037)	0.004(0.063)	0.055(0.044)	0.090(0.291)
Height	0.002(0.001)	0.001(0.001)	-0.008(0.002)***	0.000(0.002)	0.032(0.011)***
Education	0.008(0.002)***	0.001(0.003)	0.001(0.005)	0.005(0.003)	-0.023(0.020)
Marital status	0.000(0.030)	0.018(0.032)	-0.066(0.052)	0.011(0.035)	0.116(0.272)
Health conditions	0.025(0.026)	0.001(0.025)	0.031(0.042)	0.023(0.030)	0.334(0.157)**
Dependency ratio	0.032(0.013)**	0.024(0.014)*	-0.006(0.030)	0.018(0.021)	0.001(0.126)
SPEI	-0.010(0.111)	-0.122(0.103)	-0.045(0.181)	0.143(0.138)	-4.468(0.607)***
Distance	-0.001(0.001)	-0.002(0.001)**	0.002(0.002)	-0.001(0.001)	-0.019(0.007)**
N	**551**	**551**	**551**	**551**	**551**

Source: Authors' calculations

CHAPTER 3: FARMERS' KNOWLEDGE AND FARM PRODUCTIVITY IN RURAL THAILAND AND VIETNAM

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Abstract

With the increasing complexity of farming in the developing countries in Asia and the growing challenge arising from climate change, management, technical knowledge, and skills become more and more important for smallholder farmers. So far, little is known about how knowledge, skills, and cognitive abilities of farm decision-makers affect agricultural productivity. Most empirical studies lack the necessary parameters to adequately measure knowledge and skills and often rely on simple parameters like educational attainment and years of formal schooling. However, to generate a better understanding of how knowledge and skills enable farmers to meet the challenges of increasingly obstacle farming environments, more direct measures of education are needed. This paper investigates the impact of farmers' knowledge on agricultural productivity by making use of specific agricultural knowledge questions and management tests conducted with 1,290 small-scale farmers in two provinces in Thailand and Vietnam, carried out in 2014. Applying OLS and 2SLS approaches and combining the knowledge and skills test results with productivity data of later waves allows for identifying the effect of agricultural knowledge and skills on agricultural productivity. Results show that farmers' specific agriculture knowledge is significantly and positively associated with profits but significantly negative with yields and total input costs. Hence, better farmers may strive for optimal instead of maximum yields, are more judicious in the use of inputs, and as a result, make more money in rice production.

Keywords: *Education, knowledge, skills, human capital, agricultural productivity.*

***JEL classification**: D83, O15, I25*

3.1 Introduction

As a driver of economic development, human capital is one of the main input factors in production progress in industry and agriculture (Lucas, 1988; Mankiw et al., 1992; Barro & Lee, 1994; Behrman, 2010). Human capital encompasses both innate and learned skills as broadly conceived to include experience, skill, knowledge, and formal education (Welch, 1970; Hayami & Ruttan, 1970; Foster & Rosenzweig, 1995; Becker, 2009; Behrman, 2010; Holden & Biddle, 2017). The literature shows that educational attainment is a significant factor in career choice, income, and economic growth (Welch, 1970; Barro & Lee, 1994; Schultz, 1988); Huffman, 2001; Gregorio & Lee, 2002). However, in agriculture, this linkage remains unconvincing (Lockheed et al., 1980; Asadullah & Rahman, 2009).

Investigating the returns to human capital in farm production is frequently mentioned in the economic development literature, primarily focusing on formal elementary education, i.e., years of schooling with different measurement approaches (Huffman, 1974; Barro, 1991; Asfaw and Admassie, 2004; Asadullah & Rahman, 2009; Reimers & Klasen, 2013; Paltasingh & Goyari, 2018). Fundamental formal education, such as primary and secondary schooling, enables people to read, write, and calculate. However, these basic skills of formal education are insufficient for making good decisions in agriculture (Huffman, 2001). Therefore basic formal education is not a reasonable explanation for agricultural productivity growth (Pritchett, 2001). In addition, years of schooling says nothing about education quality; therefore, it cannot capture the heterogeneity among farmers with the same level of formal education. Clearly, education is more than just years of going to school. It is also the accumulation of knowledge and skills through own experience and observing others.

In some studies, informal education was included, and such as specific skills and knowledge were measured (Foster & Rosenzweig, 1995; Tao Yang, 2004; Paltasingh & Goyari, 2018, Kijima et al., 2012; Mariyono. 2019). However, most of these studies use age as a proxy for farming experience (Tao Yang, 2004; Paltasingh & Goyari, 2018). In other studies (e.g., Kijima et al., 2012; Mariyano, 2019), the number of participants in participatory training programs was used as the explanatory variable. Both approaches are imperfect in capturing farmer knowledge, skills, and experience.

In this paper, we examine the effect of specific agricultural knowledge and technical skills, as well as the financial literacy of farmer decision-makers by means of knowledge and skill tests. In addition, we also have information on age and schooling years. Hence we are able to investigate to what extent these factors are related to yields, costs, and profits of farm enterprises of the households in two provinces in Thailand and Vietnam.

The condition of agricultural production in Thailand and Vietnam is suitable for the purpose of this study due to two main reasons. First, in rural areas of two provinces in both countries, agriculture is still a major source of livelihood, albeit at a small scale, and household labor is dominant (OECD-FAO, 2017). Second, farmers in these areas mostly make farm decisions based on their experience and gain knowledge by doing.

To address the research questions, we use a cross-section household dataset from the Thailand Vietnam Socio-Economic Panel (TVSEP). We combine data from different waves of the TVSEP project. Our main independent variables of interest are technical knowledge, financial literacy scores, and decision-making capacity are taken from a 2014 special survey. The agricultural production data such as yields, costs, and profits are attained in the 2017 survey instead of the 2016 survey. The reason is that 2016 was an extreme year in terms of drought events which could have biased the results. Furthermore, other control variables such as household and village characteristics are taken from the 2013. We then apply the basic cross-sectional strategy for a pooled regression, using the Ordinary Least Square (OLS). To circumvent possible endogeneity also use a Two-Stage Least Square (2SLS) Instrumental Variable (IV) approach.

In brief, our results show that farmers who have the better technical knowledge and more experience are better farm managers and are better in the allocation of agricultural inputs. They have higher profits, although, on average, they achieve lower yields. This suggests that farmers who are less knowledgeable in these aspects may overuse inputs because they strive for maximum instead of optimum yields. We also find that more years of formal schooling are positively and significantly related to rice yields but are not significant as regards the allocation of agricultural inputs.

The rest of the paper is structured as follows. Section 2 is the literature review. Data and methodology are presented in Section 3. Section 4 shows results and discussion. The final section 5, includes a summary and policy implications.

3.2 Literature review

The role of knowledge and skills in farming has been studied widely in both developed and developing countries. However, the results and conclusions are rather ambiguous. This is perhaps due to the lack of a precise parameter to capture the effect on productivity and profitability.

From reviewing the literature, it appears that the reason for the ambiguous findings on the relationship between education and agricultural productivity is how education is defined in many studies (Reimers & Klasen, 2013; Paltasingh & Goyari, 2018). Studies in the sixties and seventies (e.g., Griliches, 1964; Welch, 1970; Hayami and Ruttan, 1970) in developed and developing countries found that the years of schooling of farm laborers was an essential determinant of agricultural production. Later studies, e.g., Asfaw & Admassie, (2004) in Ethiopia; Alene & Manyong, (2007) in Nigeria, and Asadullah & Rahman, (2009) in Bangladesh also found that farmers with higher education are more likely to adopt modern agricultural inputs (e.g., fertilizer, varieties), and achieve higher crop yields. On the other hand, a recent study in Vietnam (Ninh, 2021) did not confirm these findings.

Recognizing the limitations of using years of schooling as an explanatory variable, some studies used more refined measures. For example, Reimers & Klasen, (2013) used the enrollment ratio and adult literacy as variables but did not find a significant relationship. Asfaw & Admassie (2004), in their study in Ethiopia, refined the schooling variable by differentiating between the schooling years of household heads and adult household members. Surprisingly, they found that the education of other household members has a stronger effect on fertilizer adoption than the education of the household head. Maini et al. (2021), in a study in Russia, also found that the education level of family members was decisive for the adoption of sustainable farming practices. On the contrary, Alene & Manyong, (2007) in Nigeria found a significant effect of household heads' education on adopting improved varieties but not those of other adult household members.

Literature also exists on the education spillover effects, i.e., neighbor's education on agricultural productivity, as found by Foster & Rosenzweig, (1995) in India and Appleton & Balihuta, (1996) in Uganda. The latter study even found that education spillover effects were more robust than household member education itself.

Some studies looked beyond formal education and included indigenous knowledge, skills, and experience. For example, Foster & Rosenzweig (1995) capture farmers' knowledge via learning by doing and learning from others. They used panel data from India on farmers' behavior and data on the rate of adoption of new high-yielding of rice and wheat varieties as well as crop profitability. They also found that a lack of knowledge about how to use new varieties is a significant barrier to adopting these varieties. Another strand of literature captures farmers' knowledge and skills by means of agricultural training programs, i.e., comparing training participants and non-participants. For example, in a study of rice farmers in Uganda, Kijima et al. (2012) showed that farmers who participated in a training program on rice production, increased their adoption of the improved cultivation practices. Mariyono (2019), across 12 regions in Indonesia, confirmed these findings and was able to show that with a higher number of participants in farmer field schools, the output of rice and soybeans increased.

Godtland et al. (2004), in a Peruvian study, used the knowledge test score of farmer field school participants and found that farmers with higher scores significantly improved potato productivity. A limitation of the study is that knowledge was measured immediately after the farmer field school training, and therefore, only the short-term effects were measured. It is quite possible, and even likely, that acquired knowledge may depreciate over time unless retraining is undertaken.

In a cross-country study, Hayami & Ruttan (1970) measured agricultural knowledge by means of specific agricultural technical education at the tertiary level of formal education. They found a positive and significant on the gross agriculture output. Similarly, Tao Yang (2004) shows that farmers' experiences had a positive impact on household income in rural China. On the other hand, Paltasingh & Goyari (2018), in a study in India, found that farming experience was insignificant to modern varieties adoption.

This review of literature has shown that it is important to capture the right measure of education if one wants to find significant effects on farm productivity and output. The findings from the literature allow us to develop a hypothesis for this paper. The hypothesis is: provided adequate education indicators can be found, better knowledge, management skills, and experience, will improve agricultural productivity and profitability.

3.3 Data and methods

3.3.1 Data and measurement of variables

The data set was collected as part of the Thailand Vietnam Socio-Economic Panel (TVSEP; https://www.tvsep.de). In this paper, we use a sub-sample of the partial household panel survey in 2014, i.e., in the province of Ubon Ratchathani in Thailand and Thua Thien Hue in Vietnam. In this panel wave, complementary to a shortened version of the household questionnaire, further specific questions on technical knowledge in agriculture, and choice tests of farmers' decision-making skills were added. The study was focused on rice farmers; hence a subset of the full provincial sample of some 1700 households, was used, i.e., 1,290 rice farming households in both provinces. The data of the 2104 special survey was combined with the data from the complete household survey waves in 2013 and 2017. In the following, the main variables of interest are described.

The main dependent variables of interest in this paper are indicators of agricultural performance measured in 2017, i.e., yields, input costs, and profit of rice production[12]. Yields are those reported by farmer respondents, converted to kg per unit area (ha). Input costs are the sum of expenditures for all materials and hired labor related to land preparation, seeding, planting, pesticide and fertilizer application, harvesting, and irrigation measured in local currency and converted into PPP USD. Profit per ha is calculated as gross revenue less variable costs[13]. The upper panel of Table 3.1 shows the descriptive statistics of these outcome variables for rice crops. On average, farmers achieve rice yields of 2,995.4 kg per hectare, and input costs account for around $PPP 700. The average profit for rice per hectare is $PPP 487.2.

The main explanatory variables of interest are indicators of agricultural knowledge and decision-making, education, and experiment obtained from the survey wave in 2014. By means of a set of tests, knowledge, financial literacy score, and decision-making were measured. Regarding knowledge and financial literacy scores, two sets of questions are given. On the one hand, the knowledge score is constructed by assessing respondents' answers to specific questions about rice production. The questions addressed respondents' knowledge about specific agricultural practices such as land preparation, fertilizer, and pesticide application and

[12] Revenues are also considered performance parameters; however, economic theory suggests that small-scale rice farmers are price takers. Thus, we do not include the revenue variable in this study.
[13] Farm gate prices were collected to calculate the gross revenues of rice.

were established in cooperation with rice experts[14]. Summing up the number of correct answers yields the *knowledge score*, which takes a value from 1 to 10. Financial literacy was measured via a set of five questions related to financial topics, which capture skills and behaviors of financial decision-making[15]. Similar to the knowledge score, the *financial literacy score* was calculated by summing up the number of correct answers, getting a value between 0 and 5.

Regarding the decision-making test, we offered a hypothetical but realistic situation about two new rice varieties in which all needed information to make a choice is given. The respondents then make their decisions based on the given information and state the main reason for the decision. We then, based on the reason for the respondent's choice, formed our category *decision-making variable* taking the value from one to four, presenting four categories of the reason for the decision-making, namely, higher yield, higher profit, higher prices, or lower costs, respectively.

In addition to the variables measuring technical knowledge in agriculture, financial literacy farm and management decision-making tests, we also capture the respondents' education information and experience. The schooling years attainment are proxy of the respondents' education. Following Tao Yang (2004), we measure farm experience based on age and education information[16]. The experience is measured by the respondent's age minus his/her years of schooling[17]. The *education* and *experience* variables were measured during the 2013 survey wave. Since the TVSEP panel keeps interviewing identical household heads and identical households over the panel waves, the interview member section was not included in the add-on survey in 2014. We then standardized four variables of our interest by subtracting the sample mean and dividing by its standard deviation, which allows comparisons of the main explanatory variables over time.

The descriptive statistics of knowledge score, financial literacy score, and decision-making, which are measured by experiment tests, are presented in section 4. The lower panel of Table 3.1 shows the descriptive statistic of two explanatory variables, which are education and

[14] See Table 3.A1 in the Appendix for a complete list of knowledge questions.
[15] See Table 3.A2 in the Appendix for a complete list of financial literacy questions.
[16] Tao Yang (2004) measured farm experience based on age minus schooling year and minus seven. However, minus a constant number (i.e., 7) will not change the distribution of this variable, so we did not include it.
[17] Our experience variables are highly correlated with age, and we assume that all respondents in our sample are farmers after their education.

experience. In terms of education, respondents spend, on average, five years in school and have 51 years of experience with farming.

Table 3.1 Descriptive statistics of alternative dependent and two explanatory variables

	Mean	SD
Dependent variables (2017)		
Rice yields (kg/ha)	2,995.43	1,612.33
Rice costs ($PPP/ha)	700.59	434.73
Rice profits ($PPP/ha)	487.18	582.38
Explanatory variables(2013)		
Education (years)	5.19	3.19
Experience (years)	51.70	14.29
N	1,290	

Source: Authors' calculations

Finally, the data set includes other control variables at the household and village levels observed in the survey wave of 2013. Table 3.2 shows the definition and summary statistics of these variables. The average household head is, in one out of three cases, female. Taking all household members into account, the average household age is 39 years, and approximately 53% of the households' working force (those between 16 and 65) is engaged in agriculture. With respect to household wealth, the average value of agricultural assets is $PPP 1,069.

Regarding village-level characteristics, the distance from villages to its district town is, on average, 13.67 km. There are 90% of villages have single-lane or two-lane made roads. The standardized precipitation evapotranspiration index (SPEI) captures the extreme weather, the SPEI on average is -1.521, meaning that drought happened in the study sample.

Table 3.2 Descriptive statistics of other control variables

Variable	Description	Mean	SD
Household			
Mean age	Average age of household members (years)	38.629	13.621
Max. education	Maximum year of education of household head (years)	8.350	3.902
Female	Household head is female=1, otherwise=0	0.262	0.440
Ethnicity	Household head is ethnic= 1, otherwise=0	0.100	0.300
Household size	Total number of nucleus household members	4.161	1.701
HH members in agriculture	The share of HH members working in agriculture in the total independent member of household (%)	0.533	0.380
Agricultural assets	The depreciated value of agricultural asset per capita ($PPP)	1,069.811	2,345.36
Village			
Distance	The distance from villages to district towns in Km	13.677	9.464
Paved road	Main road is pave road=1, otherwise= 0	0.944	0.229
SPEI	Standardized precipitation evapotranspiration index	-1.521	0.250
N		1.290	

Source: Authors' calculations

3.3.2 Empirical strategy

Based on the availability of variables in different survey waves, we apply the following basic cross-sectional empirical strategy for a pooled regression of identical households in the provinces of Ubon Ratchathani, Thailand and Hue, Vietnam:

$$Y_{i2017} = \alpha + \beta Main\ X_{i2014} + \gamma X_{i2013} + \delta V_{v2013} + \epsilon_i \qquad (1)$$

where Y_{i2017} represents one of the three alternative outcome variables, i.e., the log of agricultural yields, input costs and profit, observed for a households i in 2017. The main alternative explanatory variables, knowledge score, decision-making, financial literacy and education, experience, observed at household level in 2014 and 2013 respect, are captured by $Main\ X_{i2014}$. Further control variables, represented by X_{i2013}, include the household heads' gender and ethnicity; mean age, maximum education of household members, share of actively working members in agriculture and log of agricultural assets per capita. V_{v2013} includes village characteristics such as distance to district town, type of main road to the village, and SPEI, which measures the deviation in precipitation from the long-term mean at the village level. Both household and village level control variables are observed in the survey wave 2013. Finally, ϵ_i is the error term clustered at the village level.

The setup of the regression model in equation (1), where we explain outcomes observed at a later point in time by regressors observed at an earlier point for the same household i, reduces the concern of endogeneity to some extent. However, to detect whether the nature of our dataset can address the endogeneity issue, we also apply a Two-stage Least Squares (2SLS) approach, where the first stage is:

$$Main\ X_{i2014} = \alpha + \sigma Z_{i2014/2013} + \gamma X_{i2013} + \delta V_{v2013} + \mu_i \quad (2)$$

Hereby, Z_i is a vector of instruments observed in 2014 or in 2013. The instrumental variable used to explain agricultural knowledge, and farm experience is the share of households in a village that received advice from an agricultural extension worker in 2014. A variable that captures the access to extension service at village level is likely to be correlated to a farmer's agricultural knowledge, management skills and experience, but not necessarily to farm performance. Furthermore, we employ a binary variable of pupils that prematurely left school because of exogenous problems observed in 2013 as the instrument to explain education and financial literacy. The use of this instrumental variable is adequate as it is correlated with educational outcomes, but not directly correlated with agricultural outcomes. The second stage can then be formulated as in equation (1) above.

The main coefficient of interest is β, which measures the correlation between agricultural knowledge and management skills and agricultural performance in terms of yields, input costs and profit. We hypothesize that a farmer who has better agricultural knowledge, experience and management skills will achieve higher yields, is more cost-effective and gets higher profits.

3.4 Results

In this section, the results of the experiments are presented in the first sub-section. The model results are shown in two sequent sub-sections. There, we present the effect of alternative indicators of human capital on rice yield, costs, and profits. Finally, we examine the impact of decision-making on agricultural performance.

3.4.1 Descriptive statistics of knowledge, financial literacy, and decision-making experiments

a. Technical agricultural knowledge test

A technical agricultural knowledge test was executed by a set of 10 questions that covered different aspects of rice production[18]. The set of 10 questions addressed respondents' knowledge about specific agricultural practices such as land preparation, fertilizer, pesticide application, and harvesting progress. The corresponding answers to all these ten questions can either be "Yes" or " No". For some questions "yes" is the correct answer, and for others it is "no". For example, a question was: " *The more fertilizer you apply, the better for the crop*". The correct answer is "no". Summing up all correct answers yields the knowledge score.

Figure 3.1 shows the distribution of knowledge scores in the pooled data set, i.e., both in Thailand and Vietnam. It illustrates that in our sample, no farmer failed with all the questions but only a minority could answer all questions correctly. However more than 50 % of the farmer respondents answered at least half the questions correctly.

[18] See Table 3.A1 in the Appendix for a complete list of knowledge questions.

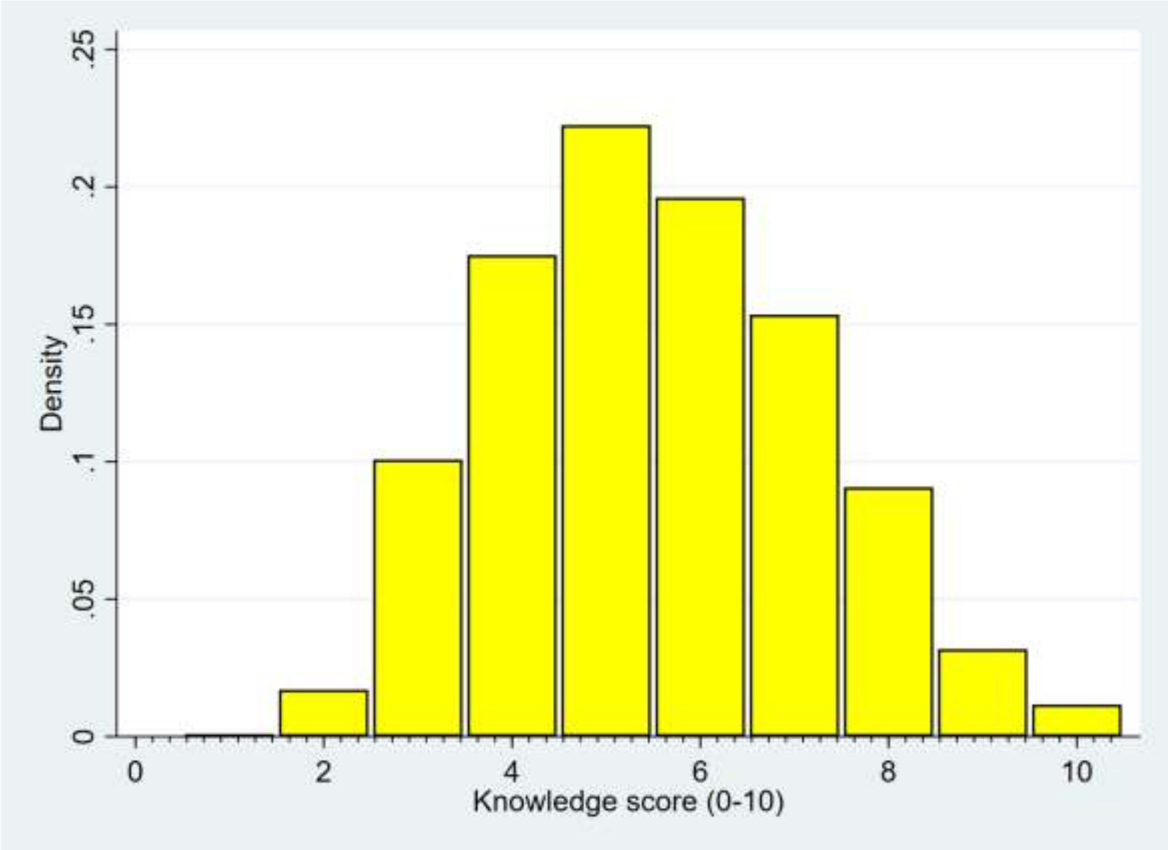

Figure 3.1 Distribution of knowledge score test

Source: Authors' calculations

b. Financial literacy test

As regards the financial literacy test, five financial questions involve calculations. Respondents were allowed to use a calculator[19]. An example of financial literacy question (Vietnam) was: "*If you have 10 Mio VND in an account, the interest rate on the account is 1 % per year, and during this time, the price of goods and services rises by 2% per year, after one year you can buy: (1) Less than what you can buy today; (2) More than what you can buy today; (3) Exactly the same as today; or (4) Do not know".* Similarly to the knowledge test, we assessed whether the respondents' answers were correct or wrong. The sum of correct answers constitutes the financial literacy score. A do not know answer, was counted as an incorrect answer. The distribution of financial literacy scores which takes values from zero to five, is shown in Figure 3.2. The vast majority of respondents answered three or more questions correctly, while only 1 % could not answer any question.

[19] See Table 3.A2 in the Appendix for a complete list of financial literacy questions.

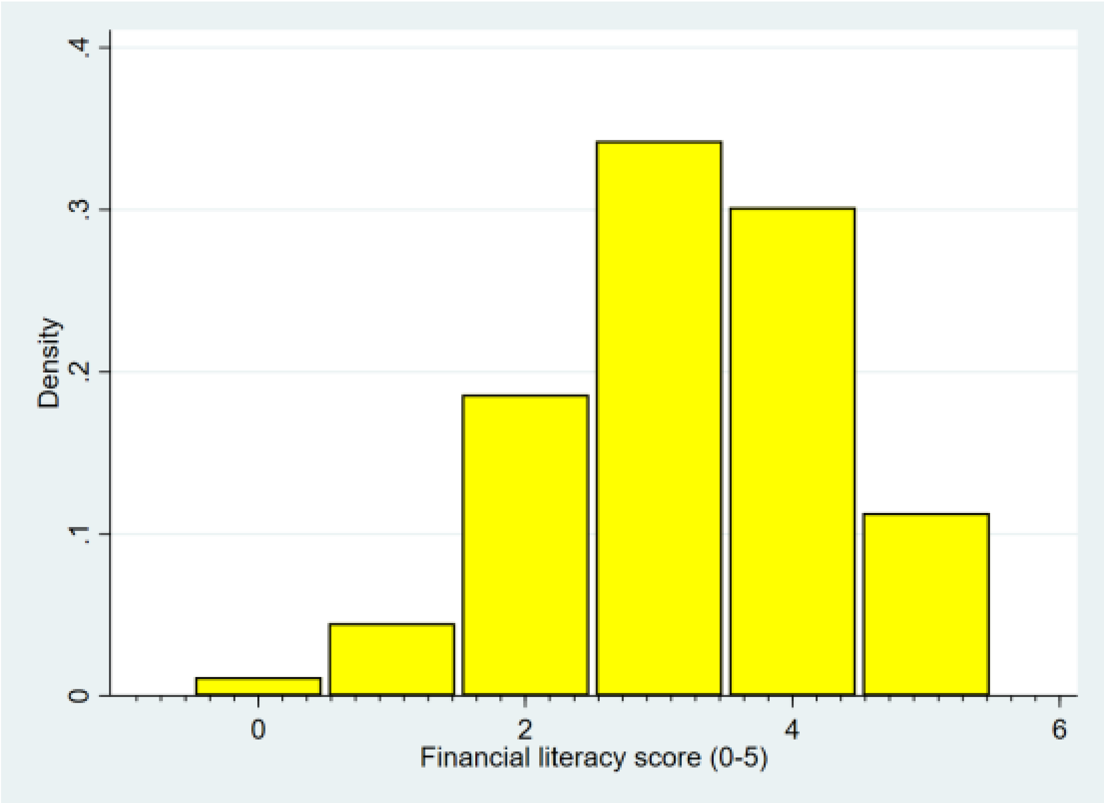

Figure 3.2 Distribution of financial literacy score test

Source: Authors' calculations

c. Crop decision-making test

To capture the decision-making variable, we execute an experiment capturing the reason behind the decision-making of the respondents. The decision-making test confronts the respondents with a hypothetical but realistic crop decision situation about two new rice varieties. All necessary information is given, such as the variable costs, and yield per unit area unit (i.e., "sao" in Vietnam and "rai" in Thailand), and the sales price per kilogram of rice. Respondents were asked to make a decision about either variety and give a reason for their choice [20]. We were interested which criteria was the most important one, e.g., yield or profit.

Hence the assessment is not based on right or wrong but simply on the type of decision criteria, namely higher yield, higher profit, higher price, or lower costs. Figure 3.3 visualizes the reasons

[20] See Table 3.A3 in the Appendix for a complete list of decision-making questions.

for decision-making. For over half of the respondents, crop price is the major criterion, followed by higher yield and lower costs. Only 6% of the respondents based their choice on the profit criterion.

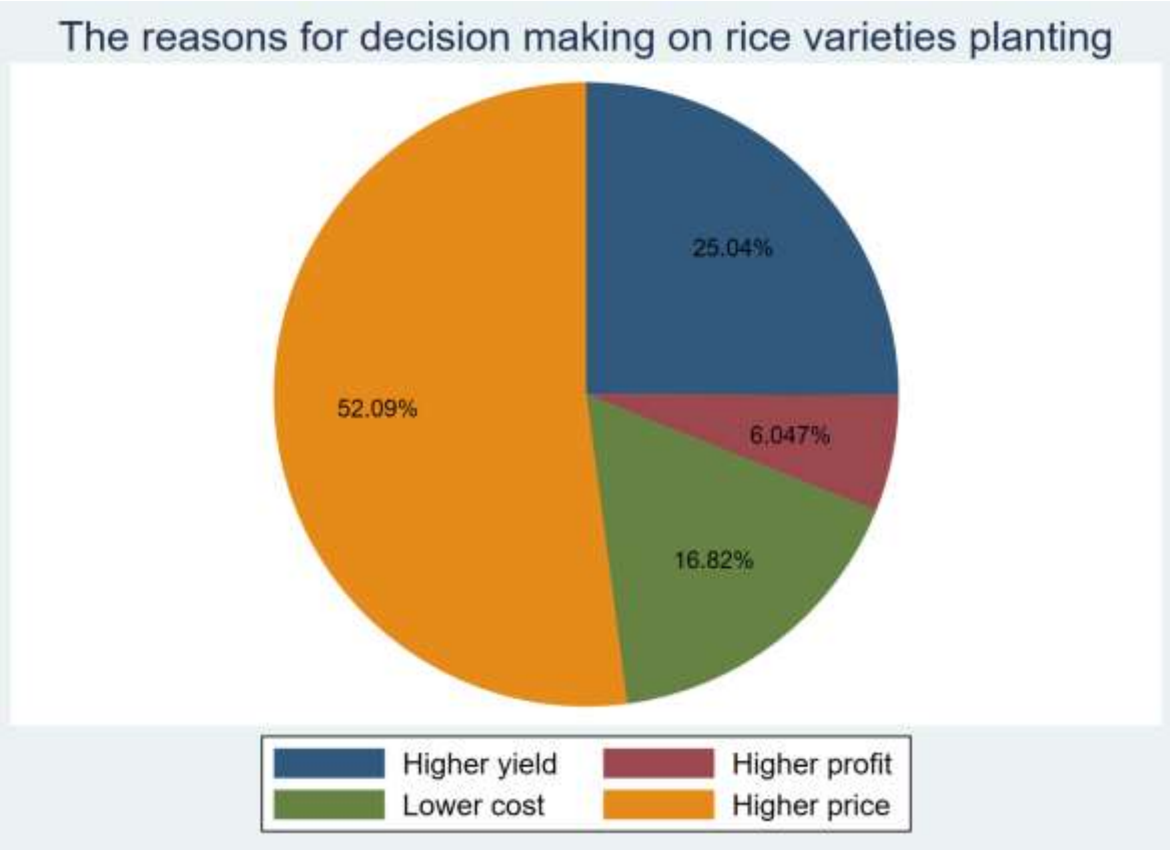

Figure 3.3 The reasons for decision-making on new rice varieties

Source: Authors' calculations

3.4.2 Effects of alternative indicators of human capital on agricultural performance

We start this sub-section by presenting and discussing our main empirical results of four alternative explanatory variables in the relationship with rice production performance. Table 3.3 shows the OLS and 2SLS results of the correlation of alternative indicators of human capital with different agricultural performance indicators. Since the variables of interest are standardized, the regression coefficient is interpreted as the effect of one-standard-deviation change on knowledge, financial literacy, education, and experience on a specific outcome variable.

With respect to agricultural knowledge and farm experience, in the upper panel of Table 3.3, agricultural knowledge is negatively associated with rice yields and costs but positively associated with profit. According to the OLS results, an increase in agricultural knowledge by one standard deviation unit leads to a 5% and a 6% decrease in yields and costs, respectively. However, one standard deviation increase in agricultural knowledge increases profits by 13%. With the presence of instrument variables[21], the 2SLS results point in the same direction; however, the magnitude of the effect is significantly larger. As the agricultural knowledge score increase by one standard deviation unit, yields and costs decrease by approximately 13% and 15%, while the profit increase by 16%, respectively. In terms of experience, which is calculated as the respondent's age minus the years of schooling, it has a significant relationship with yields, costs, and profit in both OLS and 2SLS models. Greater farm experience is positively related to rice profit but negatively with yields, and costs of rice production. The knowledge variable shows a similar pattern. However, the knowledge indicator predicts rice production outcomes better in comparison to the experience indicators. In case both coefficients are significant, the level of significance for the knowledge indicator is more robust than the experience indicator.

In terms of financial literacy and schooling years of education, we obtain the opposite results compared with knowledge and experience. These two indicators have the same positive effect on yield and total input cost but are negative on profit. The OLS results show that higher education and better financial literacy boost rice yield per hectare and more input expenditures. The direction of coefficients in the 2SLS remains the same but shows a higher level of significance and a higher magnitude. With regards to the relationship between education and rice yields, the coefficients in the OLS model are interpreted as the effect of a one-standard-deviation change of years of schooling, increasing the rice yields by around 5% at the 90% confidence interval. In the 2SLS model, if the schooling years of farmers increase by one standard deviation, yields of rice increase 15% at a 99% confidence interval.

The consistency between OLS and 2SLS models' results suggests that the approach of regressing data of identical households observed at a later point with those at an earlier point

[21] Results of the reduced form regression in Table 3.A4 in the Appendix show that the chosen instrument works well.

is valid. However, the statistical quality of the 2SLS model is better, which in principle, makes it the preferred among the two model variants.

Table 3.3 Effects of alternative indicators of human capital on rice yields, costs, and profits

	Yields - Kg/ha (ln)		**Total costs-$PPP/ha (ln)**		**Profits-$PPP/ha (ln)**	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Knowledge	-0.050***	-1.287***	-0.064***	-1.469***	0.135*	1.606**
	(0.019)	(0.349)	(0.020)	(0.355)	(0.069)	(0.819)
Financial	0.076***	1.845***	0.067***	2.025***	-0.009	-2.865**
literacy	(0.021)	(0.669)	(0.022)	(0.771)	(0.052)	(1.458)
Education	0.048*	1.552***	0.031	1.704***	-0.077	-2.411**
	(0.025)	(0.428)	(0.029)	(0.518)	(0.076)	(1.074)
Experience	-0.051**	-2.108***	-0.042*	-2.406**	0.122**	2.630*
	(0.017)	(0.735)	(0.024)	(0.820)	(0.059)	(1.525)
N	1,290	1,290	1,290	1,290	1,290	1,290

Note: Additional controls include female, ethnicity of household head; average age, maximum education of household members, household size, the share of actively working members in agriculture, agricultural asset per capita at the household level; distance to district town, type of main road to the village, and SPEI at village level. Extension service at village level is used as IV of knowledge score and farm experience. Family reason to quit school is used as IV of education and financial literacy. Single, double, and triple asterisks (*, **, ***) denote $p < 0.10$, 0.05, and 0.01, respectively. Standard errors are clustered at the village level. All dependent variables are standardized.

Source: Authors' calculations.

Overall, results suggest that farmers who performed better in the agricultural knowledge tests and have more experience in farming tend to spend less on inputs. At the same time, despite lower yields, they obtain higher profits. Hence these farmers use inputs more judiciously and perhaps are the more efficient farmers. Hereby possible effects of output prices are excluded. Small-scale farmers are price-takers[22], and technical knowledge and farming skills is unlikely a possible explanation for higher prices. Rather these are random or possibly related to profits and positively related to input costs deserve more investigation. The same holds for financial literacy and decision-making capacity.

[22] However, we also include rice revenue variables to capture the determinant of the price. The results in Table 3. A5 in the Appendix shows that coefficients of rice revenue mostly have the same direction and are statistically significant as the profits variable.

The comparison of the results of our findings reveals both similarity and dissimilarity to the finding of other studies. For example, regarding agricultural knowledge, our result aligns with Hayami & Ruttan (1970), who finds that technical education in agriculture has a positive and significant effect on output in developed and less developed countries. Godtland et al. (2004) report that intensive technical training via farmer field schools increased the productivity of potato production in Peru.

With respect to schooling years as a proxy of education, our finding that farmers with higher years of schooling spend more for inputs aligns with Asfaw & Admassie, (2004) in Ethiopia. Our results that farmers with more years of formal schooling have higher yields is similar with the finding of Asadullah & Rahman, (2009) in Bangladesh.

In summary, four human capital indicators in our study significantly correlate with performance parameters in rice production. By using more advanced measures for human capital as explanatory variables, we add new evidence to the literature. The most important message is that farmers with more agricultural knowledge and farm experience obtain higher profits. Obviously, the better farmers have a better notion of the concept of optimal versus maximum yields.

3.4.3 Effects of interaction between knowledge with financial literacy and education on agricultural performance

To better understand whether the knowledge score, is really a good indicator for investigating the impact of human capital on agricultural production, we investigate the interaction among variables. The effect of agricultural knowledge and experience has the same direction on three outcomes of rice production: yields, costs, and profits. We, therefore, examine the interaction between knowledge and other alternative indicators, i.e., knowledge score with financial literacy score, and knowledge with education level with regards to yields, costs, and profits of rice production.

Table 3.4 illustrates the OLS and 2SLS results of the effect of the interaction between knowledge with financial literacy, and education, respectively. The upper panel of Table 3.4 shows that the effect of the interaction term between knowledge and financial literacy has the same direction as the impact of knowledge on yields, costs, and profits, i.e., negative association with yields as well as costs, but associated positively with profits. Moreover, the effect of the financial score on rice profits is negative, given a mean knowledge score of zero. By an increase in the financial literacy score of one standard deviation, the effect of knowledge becomes more significant. The interaction coefficient between knowledge and financial literacy is positive and significant with rice profits. These results confirm that technical knowledge matters in rice productivity when better technical agriculture knowledge combine with higher financial literacy, this interaction robust the positive impact of agricultural knowledge on rice profits.

In the lower panel of Table 3.4, the effects of the interaction between knowledge with education are presented. It is shown that the relationship of the interaction between knowledge and education on rice yields, costs, and profits is in line with the relationship of the interaction between knowledge and financial literacy. The interaction between knowledge and education is negative with yields and costs but positive with profit. On the one hand, the results of the 2SLS model show that the relationship between education and rice yields and costs is positive but negative for profits, given a zero mean knowledge score. These results are all significant. On the other hand, the interaction between knowledge score and education level shows opposite results. The interaction between knowledge and education has significant positive coefficients for rice profits. One-standard-deviation increase in knowledge interacts with increasing one-standard-deviation of education, increasing the rice profits by 71% at the 95 confidence interval.

In short, one main message that can be drawn from Table 3.4 is that technical agricultural knowledge in farming is more important than knowledge on financial matters. However, the combination of more years of formal schooling or higher level of financial literacy combined with better technical knowledge in agriculture helps farmers be more economical in rice production.

Table 3.4 Effects of interaction between knowledge with financial literacy and education

	Yields - Kg/ha (ln)		**Total costs-$PPP/ha (ln)**		**Profits-$PPP/ha (ln)**	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Knowledge & Financial Literacy						
Knowledge	-0.057***	-0.043**	-0.069***	-0.050*	0.137**	0.137*
	(0.019)	(0.020)	(0.020)	(0.026)	(0.069)	(0.076)
Financial literacy	0.081***	0.077***	0.073***	0.066**	-0.020	-0.101
	(0.021)	(0.020)	(0.022)	(0.026)	(0.052)	(0.090)
Knowledge*	-0.017	-0.098*	-0.025	-0.184**	0.018	0.510*
Financial literacy	(0.024)	(0.061)	(0.025)	(0.085)	(0.057)	(0.318)
Knowledge & Education						
Knowledge	-0.055***	-0.057**	-0.067***	-0.070**	0.142**	0.185**
	(0.018)	(0.022)	(0.020)	(0.028)	(0.069)	(0.082)
Education	0.056**	0.133***	0.039	0.152***	-0.089	-0.446***
	(0.025)	(0.042)	(0.030)	(0.054)	(0.076)	(0.166)
Knowledge * Education	-0.037*	-0.346***	-0.026	-0.401***	-0.024	0.710**
	(0.022)	(0.079)	(0.033)	(0.082)	(0.066)	(0.295)
Control	Yes	Yes	Yes	Yes	Yes	Yes
N	1,290	1,290	1,290	1,290	1,290	1,290

Note: Additional controls include female, ethnicity of household head; average age, maximum education of household members, household size, the share of actively working members in agriculture, agricultural asset per capita at the household level; distance to district town, type of main road to the village, and SPEI at village level. Extension service at village level is used as IV of knowledge score and farm experience. Family reason to quit school is used as IV of education and financial literacy. Single, double, and triple asterisks (*, **, ***) denote p < 0.10, 0.05, and 0.01, respectively. Standard errors are clustered at the village level. All dependent variables are standardized.
Source: Authors' calculations.

3.4.4 Effects of decision making on agricultural performance

In this sub-section, we investigate the correlation between the reasons for decision-making on rice production performances. The decision was made to choose two new rice varieties based on the given information on experience, discussed in the previous section. The four main reasons to make this decision are based on higher yields, higher profit, lower costs, or higher crop prices. We keep the decision-making based on higher yields as our base reference among four reasons for decision-making. We then estimate the impact of these decision-makings on rice yields, costs, and profits.

The OLS in Table 3.5 shows the impact of farmers' decisions based on different reasons (i.e., yield, profit, cost, and price) on three alternative indicators of rice performance. In the upper panel, Table 3.5, we compare the performance of farmers who prefer to choose a particular rice variety because of higher profits and not because of higher yields. The model suggests that farmers who choose a rice variety because of higher profit reason achieve rice yields 12% and have 15% higher production costs than those who prefer the yield trait of a variety.

In terms of production costs, farmers who choose a rice variety because of lower variable costs show an adverse effect on rice yields and costs compared with farmers who choose the yields criterion for decision-making. They have significantly lower production costs of around 18% as compared to those who chose the yields criterion. Again farmers who are cost-conscious tend to achieve higher profits as compared to those who go for yields. Finally, farmers who base their decision on the price instead of yield, show a negative but insignificant correlation with rice yields.

In summary, unfolding the relationship between the reasons for decision-making and performance indicators of rice production provides some novel insights. As shown above, we can confirm that farmers who judge costs of production higher than yields tend to achieve higher profits with less input costs, in spite of lower yields. Hence these farmers are optimizers rather than maximizers and thus tend to behave economically. Implicitly this also suggests that financial literacy is an important component of farmer education.

Table 3.5 Effects of decision-making on rice yields, costs, and profits

	Yields - Kg/ha (ln)	Total costs-$PPP/ha(ln)	Profits-$PPP/ha (ln)
Decision making			
Based on higher profit	0.128**	0.154**	0.233
	(0.059)	(0.072)	(0.333)
Base on lower costs	-0.234***	-0.189***	0.420*
	(0.064)	(0.060)	(0.217)
Base on higher price	-0.110**	-0.053	0.229
	(0.047)	(0.063)	(0.190)
N	1,290	1,290	1,290

Note: Additional controls include female, ethnicity of household head; average age, maximum education of household members, household size, the share of actively working members in agriculture, agricultural asset per capita at the household level; distance to district town, type of main road to the village, and SPEI at village level. Single, double, and triple asterisks (*, **, ***) denote p < 0.10, 0.05, and 0.01, respectively. Standard errors are clustered at the village level.
Base case: Decision making based on higher yield option
Source: Authors' calculation

3.5 Summary and policy implications

In this study, we conducted knowledge, financial, and decision-making experiments in a particular year, that is, in 2014, combined with agricultural outcomes and household information collected before and after the implementation of knowledge tests, i.e., in 2013 and 2017. We investigate the relation between technical knowledge and agricultural production performance. By using different indicators of human capital in the relationship with rice production performance, we have a have gained new insights of the role of human capital in agriculture.

Our study advances the literature in at least four points. First, by conducting technical knowledge and management skills tests, we have a more direct measure to capture agriculture knowledge and financial literacy. Second, examining the association of these indicators with different rice production performance parameters we can show that, essentially, farmers with better technical knowledge achieve higher profits. In comparison, this is not necessarily the case for those with better knowledge of financial management. Third, farmers with higher formal education tend to have higher yields but not higher profits. Fourth, by observing the correlation between the rationale for decision-making with rice production outcomes, a better understanding of the reasons for farming success is obtained.

As regards policy implications, it is clear that with the growing challenges in agriculture, knowledge and understanding are more critical than ever. Therefore, training and face-to-face extension remain to be essential vehicles for knowledge dissemination of new information and communications technologies must come in at the global and local levels. For example, FAO (2017) found that adult education programs promote profitably and, at the same time, more sustainable agricultural systems. As Foster & Rosenzweig (1995) and Appleton & Balihuta (1996) had emphasized the role of spillover effects, there is perhaps some merit for local authorities in Thailand and Vietnam to facilitate the formation of specific farming groups for sharing knowledge and experiences. This can help to rebuild the recognition for the common good, which will be necessary if the tremendous challenges of the inevitable global warming process can be coped with.

Considering the increasingly difficult conditions for farmers in developing countries due to extreme weather events, climate change and rising energy costs, education, knowledge, and skills will become more important. As this paper has shown, meaningful parameters must be used if one wants to capture the true role of human capital in agriculture. In some way, our study confirms Theodore W. Schulz’s insights, gained over 50 years ago, that farmers are not stupid. They may be poor but they are efficient. Our study shows that higher profits can be achieved with less inputs. This is a positive message, good for the economy and good for the environment.

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Appendix

Table 3.A1 Knowledge questions in crop production used in Thailand and Vietnam

1. Land preparation should be done one day before the rice transplanting.		A
2. In a 50kg bag of 16-20-0, there is 50kg of nitrogen.		A
3. The most important fertilizer for high yields is nitrogen.		A
4. The more fertilizer one can apply the better for the yield.		A
5. Transplanting is good for weed control.		A
6. Land preparation is not important for the water management during the cropping season in rice.		A
7. The more water in the field is always better for growth of rice.		A
8. All insects in the rice field are pests.		A
9. The principle to apply pesticides is to spray only when you see the pests.		A
10. Harvesting methods does not effect on the grain yield.		A
Code A: 1. Correct 2. Wrong		

Source: TVSEP Survey 2014

Table 3.A2 Financial literacy question used in Thailand and Vietnam

Vietnam

1. If today you borrow 10 Mio VND, at an interest rate of 2% per month, after 3 months how much do you own totally (principal + interest)?	A
2. If you have 10 Mio VND in an account, the interest rate on the account is 1 % per year, and during this time, the price of goods and services rises by 2% per year, after one year you can buy:	B
3. For the same amount of money, a person can choose either one of the following two lotteries. Lottery A pays a prize of 10 Mio VND, and the chance of winning is 5%. Lottery B pays a prize of 500 000 VND, and the chance of winning is 10%. Which Lottery pays the higher expected amount?	C
4. Suppose you need to borrow 50 Mio VND. Two person offer you different loans, the first loan you have to pay back 55 Mio VND in one month, with the second loan you have to pay back 50 Mio plus 15% in one month. Which loan is the better option?	D
5. Please indicate if the following statement is true or false. “It is safe to keep cash at home than to take it to the bank”.	F

Code A:	Code B:	Code C:	Code D:	Code F:
1.Less than 10 Mio VND	1.Less than you can buy today	1. Lottery A	1. The first loan	1. True
2. More than 10 Mio VND	2. More than you can buy today	2. Lottery B	2. The second loan	2. False
3. Exactly 10 Mio VND	3.Exactly the same as today	3. Two lotteries pay the same expected amount	97. Do not know	97.Do not know
97. Do not know	97. Do not know	97. Do not know		

Source: TVSEP Survey 2015

Thailand

1. If today you borrow 10 000 THB, at an interest rate of 2% per month, after 3 months how much do you own totally (principal + interest)?	☐	A
2. If you have 10 000 THB in an account, the interest rate on the account is 1 % per year, and during this time, the price of goods and services rises by 2% per year, after one year you can buy:	☐	B
3. For the same amount of money, a person can choose either one of the following two lotteries. Lottery A pays a prize of 2 000 THB, and the chance of winning is 5%. Lottery B pays a prize of 100 THB, and the chance of winning is 10%. Which Lottery pays the higher expected amount?	☐	C
4. Suppose you need to borrow 50 000 THB. Two person offer you different loans, the first loan you have to pay back 60 000 THB in one month, with the second loan you have to pay back 50 000 THB plus 15% in one month. Which loan is the better option?	☐	D
5. Please indicate if the following statement is true or false. “It is safe to keep cash at home than to take it to the bank”.	☐	F

Code A:	Code B:	Code C:	Code D:	Code F:
1.Less than 200 THB	1.Less than you can buy today	1. Lottery A	1. The first loan	1. True
2. More than 200 THB	2. More than you can buy today	2. Lottery B	2. The second loan	2. False
3. Exactly 200 THB	3.Exactly the same as today	3. Two lotteries pay the same expected amount	97. Do not know	97.Do not know
97. Do not know	97. Do not know	97. Do not know		

Source: TVSEP Survey 2015

Table 3.A3 Decision-making test in crop production

Vietnam

The Agricultural Extension Center offers to introduce two new rice varieties (variety A and variety B). Variety A has lower input but also lower yield. Variety B has higher input cost but also higher yield. The center gives you the following information about the two varieties. Suppose that you could grow both varieties in your land, which variety you choose?

	Options	
	Variety A	Variety B
Area	1 Sao	1 Sao
Cost per Sao (1000 VND)	300 000 VND	600 000 VND
Yield per Sao (kg)	100 kg	200 kg
Price per kg (1000 VND)	15 000 VND	10 000 VND
Your option:	Variety A ☐	Variety B ☐

Why did you choose that option:……………………………………………………………...

Thailand

The Agricultural Extension Center offers to introduce two new rice varieties (variety A and variety B). Variety A has lower input but also lower yield. Variety B has higher input cost but also higher yield. The center gives you the following information about the two varieties. Suppose that you could grow both varieties in your land, which variety you choose?

	Options	
	Variety A	Variety B
Area	1 Rai	1 Rai
Cost per Sao (1000 THB)	600 THB	1800 THB
Yield per Sao (kg)	200 kg	400 kg
Price per kg (1000 VND)	30 THB	20 THB
Your option:	Variety A ☐	Variety B ☐

Why did you choose that option:……………………………………………………………...

Source: TVSEP Survey 2014

Table 3.A4 First stage results of the 2SLS model

	Dependent variables:			
Instrument	Agricultural knowledge	Experience	Education	Financial literacy
Extension at village level	1.085*** (0.113)	7.880*** (1.663)		
Leaving school early because of social and family problems			0.846*** (0.214)	0.340*** (0.066)
F-stat	91.64	22.45	15.62	25.97
P-value	0.000	0.000	0.000	0.000
Observations	1,290	1,290	1,290	1,290

Note: Single, double, and triple asterisks (*, **, ***) denote p < 0.10, 0.05, and 0.01, respectively.
Source: Authors' calculations.

Table 3.A5 Effects of alternative indicators of human capital on rice revenues

	Revenues - $PPP/ha (ln)	
	OLS	2SLS
Knowledge	0.201*** (0.065)	2.898*** (0.899)
Financial literacy	-0.058 (0.050)	-4.328** (1.836)
Education	-0.085 (0.073)	-3.646*** (1.278)
Experience	0.118** (0.051)	4.714*** (1.924)
N	1,290	1,290

Note: Additional controls include female, ethnicity of household head; average age, maximum education of household members, household size, the share of actively working members in agriculture, agricultural asset per capita at the household level; distance to district town, type of main road to the village, and SPEI at village level. Extension service at village level is used as IV of knowledge score and farm experience. Family reason to quit school is used as IV of education and financial literacy. Single, double, and triple asterisks (*, **, ***) denote p < 0.10, 0.05, and 0.01, respectively. Standard errors are clustered at the village level. All dependent variables are standardized.
Source: Authors' calculations.

CHAPTER 4: EXTREME WEATHER AND AGRICULTURAL INPUT MANAGEMENT IN RURAL THAILAND AND VIETNAM: INTENSIFY OR DE-INTENSIFY?

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Abstract

In this paper, we explore the impact of drought events on small-scale farmers’ input management decisions in Northeastern Thailand and Central Vietnam. More specifically, we investigate whether small-scale farmers intensify the use of agricultural inputs in response to extreme weather events in order to minimize yield losses, or do they reduce the use of inputs to save production costs. To that end, we combine longitudinal household data from the two regions (i.e., the Thailand Vietnam Socio Economic Panel) from 2007-2017 with monthly high-resolution (0.5 degree) rainfall and temperature data from the Global Historical Climatology Network Version 2 and the Climate Anomaly Monitoring System (respectively) to characterize droughts at the sub-district level. We find a couple of interesting observations. First, our results indicate that farmers tend to de-intensify agricultural production in terms of hired labor, pesticides, number of crops grown, and agricultural durable good investments in response to severe droughts. Second, farmers increasingly hire machinery as a substitute for own investments and own household labor. Third, the magnitude of effects increases as the severity of droughts increases. Differentiating the analysis between countries, and upland and lowland rice production, shows that the level of de-intensification varies. For example, Thai farmers allocate more family and hired labor to agricultural production, and Vietnamese farmers invest in agricultural assets. Upland rice farmers focus on several inputs such as pesticides, machinery, and agricultural assets, while lowland farmers focus on available irrigation systems.

Keywords: Input intensification, drought, SPEI, Southeast Asia
JEL codes: Q12, Q54, O13

4.1 Introduction

Extreme weather events such as floods, droughts, typhoons, or cyclones have increased and spread in every region worldwide under climate change conditions (IPCC, 2014a). Extreme weather events have seriously harmed society, human life, and all sectors of the economy, especially the agricultural sector (Hagman, 1984; Fisher et al., 2012; Carter et al., 2018). Weather-induced risks have considerable impacts on all aspects of agricultural production in both developed and developing countries (Mendelsohn et al., 1994; Miyan, 2015; Kunze, 2021). These effects vary across regions and among crop varieties (Reidsma et al., 2010; IPCC, 2014a). An improved understanding of the relationship between extreme weather events and agricultural activities is necessary for extension organizations as well as policymakers. However, comprehensive studies of how farmers make agricultural input decisions under environmental risks, are scant, especially in developing countries (Iizumi & Ramankutty, 2015).

A growing number of works have investigated the adverse effects of extreme weather events on agricultural outputs, such as crop yields (Schlenker & Lobell, 2010; Lesk et al., 2016; Gammans et al., 2017), farmland value (Mendelsohn et al., 1994), crop revenue (Wang et al., 2009; Deschênes & Greenstone, 2012), or farmer's strategies to adapt to the negative impacts of natural hazards, both in developed countries and in developing countries.

However, only a few studies investigated the impact of weather variability on farmers' input management. In reviewing this literature, one can observe that the extent to which farmers adjust inputs depends, in particular, on the type of weather indicator used in the study (Alem et al., 2010; Mendelsohn & Wang, 2017; Aragón, Oteiza, & Rud, 2018). For example, slight seasonal temperature and precipitation variations induce farmers to intensify inputs in the time of the season with more favorable weather conditions. In the case of temperature spikes, Mendelsohn and Wang (2017) and Aragón, Oteiza, and Rud (2018) find that farmers increase the use of land and domestic labor. A few studies address the effect of extreme weather events (e.g., drought) on input management, but then focus on only one specific input. For example, Koundouri et al. (2006) and Taraz (2017) investigate the role of irrigation and explore that farmers invest in irrigation to minimize the adverse effects of dry spells. Recently, Steinhübel, Wegmann and Mußhoff (2020) investigate farmers' decision to adopt the specific borewell technology in Bangalore, India.

In this paper, we investigate the effect of severe drought events on a range of different farm input decisions related to land use, labor, pesticides, fertilizer, machinery, irrigation, and investments in other productive assets such as water tanks, water pumps, tractors among rural households in Northeastern Thailand and Central Vietnam. More specifically, we ask: Do farmers intensify the use of agricultural inputs in response to extreme weather events in order to minimize yield losses, or do they reduce the use of inputs to save production costs?

Thailand and Vietnam offer an interesting stage to study the effects of extreme weather on farm input decisions. The agricultural sector has been important in both countries, especially in rural areas. In Thailand, there is a long history of commercialization and market orientation. Vietnam, in contrast, was influenced by the centrally planned economic system until the "Doi moi" reform introduced a market-based pricing system in 1986. In both countries, agriculture has been undergoing profound changes. For example, in many cases the contribution of agricultural income to total household income is less than 50% (OECD-FAO, 2017) but farming remains the backbone for rural households especially during the time of crisis. However, the farm size structure has basically remained the same, and small-scale farming dominates, in which small-scale farmers' response may differ from large-scale farming (Morton, 2007; Cohn et al., 2017). At the same time, the region is highly vulnerable to extreme weather events (ADB, 2009). It is predicted that specifically drought events could become more frequent, severe, and longer-lasting (IPCC, 2014a; Miyan, 2015).

To address the research question, we combine a unique longitudinal household dataset, the Thailand Vietnam Socio Economic Panel (TVSEP), with monthly high-resolution (0.5) precipitation data from the Global Precipitation Climatology Centre (Schneider et al., 2018) and temperature data from the Global Historical Climatology Network Version 2 and the Climate Anomaly Monitoring System (GHCN + CAMS; Fan & Dool, 2008). The TVSEP data set contains detailed information about agricultural practices among the same households observed over six survey waves between 2007 and 2017. We use the gridded precipitation and temperature data and construct the Standardized Precipitation-Evapotranspiration Index (SPEI) to characterize severe to extreme drought events at the sub-district level during the study period. Empirically, we exploit plausibly exogenous variation in the timing and location of droughts to identify their impact on farm input management. We hereby consider the most important crops grown in the study area, i.e., rice and perennial crops such as coffee that is an important cash crop grown in Vietnam's Central Highlands. In addition, we investigate the heterogeneity of effects related to country-specific differences, and lowland versus upland rice farming.

Our results suggest that farmers rather pursue a cost-saving strategy specifically in rice production. In the case of perennial crop cultivation, however, farmers seem to intensify selected inputs such as yield-enhancing and mechanical inputs depending on the severity of the drought event and agro-climatic zones (i.e., countries) in order to regain the longer-term investment in the cash crop. For example, Thai farmers intensify pesticides, machinery and irrigation when exposed to severe and extreme drought, respectively. Looking at rather long-term effects in response to droughts in the previous year, however, shows that drought exposure manifests the input saving rationale among both perennial and non-perennial crop farmers.

Investigating country-specific differences, we find that both Thai and Vietnamese perennial crop farmers increase irrigation expenditures in the short-term. This effect vanishes in the longer-term. Instead, Thai perennial crop farmers intensify own household labor while Vietnamese invest in durable agricultural assets.

Finally, we examine differences between upland and lowland rice farming. Upland rice is strictly rain-fed and specifically practiced by farmers in one district (i.e., Aluoi) in Hue province and mostly all districts in Dak Lak province in Vietnam. Upland rice farmers intensify different inputs such as pesticides, machinery, and investments in durable goods, while farmers operating on lowland rice farms invest in irrigation.

The rest of the paper is organized as follows. Section 2 presents the literature review and our conceptual framework. Data and methods are presented in sections 3 and 4, while Section 5 shows the results. The final section 6 concludes and suggests policy implications.

4.2 Literature review

The impact of weather variability on the agriculture sector has been widely investigated. Weather variabilities have most often been observed as (i) the long-and short-term changes of the average temperature or precipitation, and (ii) the exposure to extreme weather events such as droughts, floods, typhoons, heatwaves, cyclones, and wildfires (ADB, 2009; Pachauri et al., 2014). These weather variabilities have multiple impacts on agricultural activities both related to input decisions and output generation (Carter et al., 2018). However, research primarily focused on measuring the physical and economic effects on agricultural output and left agricultural input management as an interesting subject of research.

Looking at the literature that investigated the effects of changes in average temperature and precipitation on agricultural outputs shows mixed results, although positive impacts have been less common than negative impacts (Pachauri et al., 2014; Mendelsohn et al., 1994; ; Mendelsohn & Dinar, 1999; Seo et al., 2005). The effects of extreme weather events such as flood, drought, storm, typhoon or heat waves, however, are found generally disastrous (Mendelsohn, 2008; Schlenker & Lobell, 2010; Burke & Emerick, 2016; Chen, Chen, & Xu, 2016). Among the list of extreme weather events, drought is one of the costliest natural hazards and is ranked first place in disaster statistics. This is even more worrisome, given that drought impact may often be underreported because of its complex characteristics due to its slow process and that its onset and termination are hardly recognizable (Hagman, 1984; Wilhite, 1993; Wilhite, 2000; Pandey, Bhandari, & Hardy, 2007; Svoboda et al., 2016).

Drought explains 10% to 70% decline of crop yields at the global scale (Dilley, 2005; Lesk et al., 2016; Vogel et al., 2019). The adverse impact of drought varies across regions (Wilhite, 1993; Lesk et al., 2016; Lobell et al., 2014), and largely depends on the regions' resilience ability (Wilhite & Glantz, 1985). For example, drought caused average annual losses of about US$ 700 million in the Great Plains region of the United States in 1975 (Wilhite, 2000). Given reporting in Germany, the drought year 2018 reduced grain harvest by 16 percent from the previous years (WWF, 2019). Droughts also induced massive losses in the developing world (Miyan, 2015). For example, drought reduced 44-71% of agrarian production in India, Thailand, and China (Pandey et al., 2007), affected about 70% of agricultural land in the Central Highlands of Vietnam (CGIAR, 2016), and caused physical and economic losses in Vietnam. The total estimated loss from storms, floods, and drought in Vietnam from 1995 to 2006 was at VND 61,479 billion (around USD 3.236 billion) (Nguyen et al., 2013).

Besides impacts on agricultural output, early studies based on drought data statistics show that farmers have been adopted a number of on-farm and off-farm strategies (e.g., mixed cropping, livelihood diversification) to adapt and mitigate the adverse drought impact (Jodha, 1991). During successive drought episodes, farmers even had to mortgage or sell their main productive asset (i.e., land) to smooth household consumption, changing their status from farmers to landless laborers and migrants (Jodha, 1978). In developing countries, where the formal and full-fledged market for credit and insurance are either absent or immature, these adaption and mitigation strategies at the household level are common over time until today (Huang et al., 2014; Carter et al., 2018; UNDRR, 2019). These studies have been focused on adjustments within farming or livelihood system, rarely paying attention to farmer's behavior toward the ongoing agriculture production in terms of input management under drought stress.

Only a few studies examine the role of weather variability in explaining input management decisions. For example, Basurto-Hernandez et al., 2018 show that weather conditions play a significant part in agricultural production decisions in Mexico. Mendelsohn and Wang (2017), using mean seasonal historical temperature and precipitation data, found that farmers adjusted their input intensity to weather variabilities. In unfavorable weather conditions, farmers in China usually reduce their input use (i.e., fertilizer, irrigation, and machinery). In contrast, Aragón, Oteiza, & Rud (2018) found that farmers increase land use and household labor during high temperature days in Peru. Using panel data from Ethiopia, Alem et al. (2010) found different responses to input use depending on whether the average rainfall level or rainfall variability was used. While a higher average rainfall level of the previous year had a positive correlation on the investment of the current year's fertilizer use, the increasing variability of rainfall was the reason for reducing crop fertilizer intensity. While these studies document the effect of average rainfall or temperature changes and their variability, the effect of extreme weather events may be different (Iizumi & Ramankutty, 2015; Lesk et al., 2016). The few extant studies that investigate the effect of droughts focus on the role of irrigation, such as Koundouri et al. (2006) in Greece or Taraz (2017) in India, and show that farmers who invest in irrigation systems can reduce the negative drought impact.

In this paper, we investigate the effect of adverse weather events on input intensity among small-scale farmers in Thailand and Vietnam. The basic premise of our hypothesis is that extreme weather events adversely affect agricultural production, which will affect farmers' input management decision. We assume that the input response depend on the severity of droughts, the characteristics of different crop varieties and terrain conditions. For this reason, we examine the impact of droughts at different severity levels on input decisions related to crop production under three scenarios that focus either on (i) rice as the major crop grown, (ii) perennial crops, or (iii) all crops grown in the study area. We also examine the heterogeneity of effects across the two countries, and across lowland rice and upland rice.

4.3 Data

We use two data sources in this study: (i) a household panel survey conducted in six waves from 2007 to 2017, and (ii) historical precipitation and temperature data containing monthly observations from 1948 until 2016.

4.3.1 Household panel survey

The individual-level panel data come from the Thailand Vietnam Socio-Economic Panel (TVSEP 2021) project, a comprehensive survey initiated in 2007 and spanning a decade period in six provinces of Thailand and Vietnam. Households were selected from a stratified random sampling approach, which involves a three-stage clustering process that accounts for country-specific differences and captures the heterogeneity of agro-ecological characteristics (Hardeweg, Klasen and Waibel, (2013). The original sample of 4,400 households from 440 villages in 220 sub-districts represent the rural and vulnerable population in the purposely selected provinces with similar conditions. The overall attrition rate of the TVSEP survey over a decade is 13.88%. Two sets of questionnaires were used to collect information at the household and village level. The household questionnaire addresses the respective head of the household and infers information related to socio-economic characteristics of each household member, including e.g., occupation, health, and education. Furthermore, the survey contains a rich agricultural module, including detailed questions related to agricultural inputs and produce. The village questionnaire captures information about the local economy within a village, and its social structure by interviewing the village head. In this paper, we use a balanced household panel data set collected in 2007, 2008, 2010, 2013, 2016, and 2017 with 2,576 from the same small-scale farmers located in six provinces, i.e., Buriram, Ubon Ratchathani, Nakhon Phanom in Thailand and Ha Tinh, Hue, Dak Lak in Vietnam.

From the agricultural module of the TVSEP household survey, we can infer different input management decisions, related to land and labor allocation, use of fertilizer, pesticides, machinery, irrigation, and investments in durable goods such as tractors, water tanks, water pumps or trucks. More specifically, we define eight input intensity variables, which we will use as alternative dependent variables in our econometric analysis. Table 4.1 describes the eight dependent variables. Except for land intensity and household labor intensity, we define input intensity based on monetary expenditures for each input in relation to land area (in hectare) (Brookfield, 1972; Turner & Doolittle, 1978). Monetary values were converted from the local currencies to USD using purchasing power parity in 2015[23].

Table 4.1 Definitions of alternative dependent variables

Variable Name	Description
Land intensity	The number of planted crops per hectare.
Household labor intensity	The number of household members at working age above 15 and below 64 allocated to own agricultural production divided by the total household workforce.
Hired labor intensity	The total cost of hired labor in agricultural activities: land preparation, seed planting, hand weeding, harvesting per hectare, $ PPP.
Fertilizer intensity	The total expenditure of fertilizers per hectare, $ PPP.
Pesticides intensity	The total expenditure of pesticides per hectare, $ PPP.
Machinery intensity	The cost of hiring machinery for land preparing and harvesting as well as the cost of its fuels per hectare, $ PPP.
Irrigation intensity	The cost of irrigation for agricultural crops per hectare, $ PPP.
Investment intensity	The depreciated value of agricultural assets such as tractor, water tanks, water pumps, truck per hectare, $ PPP.

Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

Table 4.2 presents mean and standard deviation of dependent variables for each survey year from 2007 to 2017. One can observe three interesting patterns. First, on average, over the eleven years' time span, more crops are grown per hectare, and per hectare expenditures for machinery, fertilizer, pesticides and durable goods are increasing. Notable hereby is the dip in expenditures in 2008 that can be attributed to the global financial crisis. Second, own household labor allocated to agriculture is decreasing over time from 56.3% in 2007 to 42.2% in 2017. Expenditures for hired labor, however, is fluctuating over time with a peak in 2013. Third, average irrigation expenditure per hectare fluctuates over time with a high in 2008 and a low

[23] The cost of fertilizer and pesticides have been adjusted by the Global Fertilizer and Pesticides Price Index between 2006 and 2018 (see Figure 4.A1 in the Appendix) to control for price fluctuation (WB, 2017).

in 2010. Most farms in Thailand and Vietnam are rain-fed, so the fluctuations could be in response to dry spells e.g., in 2007.

Table 4.2 Descriptive statistics of alternative dependent variables

	2007	2008	2010	2013	2016	2017
Land intensity (# of crops per hectare)	4.582 (9.627)	5.265 (7.845)	4.286 (6.593)	4.544 (13.296)	7.001 (11.592)	7.751 (16.433)
Household labor intensity (%)	0.563 (0.303)	0.533 (0.294)	0.498 (0.292)	0.475 (0.292)	0.440 (0.288)	0.422 (0.294)
Hired labor intensity ($PPP/ha)	107.348 (268.609)	93.086 (224.291)	66.237 (115.86)	135.018 (261.270)	108.305 (330.174)	105.436 (409.497)
Machinery input intensity ($PPP/ha)	128.468 (439.097)	120.454 (142.653)	124.05 (136.113)	138.641 (184.806)	228.180 (252.888)	225.554 (186.712)
Fertilizer intensity ($PPP/ha)	471.449 (816.377)	259.070 (405.472)	360.774 (678.884)	300.592 (385.055)	525.553 (724.799)	538.861 (866.596)
Pesticide intensity ($PPP/ha)	58.279 (149.484)	27.923 (68.801)	44.869 (71.019)	52.143 (94.185)	86.323 (145.476)	116.204 (389.857)
Irrigation intensity ($PPP/ha)	65.536 (196.050)	33.874 (92.876)	16.975 (34.519)	60.339 (210.428)	56.865 (172.168)	46.119 (134.499)
Investment intensity ($PPP/ha)	1,219.298 (3844.853)	635.004 (2914.119)	682.362 (3026.18)	1,275.234 (3936.211)	1,489.843 (7349.122)	1,541.813 (6872.648)
N	2,576	2,576	2,576	2,576	2,576	2,576

Note: Standard deviation in parenthesis. Monetary value is measured in 2005 PPP USD. Cost of fertilizer and pesticides are adjusted by Fertilizer Price Index (WB, 2017).
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

4.3.2 Historical weather data

Drought is a multi-scalar phenomenon, so it does not have a unique and universal drought indicator. The measurement of drought in the literature varies by the availability of data in a given location. Generally, the Standardized Precipitation Index (SPI) is a commonly used index recommended by the World Meteorological Organization (WMO) (Vicente-Serrano et al., 2010; Svoboda et al., 2016). However, the calculation of the SPI includes only precipitation data and excludes other essential factors of drought determinants such as temperature and potential evapotranspiration. Vicente-Serrano et al. (2010) formulated the Standardized Precipitation Evapotranspiration Index (SPEI), which improves the deficiency of the SPI by considering temperature and potential evapotranspiration and can capture drought severity and duration over time. The SPEI has been widely used in various drought studies (Beguería et al., 2014; Labudová, Labuda, & Takáč, 2017; Stojanovic et al., 2020) and we will use it here to define our main explanatory variable of interest.

More specifically, the SPEI is a multi-scalar drought index that captures the water balance as the difference between precipitation and potential evapotranspiration. Considering both the role of precipitation and temperature in its calculation, SPEI is a reliable indicator to identify the onset, duration, and severity of drought, and it has been found suitable to estimate the impacts of drought on social and economic outcomes (Vicente-Serrano, Beguería, & López-Moreno, 2010; Beguería et al., 2014; Quiñones, Liebenehm, & Sharma, 2021). The SPEI calculation is based on monthly high-resolution (0.5) precipitation and temperature data from 1948 to 2016 from the Global Precipitation Climatology Centre (Schneider et al., 2018), and the Global Historical Climatology Network Monthly - Version 2 and the Climate Anomaly Monitoring System (GHCN + CAMS; (Fan & Dool, 2008), respectively.

To relate the gridded precipitation and temperature data to the TVSEP household data, we use third-level administrative shapefiles that represent all sub-districts in Thailand and Vietnam. As the TVSEP sampling strategy included the random selection of two villages for each of the 220 sub-districts, we extracted area-weighted average precipitation and temperature for each sub-district and then calculated the sub-district level SPEI following (Vicente-Serrano et al., 2010). The SPEI is a standardized variable and thus allows comparison of SPEI values over time and space. We define two binary drought indicators that differ in the level of severity: (i) a severe drought indicator that is equal to one if the SPEI is smaller than or equal to negative 1.5 standard deviation , zero otherwise, and (ii) an extreme drought indicator if the SPEI is smaller than or equal to negative 2 standard deviation, zero otherwise (Dai, 2011); Labudová, Labuda, and Takáč, 2017).

Another important aspect to consider is the timing of agricultural input decisions and the onset of the drought. Farmers usually make decisions at the beginning of the planting season, while the onset of a drought is difficult to anticipate. We therefor use observations of drought events both during the same reference period of each survey wave and during the previous year.

Figure 4.1 presents the distribution of the sub-district weighted SPEI across the six survey waves[24]. Particularly the year 2016, where the median SPEI value is below the value of -1.5 has been referred to as the century drought in the study area (FAO, 2016).

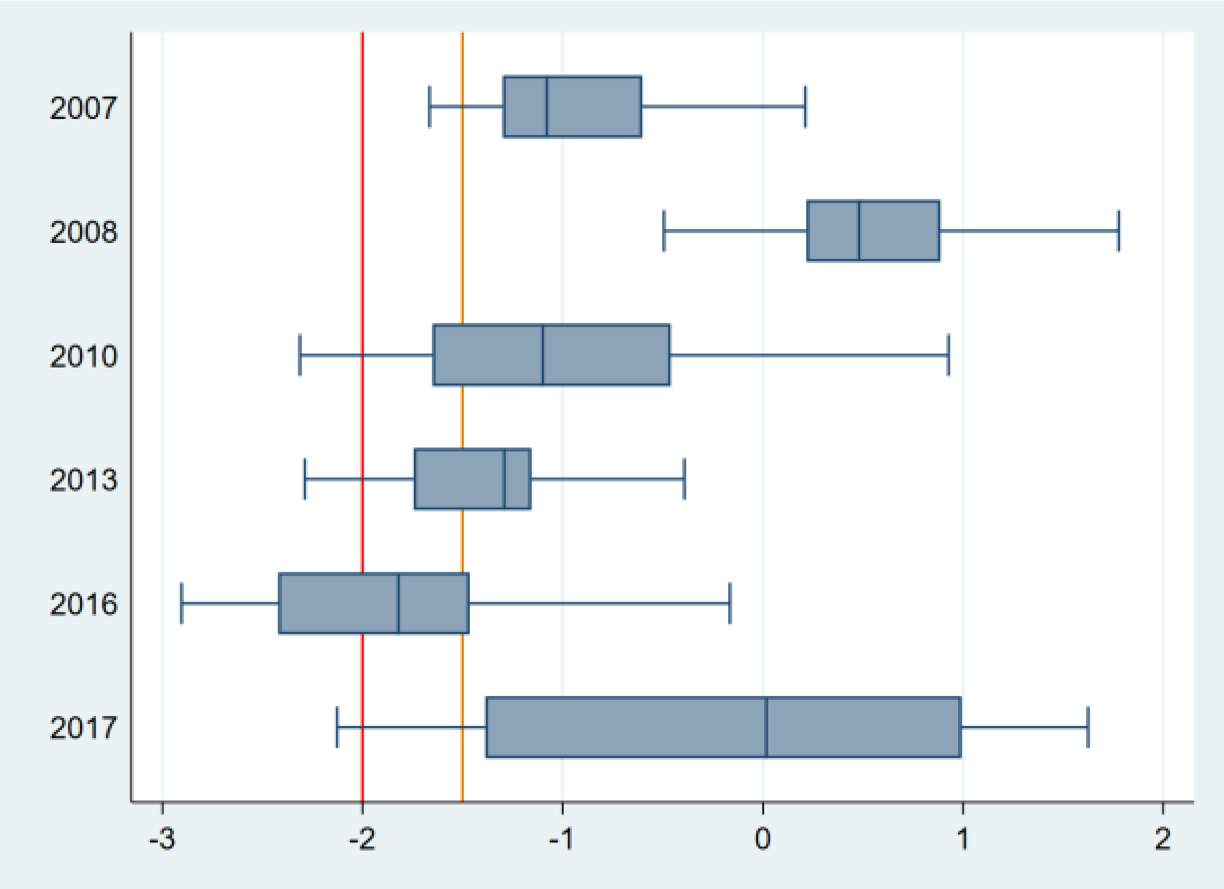

Figure 4.1 Distribution of sub-district drought severity across survey periods

Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

[24] See Table 4.A1 in the Appendix for its mean and standard deviation value and Figure 4.A7 for drought maps.

4.4 Empirical strategy

Having specified our main dependent variables representing alternative indicators of input management decisions and the main explanatory variable of a severe and extreme drought event, we specify our empirical strategy as follows.

$$Y_{ivst} = \alpha + \beta Drought_{st} + \gamma X_{it} + \delta V_{vt} + \theta_i + \sigma_v + \tau_t + \varepsilon_{ist} \qquad (1)$$

where Y_{ist} is the outcome variable representing alternative agricultural input decisions of a household i in village v and sub-district s at time t. $Drought_{st}$ is the treatment variable that measures the incidence of a drought based on the SPEI in sub-district s at time t. As described above, we use two different binary drought specifications, one that relates to a severe drought event (if the SPEI < -1.5), and one that relates to an extreme drought event (if SPEI < -2.0). X_{it} are time-variant household characteristics, including the average age of household members, the maximum education of the household head, the dependency and female ratio, and household size. V_{vt} captures time-variant village characteristics containing the total number of households in a village, the number of enterprises with more than nine employees, the distance from a village to a district town, and the infrastructure condition[25]. θ_i are household fixed effects (FEs), σ_v are village FEs, and τ_t are survey year FEs. Although the inclusion of household and village FEs goes beyond the sub-district level effect of our treatment variable, they reduce unobserved time-invariant heterogeneity at the household and village level. Finally, ε_{ist} is the error term. We cluster the standard errors at the sub-district level which corresponds to the level of our treatment variable. The coefficient of interest is β. It is identified as households within sub-districts are exposed to plausibly exogenous variations in droughts across 220 sub-districts in Thailand and Vietnam over seven survey waves between 2007 and 2017, net of time-invariant household and village characteristics that may be correlated with the agriculture input decision.

[25] See Table 4.A2 in the Appendix for a description and summary statistics of the control variables.

4.5 Results

In this section, we present the results of our empirical strategy in two sub-sections. We, first, examine the impact of droughts on farmers' input management decisions. Second, we investigate the response heterogeneity of input management decisions related to country-specific differences, and differences in topography.

4.5.1 Effect of droughts on agricultural input intensity

First, we analyze the impact of droughts on the eight different agricultural input decisions such as land, own household labor, hired labor, fertilizer and pesticides, irrigation, machinery and general agricultural investments. We hereby aggregate all households that are growing crops in the study area, and we look specifically at households that grow rice and perennial crops[26].

Figure 4.2 shows the standardized estimated β coefficient and 95% confidence interval of severe and extreme contemporary droughts as introduced in equation 1. Looking at households that grow any crop in the left panel, we find that specifically extreme droughts significantly reduce the number of crops grown per hectare, expenditures for hired labor, and expenditures for irrigation. Furthermore, extreme droughts lead to a reduction in investments in agricultural durable goods. On the other hand, households increase expenditures for fertilizer, and machinery use in response to severe droughts, and only increase machinery use in response to extreme droughts. There are, however, no significant effects related to the allocation of own household labor, and pesticide expenditures.

When we focus on rice production, we obtain similar results, except that rice growing households reduce fertilizer expenditure in response to an extreme dry spell. In contrast, households with perennial crops increase fertilizer expenditure, but only in the event of a severe drought, and not in the event of an extreme drought. In both events, they are significantly increasing spending on machinery use and hired labor.

The results, hence, suggest that in response to contemporaneous droughts, farmers rather pursue a cost-saving strategy specifically in rice production. This is understandable since lowering input use is a risk-management strategy of smallholder farmers helping minimize

[26] Main crops are defined based on the frequency of planted crops at plot level in each country. Rice is the most important crop in our sample, accounting for approximately 57% of total planted crops. Almost all rice parcels are rain-fed, the share of irrigated parcels is approximately 8%. Perennial crops are the second important crop.

financial loss in years with bad weather (Feder, Just, & Zilberman, 1985). In the case of perennial crop cultivation, however, farmers seem to intensify yield-increasing inputs in the event of a severe drought. Independent of severity they invest in mechanical inputs to endure the longer-term investment in the cash crop.

Before we compare these results with findings from similar studies, we investigate their external validity and robustness. First, since we use a balanced panel of 2,576 farm households over a eleven-year period, one major concern relates to selective attrition, e.g., households with different attitudes or skills are more likely to engage in non-farm activities in response to droughts and hence, drop out from our analytical sample.[27] To examine selective attrition in our case, we differentiate between two types of selective attrition: (i) attrition related households that were not engaged in agricultural production at baseline, and (ii) attrition related to households that were farming in 2007 but are not engaged in agricultural production in 2017. We create two binary variables of household attrition accordingly and test whether the effect our treatment variables on household attrition is statistically significant. Table 4.A4 in the Appendix shows that contemporaneous droughts are negatively associated with a household's decision to not engage in agricultural production. In other words, the negative correlation coefficient on the first attrition variable indicates that the drought event is not pushing farmers out of agriculture, but into agriculture. A closer look at the data reveals that this result is driven by 14 out of 615 households that were exposed to the drought and were not engaged in agricultural production in 2007.[28] However, the decision to leave agricultural production over time between 2007 and 2017 is not significantly related to contemporaneous drought events. As a consequence, total attrition that contains all household that are not engaged in farming since baseline, is correlated with contemporaneous droughts at the 10% level. Overall, given that the farming decision in 2007 seems to be driven by 14 households and the lack of a statistically significant correlation between drought and the farming decision over time between 2007 and 2017 suggests that our results are not driven by drought-induced attrition.

A second concern may be that our results are driven by the exclusion of income. We purposively excluded income from our set of time-variant household characteristics as income

[27] 85,96 % of households engaged in farming in 2007 and 27.16 % of households that were engaged in farming in 2007 were not farming anymore in 2017. See more details in Table 4.A3 in the Appendix.

[28] The 14 households are also clustered in Vietnam as follows: four households are from one village in Daklak and ten households are from eight villages in Ha Tinh.

could be correlated with the drought exposure and input management decisions and bias the causal estimates. Figure 4.A2 in the Appendix shows that results are not affected by the inclusion of income as an additional control variable.

Finally, we test the validity of our results that stem from the choices we made regarding the generation of our main explanatory variable, i.e., the binary drought variable based on the sub-district weighted SPEI that corresponds to the 12 months reference period of the TVSEP household survey using precipitation and temperature data at 0.5 resolution. We re-estimate equation (1) using two alternative drought variables based on (i) the 0.5 grid and clustering the standard errors at the grid level, and (ii) the sowing and growing season of rice based on farmers' information from the survey.[29] Figure 4.A3 in the Appendix shows that our results for all crops, rice and perennial crops remain unchanged when we use the SPEI at grid level. Measuring droughts in the growing season, as shown in Figure 4.A4, reveals that not all input management responses in rice production are the same. For example, while responses in terms of own household labor, irrigation, fertilizer, and machinery use remain robust, the response specifically to extreme droughts are different in terms of land intensity, pesticide use and investments in durable goods.

The comparison of our results to findings from other studies shows both differences and similarities. For example, the negative effect of droughts on the number of crops grown is different from Praneetvatakul, Phung, and Waibel (2013) that showed that farmers diversify their crop portfolio to mitigate shocks both ex-post shocks and ex-ante risk. The negative effect of droughts on irrigation is also in contrast to the finding by Koundouri et al. (2006), who found that farmers in Greece invest in modern irrigation systems to hedge against production risk. Small-scale farmers in Thailand and Vietnam, however, are located in the monsoon climate areas, where abundant rainfall is available, and the majority of farms is rain-fed[30]. In addition, the irrigation expenditure measure used in this study relates to electrical costs for pumps and accounts only for a small share of households' agricultural input costs.

With respect to similarities, our finding that households reduce the spending on hired labor in an extreme drought event aligns with Aragón, Oteiza, and Rud's (2018) findings from Peru.

[29] The rice sowing and growing season according to farmers' responses in the TVSEP survey is from May to July in Thailand and from January to June in Vietnam.
[30] There is only less than 10% of total plot are irrigated in our data. Please see Table 4.A5 in the Appendix for more detail.

Our result that less extreme droughts push fertilizer use, particularly for perennial crop production, while their use is reduced in response to more severe droughts, particularly among rice producers, is reasonable as high concentration of fertilizer can “burn” crops in the presence of extreme dry and hot conditions (Auffhammer and Kahn, 2018). Other studies also indicate that fertilizer is an input that is sensitive to precipitation and temperature variation. For example, Alem et al. (2010) find that the intensity of fertilizer use is higher in wetter (i.e., higher rainfall) than in drier (i.e., less rainfall) conditions in Ethiopia. Furthermore, Reidsma et al. (2010) find that intensive fertilizer application can largely reduce the negative effects of higher temperatures in the UK, France and Italy, while in other regions in European the effect is small or even negative.

So far, we have analyzed agricultural input decisions in response to contemporaneous droughts in the same reference period. As the onset of droughts is relatively slow and thus farmers often cannot fully assess the extent of the drought at the time they make their input decisions, we next examine the effects of droughts that occurred in the previous year.

Figure 4.A5 in the Appendix presents the results. In response to a drought in the previous year farmers also reduce the number of crops grown per hectare, irrigation expenditure, and investments. We can also identify a significant decrease in pesticide expenditures both in the case of perennial and annual crop cultivation. In addition, as contemporaneous droughts pushed fertilizer and machinery use among perennial crop farmers, in the case of past droughts these effects turn insignificant and even negative, respectively. In other words, the exposure to a drought in previous year, manifests the input saving rationale among both perennial and annual crop farmers.

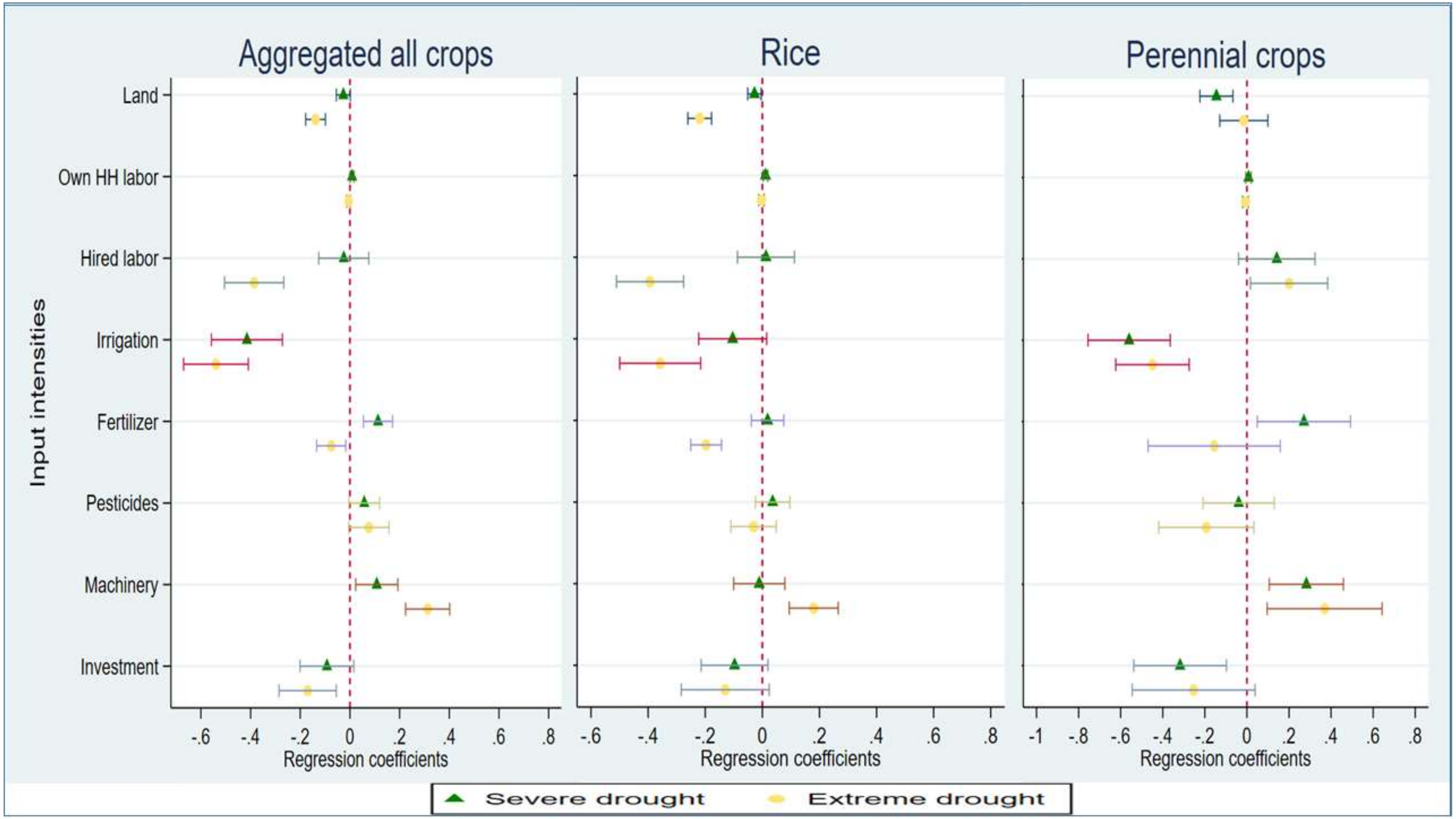

Figure 4.2 Impact of contemporary drought at severe level (SPEI < -1.5) and extreme level (SPEI < - 2.0) on input use

Note: N of aggregated all crops= 15,456; N of rice = 13,325; N of Perennial crops= 6,052.
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

4.5.2 Heterogeneity

Complementary to our investigation of the overall relationship between drought episodes and agricultural input use described above, we investigate in this sub-section whether the effect of droughts on input management varies between countries and between upland and lowland rice farming.

4.5.2.1 Country differences

The impact of extreme weather events on smallholder agriculture will vary across countries due to their location-specificity (Morton, 2007). Therefore, investigating the heterogeneous response of small farm households to weather shocks at the country level is crucial **(**Maharjan & Joshi, 2013; Carter et al., 2018).

Figure 4.3 shows the impact of contemporaneous droughts separately for Thailand and Vietnam. One can observe that reducing input use in response to droughts is highly divergent between the two countries and the type of crops grown. For example, the reduction of number of crops grown in response to contemporaneous droughts is practiced among perennial crop growers in Thailand, and among rice growers in Vietnam.

Furthermore, Thai rice growers increase own household labor and expenditures for hired labor in response to severe droughts but reduce expenditures in the face of extreme droughts[31]. In contrast, Vietnamese perennial crop growers intensify hired labor in both events.

Before splitting the sample between Thailand and Vietnam, irrigation expenditures were negatively affected by droughts. Now we can see that both Thai and Vietnamese farmers that grow perennial crops actually increase irrigation expenditures when exposed to an extreme dry spell.

When we look at chemical input intensification, we can also see a number of interesting differences. In Thailand, rice growers reduce fertilizer application, but increase pesticide application, while perennial crop growers intensify the use of both fertilizer and pesticides. In Vietnam, we can observe the opposite behavior, i.e., rice growers intensify fertilizer applications, and perennial crop growers reduce fertilizer applications.

The use of machinery is intensified by both Thai and Vietnamese rice growers, although different reactions should be noted between severe and extreme droughts by Thai rice growers.

[31] The coefficient of own household labor is very small (0.016), but statistically significant at 5% level (see Table 4.A6 in the Appendix for detail).

Thai farmers that grow perennial crops, however, increase machinery expenditure in response to both severe and extreme droughts.

Finally, in the previous section it has been observed that droughts lead to a de-investment behavior. Splitting the sample now between Thailand and Vietnam, we can observe this de-investment behavior specifically among Vietnamese rice farmers.

At this stage, the investigation of diverse contemporaneous drought impacts showed that Thai perennial crop farmers are intensifying particularly irrigation, chemical applications, and machinery use. Vietnamese perennial farmers also intensify irrigation, but - in contrast to Thai farmers - focus on hired labor and reduce fertilizer use. Rice farmers in Thailand substitute hired labor and fertilizer for pesticide and machinery when faced to extreme droughts, while Vietnamese rice farmers intensify specifically fertilizer use.

When one looks at the effects of droughts in the previous year, however, most input intensification effects among Thai perennial crop growers turn insignificant (see Figure 4.A6 in the Appendix). One can only observe a significant increase in own household labor allocated to perennial crop production. Similarly, Thai farmers also intensify own agricultural labor and hired labor in rice production. In Vietnam, droughts in the previous year lead to a significant reduction in hired labor, irrigation expenditures, pesticides and machinery use in perennial crop production. Severe droughts, however, can trigger investments in durable agricultural goods. Vietnamese rice farmers differentiate their input decisions between severe and extreme drought events in the previous year. While they are increasing pesticide use, machinery use and investments in the face of severe lagged droughts, they are decreasing hired labor, machinery use and investments in response to extreme lagged droughts.

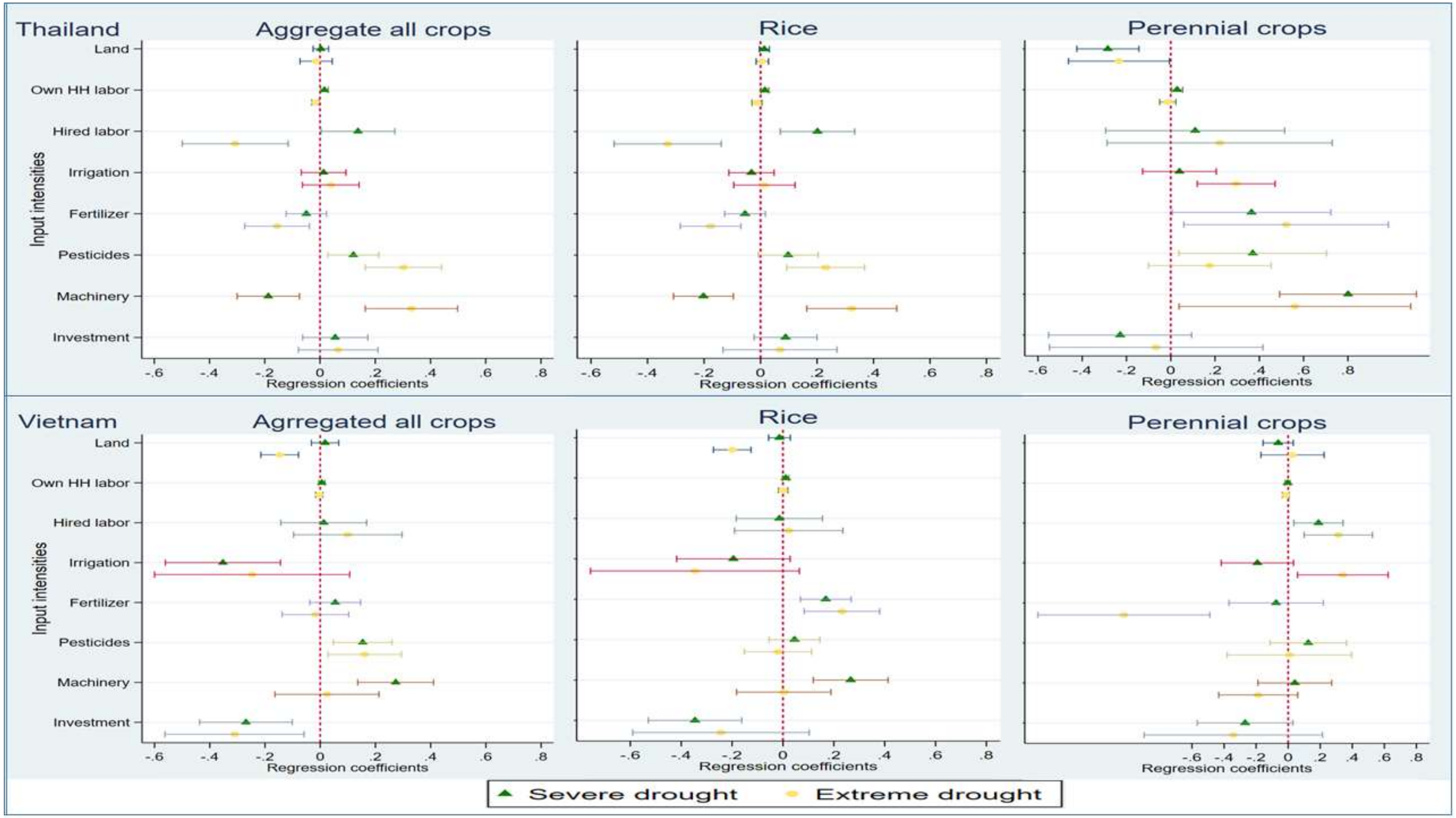

Figure 4.3 Impact of contemporaneous drought severities on input use in Thailand and Vietnam

Note: N of aggregated all crops= 7,212; N of rice = 6,958; N of Perennial crops= 1,381 in Thailand. N of aggregated all crops= 8,244; N of rice = 6,367; N of Perennial crops= 4,671 in Vietnam.

Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

4.5.2.2 Lowland and upland rice

Rice ecosystems are generally classified into irrigated, deep-water, rain-fed lowland and rain-fed upland rice (Poehlman, 2013). Due to the topography, deep-water and rain-fed are the two predominant rice systems in Thailand and Vietnam. In our sampled provinces in Northeastern Thailand and Central and Central Highlands of Vietnam, rice fields are mostly rain-fed, whereby the majority is found in the lowlands.

Lowland and upland farms exhibit a variety of soil characteristics, and are significantly affected by drought situations. For that reason, we examine the heterogeneity of drought effects on input management decisions by differentiating between lowland and upland rice farms in this sub-section.

To distinguish between lowland and upland farm, we extract the elevation information of our sample at the village level from Digital Elevation Model (DEM) via ArcGIS. We then apply the widely used upland farm threshold, which is 200 meters above sea level[32].

Figure 4.4 shows the results for contemporaneous and lagged drought events. In response to contemporaneous droughts, both lowland and upland rice farmers reduce the number of crops grown per hectare, hired labor, irrigation, and fertilizer expenditures. In contrast to lowland farmers, upland farmers also decrease machinery use and investments. Furthermore, upland farmers push pesticide expenditures, while lowland farmers push machinery use.

With respect to droughts in the previous year, lowland rice farmers cut back on the same inputs as in response to contemporaneous droughts, including also significant reductions in pesticides and investments. However, lowland farmers who experience an extreme drought in the previous year significantly increase irrigation expenditures. This is not the case for upland rice farms. Typically, in upland rice there is no artificial irrigation (Poehlman, 2013). Farmers operating on upland rice farms intensify different inputs such as pesticides, machinery, and investments in durable goods.

[32] See Table 4.A7 the appendix for the detail description of upland and lowland rice farms information.

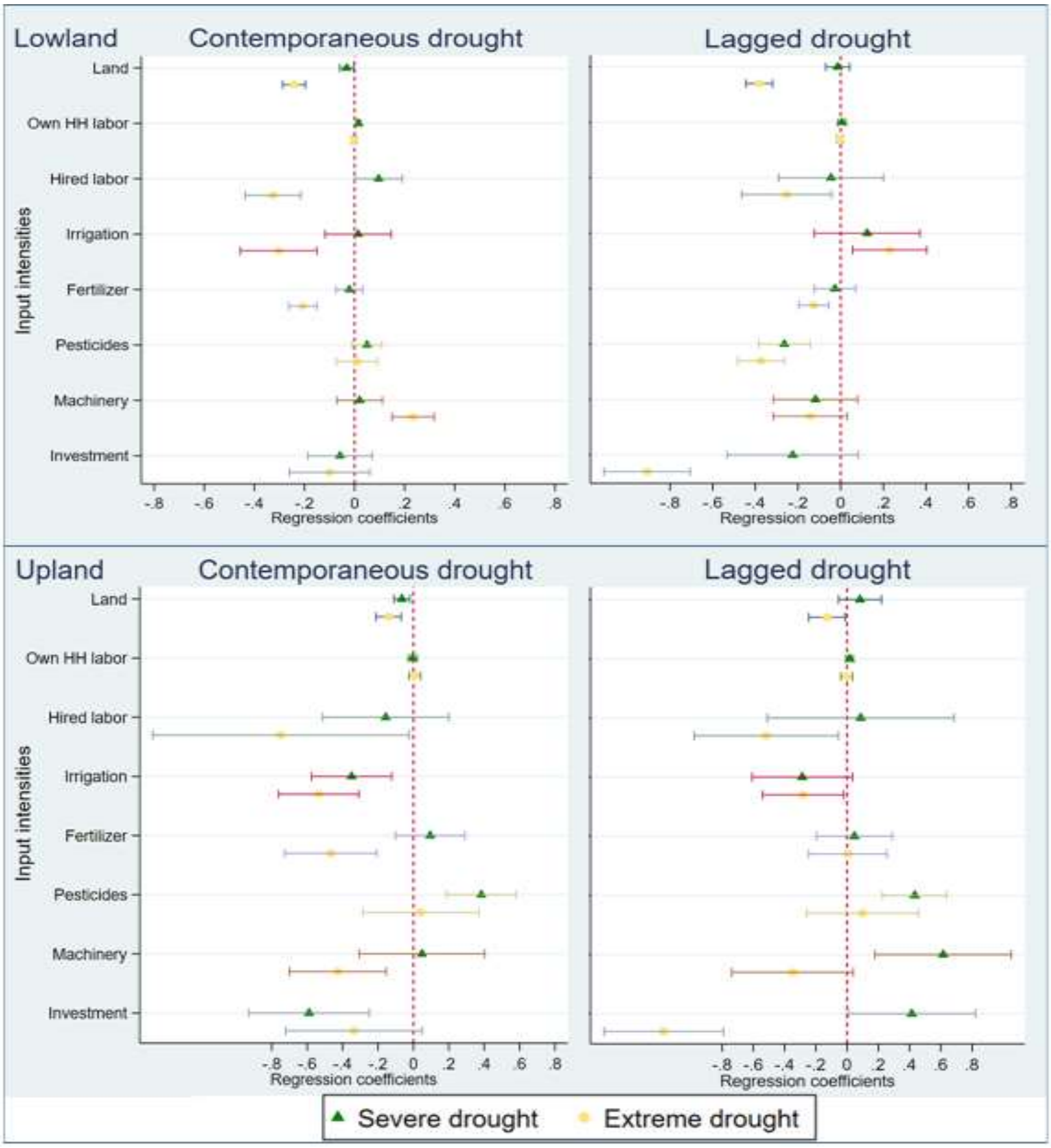

Figure 4.4 Impact of contemporaneous and lagged droughts on input use between lowland and upland rice farms

Note: N of lowland rice = 10,841 & N of upland rice = 2,484.
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

4.6 Summary and policy implications

Severe and extreme droughts have become more frequent in the last decades, in Thailand and Vietnam. The main objective of this study was to shed light on the relationship between drought and agricultural input management. We investigated the impact of severe and extreme drought events on eight agricultural input types such as the number of crops grown, allocation of own household labor, hired labor, irrigation, chemical inputs such as pesticides and fertilizer, machinery use, and investments in durable agricultural goods.

To this end, we combined the comprehensive TVSEP household panel data set with a sub-district weighted drought indicator based on historical precipitation and temperature data. We compared households' responses in agricultural input management to severe and extreme dry spells across six survey waves between 2007 and 2017 and 220 sub-districts in Northeastern Thailand and Central Vietnam. Our empirical specification considers household-specific time-invariant heterogeneity that may be correlated with drought exposure and input decisions.

Our analysis showed that droughts have a statistically significant negative effect on input intensity. In most cases farmers respond to the increased risk of drought with a reduction in the number of crops grown per hectare, irrigation expenditure, and investments in durable goods. Yield-enhancing inputs such as fertilizers are used only when drought conditions are less severe. Under more extreme conditions, the focus is on mechanical inputs such as machinery use for soil management and harvesting. In addition, droughts have dynamic effects, as the previous year's drought can even undermine mechanical inputs, thereby cementing the input saving rationale.

Investigating country-specific heterogeneity showed that farmers in the three provinces in Northeast Thailand increase labor inputs, both family and hired labor. On the other hand, farmers in the three provinces in Central Vietnam increase agricultural investments to mitigate the effects of drought.

Finally, we also investigated differences in input management between lowland and upland rice production. As upland rice farms suffer more from drought than lowland rice farms that have irrigation possibilities, upland farmers focus on machinery use and investments in durable goods such as water tanks and pumps. Lowland farmers increase spending on available irrigation facilities.

As regards policy implications, rising drought risks in some parts of Southeast Asia increases the downside risks for famers and, hence, agricultural production and income can become more uncertain in the future which can have severe consequences for food security. Therefore, more social protection for example through community-level emergency funds and affordable crop insurance schemes based on weather indices are needed. For example, Sikibo & Qaim (2020) found that crop insurance can be an essential ingredient in agricultural growth and rural development strategies against the background of rising climate uncertainties.

Governments may also undertake investments in the rehabilitation of existing irrigation schemes or establishing new irrigation systems wherever possible and ecologically justifiable. Most importantly water in agriculture must be used much more efficiently than in the past. This can be achieved through advanced irrigation technologies such as drip irrigation. Equally important is the development of drought-tolerant germplasm and water-saving crop management practices which require more investment in location-specific agricultural research to be complemented by participatory farmer training approaches. Further, the governments of Thailand and Vietnam should pay more attention to extreme droughts, develop drought mapping and forecasting, and establish forecasting and early warning systems at communal level.

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Appendix

Table 4.A1 Descriptive statistics of the different severities of the explanatory variable

	2007	2008	2010	2013	2016	2017
Standardized precipitation evapotranspiration index(SPEI)	-0.958 (0.453)	0.574 (0.579)	-0.891 (0.938)	-1.429 (0.400)	-1.834 (0.630)	-0.195 (1.190)
Drought at SPEI < -1.5	0.068 (0.252)	0	0.282 (0.450)	0.388 (0.487)	0.738 (0.439)	0.210 (0.407)
Drought at SPEI < - 2	0	0	0.142 (0.349)	0.090 (0.286)	0.432 (0.495)	0.010 (0.099)
N	2,576	2,576	2,576	2,576	2,576	2,576

Note: Standard deviation in parenthesis.
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

Table 4.A2 Definition and summary statistic of other control variables in the regression analysis

Variable	Description	2007	2008	2010	2013	2016	2017
Household							
Mean age	Average age of household members (years)	30.646	31.039	31.946	35.065	37.621	38.224
		(10.207)	(9.912)	(9.659)	(10.979)	(11.991)	(12.358)
Max. education	Maximum year of education of household head	8.921	9.185	9.776	9.842	10.279	10.203
		(3.256)	(3.256)	(3.267)	(3.456)	(3.571)	(3.659)
Dependency ratio	The number of dependent household member (above 15 and below 64) divided by the number of independent household member (below 15 and above 64)	0.314	0.301	0.278	0.270	0.274	0.285
		(0.219)	(0.217)	(0.216)	(0.232)	(0.250)	(0.256)
Female ratio	The number of female divided by the number of household size.	0.502	0.502	0.504	0.503	0.506	0.508
		(0.172)	(0.170)	(0.168)	(0.177)	(0.179)	(0.181)
Household size	The total members of the nucleus household.	5.107	5.287	5.523	5.042	4.757	4.744
		(1.744)	(1.827)	(1.937)	(1.797)	(1.756)	(1.770)
Village							
Number of households	The total number of households in the village.	152.397	152.397	158.128	175.800	184.602	184.602
		(105.868)	(105.868)	(101.921)	(106.033)	(108.620)	(108.620)
Outside working members	The percentage of villagers working outside the province.	0.227	0.227	0.220	0.165	0.208	0.208
		(0.215)	(0.215)	(0.214)	(0.160)	(0.213)	(0.213)
Enterprises, factors	The number of enterprises, factors having more than 9 employees in the village	0.101	0.100	0.117	0.223	0.310	0.310
		(1.212)	(1.212)	(0.547)	(0.891)	(1.183)	(1.183)
Distance	The distance from villages to district towns in Km.	13.783	13.783	13.357	12.913	12.574	12.574
		(9.237)	(9.237)	(8.991)	(8.562)	(9.104)	(9.104)
Paved road (dummy)	Main road is paved road= 1, otherwise=0.	0.627	0.627	0.758	0.745	0.907	0.907
		(0.483)	(0.483)	(0.428)	(0.435)	(0.290)	(0.290)
N		2,576	2,576	2,576	2,576	2,576	2,576

Note: Standard deviation in parenthesis.
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

Table 4.A3 Household attrition

Household sample at baseline (2007)	Farming decision at baseline 2007			Left farming 2007- 2017		Total attrition	
	Farm households	Non-farm households	Attrition rate (%)		Attrition rate (%)		Attrition rate (%)
4381	3,766	615	14.04	1,190	27.16	1,805	41.20

Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

Table 4.A4 Attrition bias analysis – only treatment variables

Dependent variables: HH dropped out of	Farming decision at baseline	Left farming 2007- 2017	Total attrition
Severe drought$_t$	-0.091*** (0.020)	-0.033 (0.047)	-0.094* (0.054)
N	4,381	3,766	4,381

Note: No extreme drought in 2007. Standard deviation in parenthesis. Single, double, and triple asterisks (*, **, ***) denote p < 0.10, 0.05, and 0.01, respectively. Standard errors are clustered at the sub-district level.
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

Table 4.A5 Descriptive statistic of the share of irrigated rice crops

	2007	2008	2010	2013	2016	2017
The share of irrigated rice plots	0.076	0.087	0.106	0.051	0.072	0.091
N	2,247	2,260	2,253	2,208	2,205	2,185

Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

Table 4.A6 Impact of contemporaneous drought severity on crop input intensity (In the correlation with Figure 4.3)

		Land (# of crops)(ln)	Domestic labors(ln)	Labor (ln)	Irrigation (ln)	Fertilizer (ln)	Pesticides (ln)	Machinery (ln)	Investment (ln)
Thailand									
All crops	Severe	0.002	0.016**	0.137*	0.013	-0.049	0.120**	-0.187***	0.055
	Drought_t	(0.016)	(0.007)	(0.080)	(0.048)	(0.044)	(0.055)	(0.067)	(0.071)
	Extreme	-0.014	-0.016*	-0.307***	0.039	-0.155**	0.301***	0.331***	0.065
	Drought_t	(0.035)	(0.010)	(0.115)	(0.061)	(0.070)	(0.083)	(0.100)	(0.111)
	N	7,212	7,212	7,212	7,212	7,212	7,212	7,212	7,212
Rice	Severe	0.013	0.015*	0.201**	-0.032	-0.054	0.098	-0.202***	0.088
	Drought_t	(0.010)	(0.008)	(0.079)	(0.048)	(0.043)	(0.063)	(0.063)	(0.066)
	Extreme	0.006	-0.012	-0.328***	0.013	-0.176***	0.230***	0.322***	0.069
	Drought_t	(0.013)	(0.010)	(0.114)	(0.065)	(0.064)	(0.083)	(0.095)	(0.121)
	N	6,958	6,958	6,958	6,958	6,958	6,958	6,958	6,958
Perennial crops	Severe	-0.284***	0.028*	0.110	0.039	0.364*	0.370*	0.800***	-0.228
	Drought_t	(0.084)	(0.015)	(0.243)	(0.100)	(0.215)	(0.200)	(0.185)	(0.194)
	Extreme	-0.234*	-0.013	0.220	0.295***	0.520*	0.176	0.560*	-0.065
	Drought_t	(0.137)	(0.021)	(0.306)	(0.105)	(0.278)	(0.167)	(0.315)	(0.290)
	N	1,381	1,381	1,381	1,381	1,381	1,381	1,381	1,381
Vietnam									
All crops	Severe	0.017	0.005	0.012	-0.352***	0.054	0.153**	0.273***	-0.268***
	Drought_t	(0.029)	(0.006)	(0.093)	(0.125)	(0.055)	(0.064)	(0.082)	(0.101)
	Extreme	-0.146***	-0.003	0.099	-0.246	-0.017	0.161**	0.024	-0.310
	Drought_t	(0.041)	(0.010)	(0.118)	(0.213)	(0.072)	(0.080)	(0.113)	(0.195)
	N	8,244	8,244	8,244	8,244	8,244	8,244	8,244	8,244
Rice	Severe	-0.013	0.010	-0.014	-0.194	0.168***	0.045	0.266***	-0.345***
	Drought_t	(0.025)	(0.007)	(0.102)	(0.134)	(0.060)	(0.060)	(0.088)	(0.110)
	Extreme	-0.199***	0.000	0.022	-0.345	0.231**	-0.019	0.003	-0.243
	Drought_t	(0.044)	(0.010)	(0.128)	(0.247)	(0.089)	(0.079)	(0.111)	(0.208)
	N	6,367	6,367	6,367	6,367	6,367	6,367	6,367	6,367
Perennial crops	Severe	-0.062	-0.003	0 .188**	-0.192	-0.075	0.125	0.041	-0.268
	Drought_t	(0.056)	(0.009)	(0 .092)	(0.135)	(0.177)	(0.143)	(0.138)	(0.179)
	Extreme	0.027	-0.015	0.312**	0.340**	-1.025***	0.007	-0.186	-0.342
	Drought_t	(0.118)	(0.012)	(0.128)	(0.170)	(0.323)	(0.233)	(0.148)	(0.335)
	N	4,671	4,671	4,671	4,671	4,671	4,671	4,671	4,671

Note: Single, double, and triple asterisks (*, **, ***) denote $p < 0.10$, 0.05, and 0.01, respectively. Standard errors are clustered at the sub-district level.
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

Table 4.A7 Descriptive statistics of upland and lowland areas

	Thailand		Vietnam		Pooled	
	N	Percentage	N	Percentage	N	Percentage
Up land (elevation >= 200 m asl)	384	5.32	3,600	43.67	3,984	25.78
Low land (elevation < 200 m asl)	6,828	94.68	4,644	56.33	11,472	74.22
Sum	7,212	100	8,244	100	15,456	100

Note: Upland and lowland are defined based on elevation information which is extracted from GPS information (longitude and latitude) by ArcGIS. Asl= above sea level
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

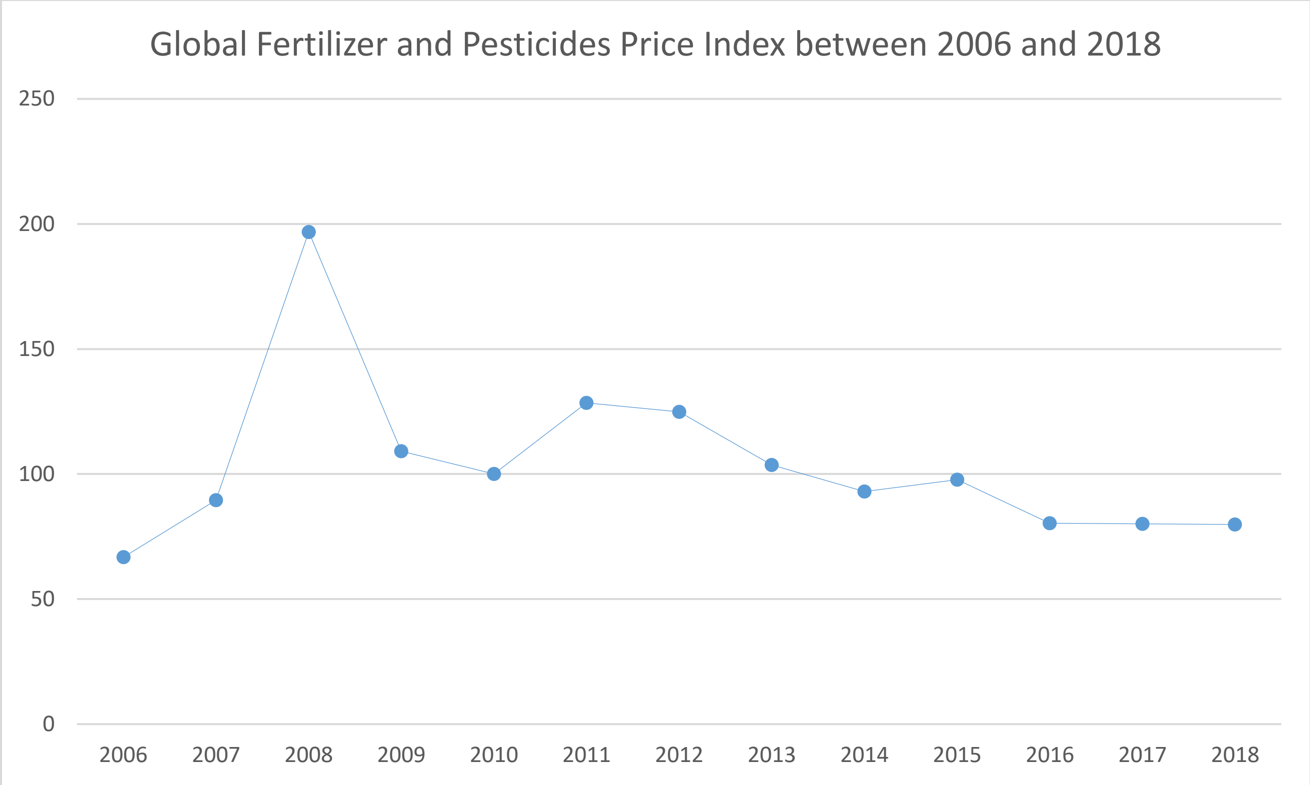

Figure 4.A1 Global Fertilizer Price Index

Note: Global fertilizer and pesticides price index, measured relative to real price in 2010 (where 2010=100).
Source: World bank, 2017

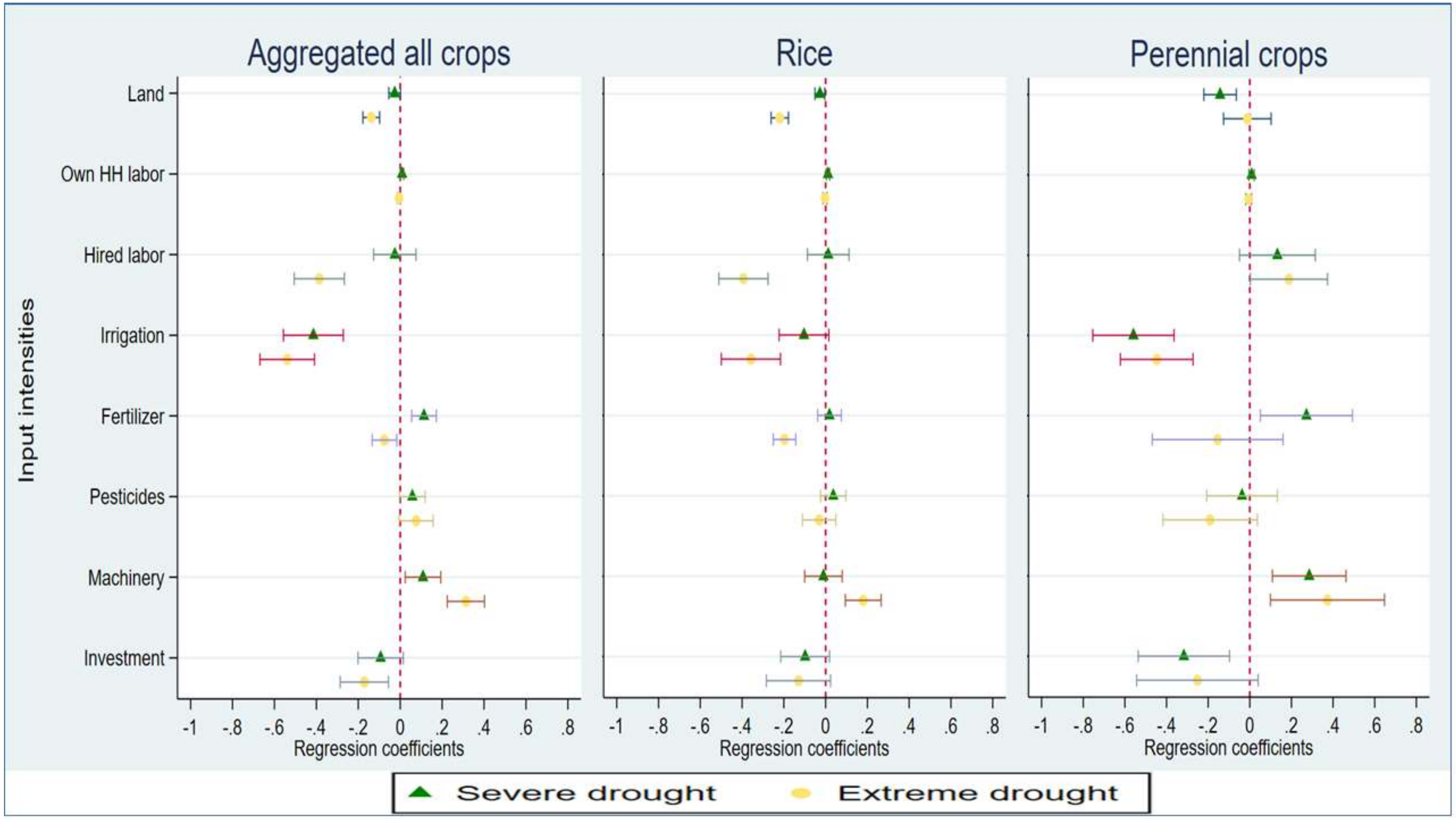

Figure 4.A2 Impact of contemporary drought at severe level (SPEI < -1.5) and extreme level (SPEI < -2.0) on inputs use, including income as additional control variable

Note: N of aggregated all crops= 15,456; N of rice = 13,325; N of Perennial crops= 6,052.

Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

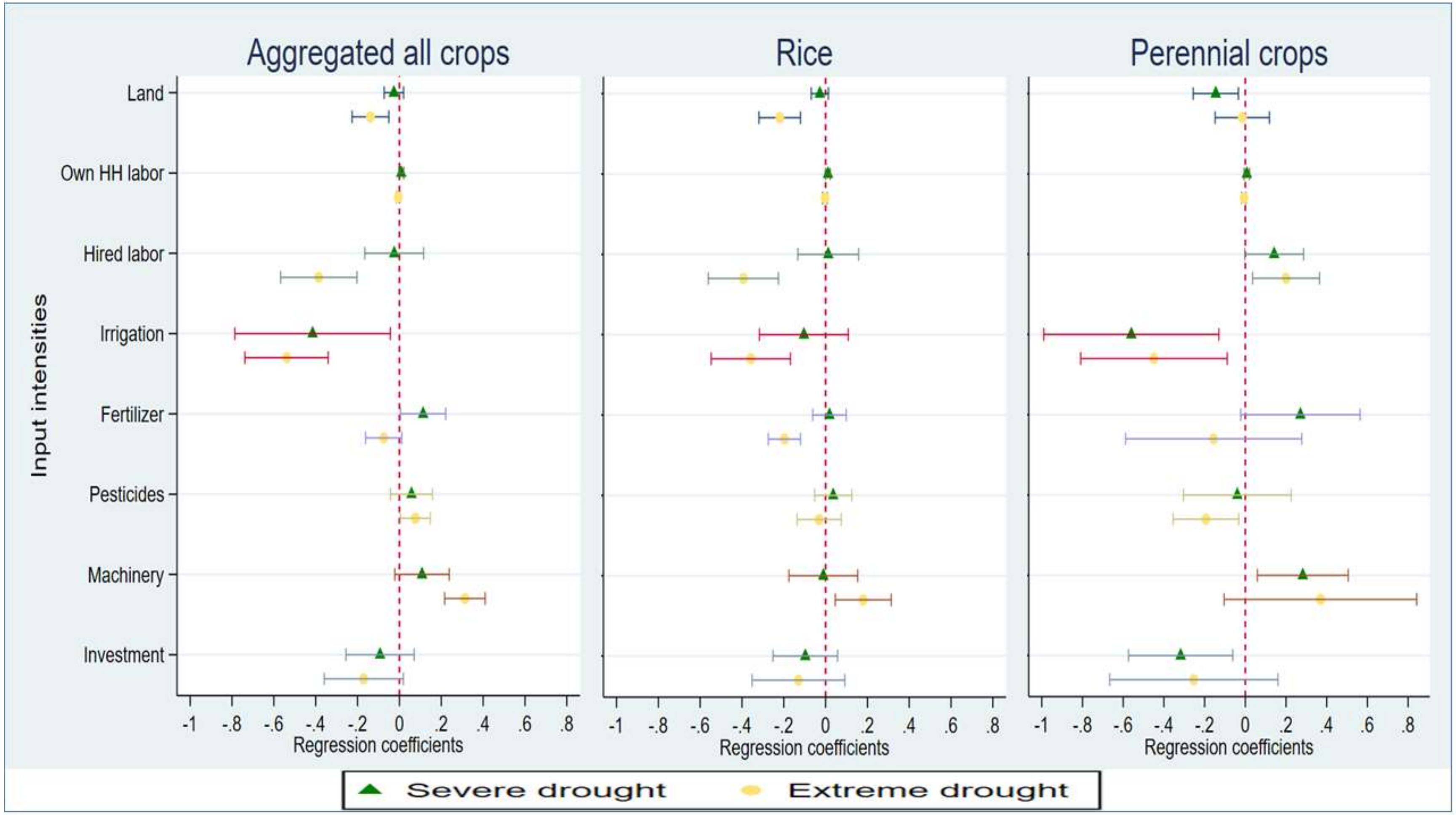

Figure 4.A3 Impact of contemporary drought at severe level (SPEI < -1.5) and extreme level (SPEI < -2.0) on inputs use, cluster at grid level

Note: N of aggregated all crops= 15,456; N of rice = 13,325; N of Perennial crops= 6,052.
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

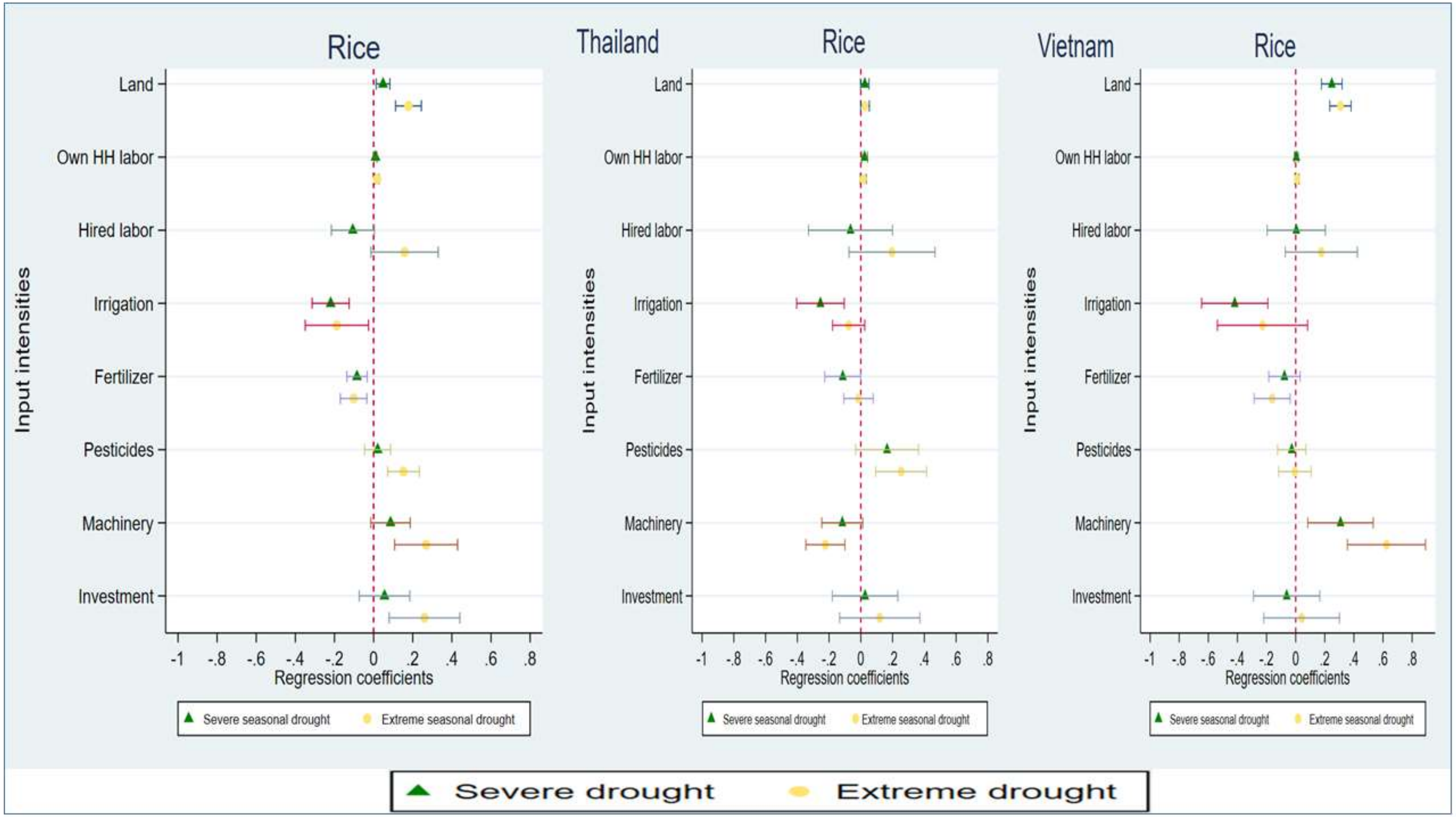

Figure 4.A4 Impact of contemporary drought at severe level (SPEI < -1.5) and extreme level (SPEI < -2.0) in the growing season on inputs use

Note: N of rice of pooled data= 13,325. N of rice in Thailand= 6,958. N of rice in Vietnam=6,367.
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

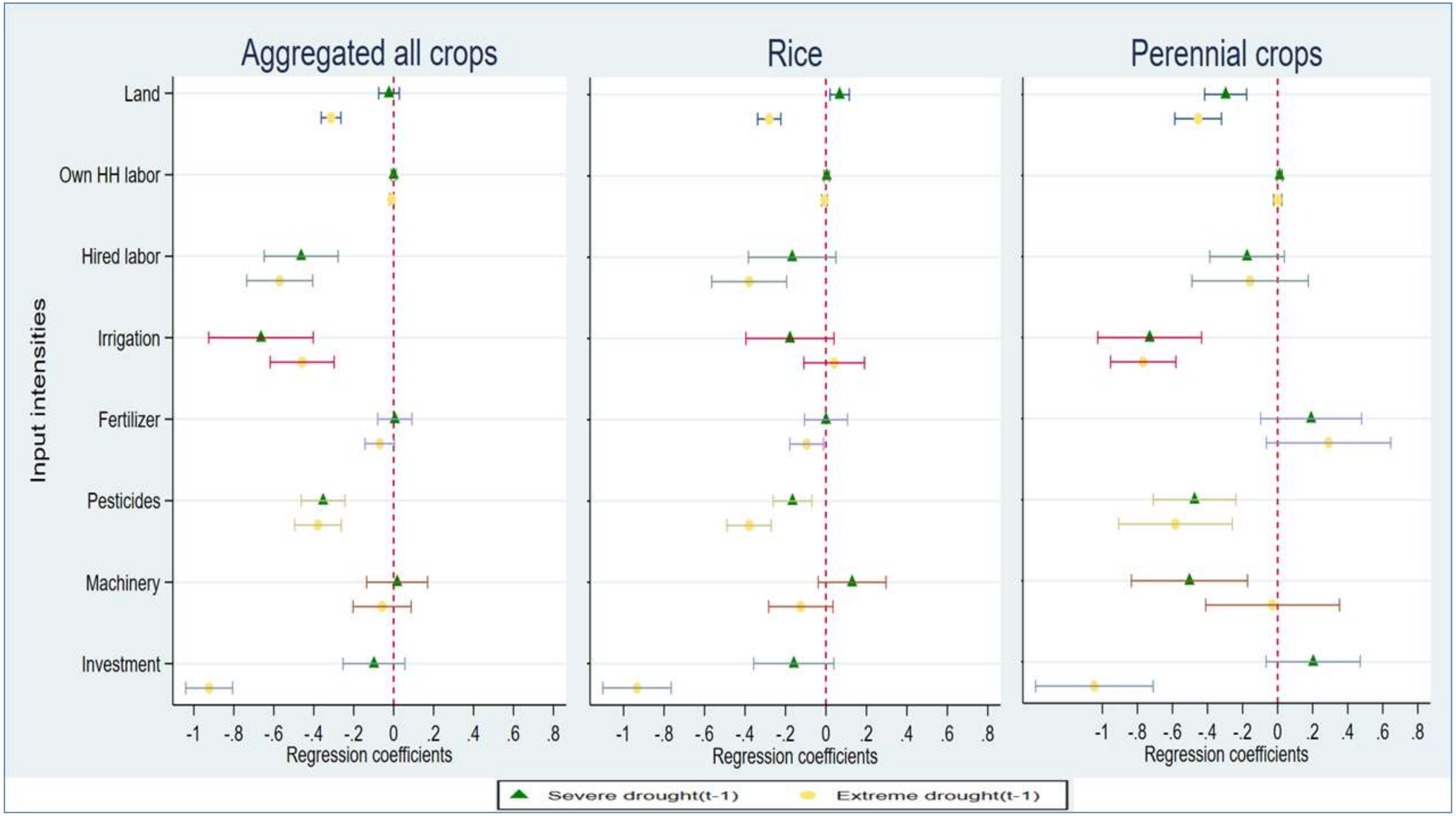

Figure 4.A5 Impact of one -year lagged drought severities on input use

Note: N of aggregated all crops= 15,456; N of rice = 13,325; N of Perennial crops= 6,052.
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

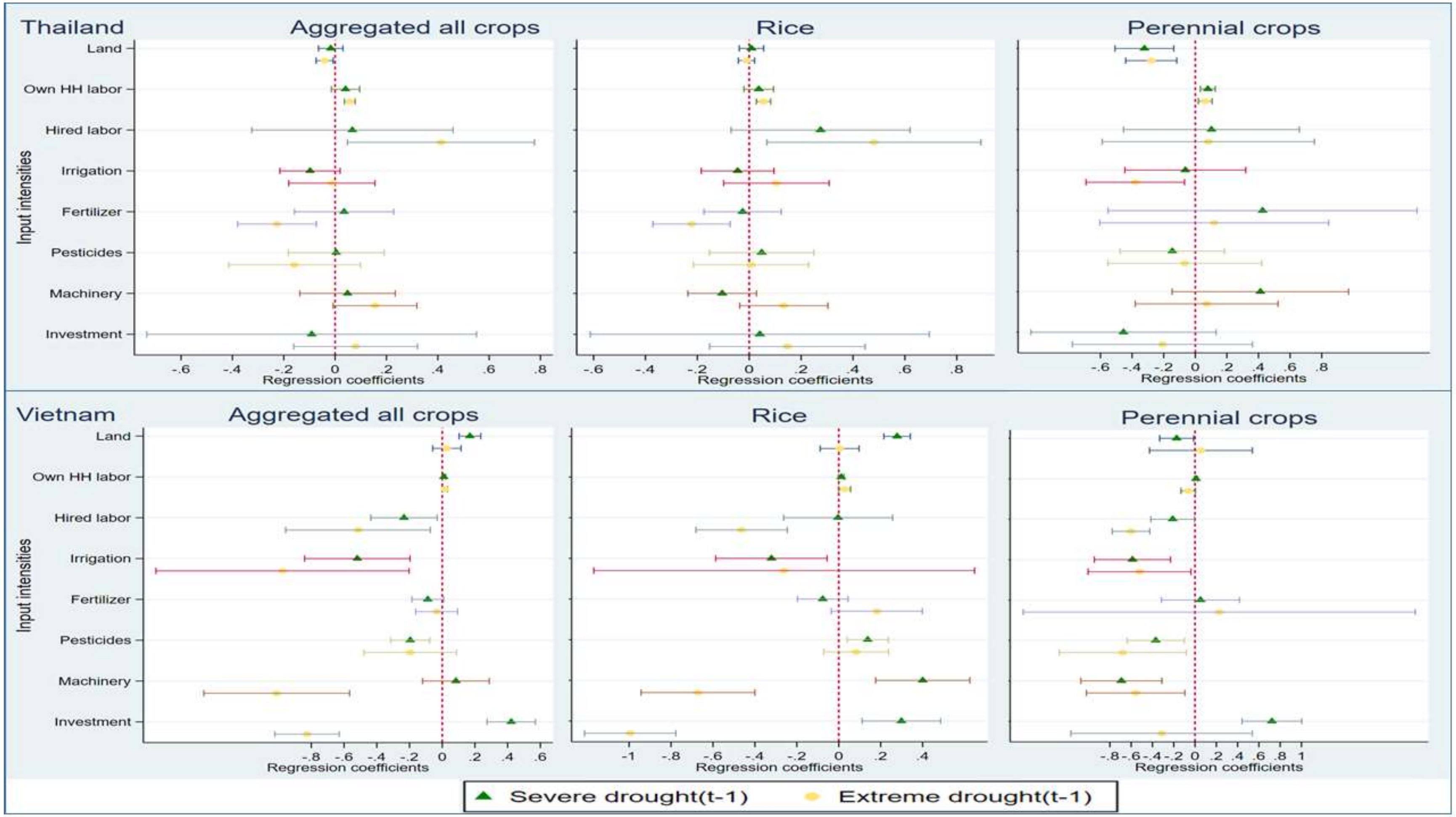

Figure 4.A6 Impact of one-year lagged of drought severities on input use in Thailand and Vietnam

Note: N of aggregated all crops= 7,212; N of rice = 6,958; N of Cassava= 794; N of Perennial crops= 1,381 in Thailand.
N of aggregated all crops= 8,244; N of rice = 6,367; N of Cassava= 1,051; N of Perennial crops= 4,671 in Vietnam.
Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.

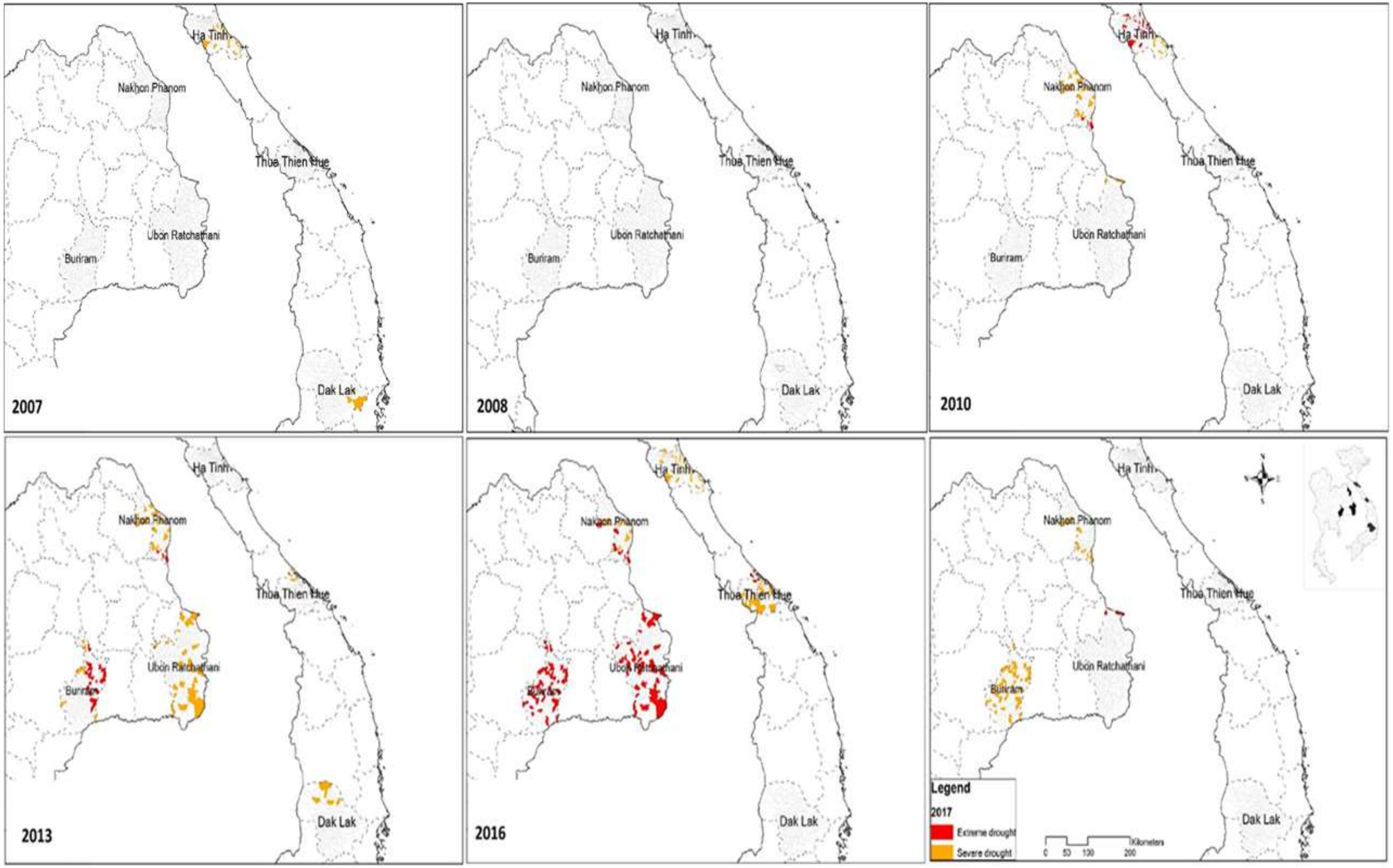

Figure 4.A7 Maps of severe and extreme drought between 2007 and 2017

Source: TVSEP survey 2007, 2008, 2010, 2013, 2016, 2017, own calculations.